Generative Adversarial Network Enabled Sparse Signal Compression and Recovery for Internet of Medical Things

Tiankuo Wei
weitk@stu.xmu.edu.cn
Xiamen University
Xiamen, Fujian, China

Danping Su
sudanping@stu.xmu.edu.cn
Xiamen University
Xiamen, Fujian, China

Sicong Liu*
liusc@xmu.edu.cn
Xiamen University
Xiamen, Fujian, China

ABSTRACT

Due to the limitation of energy supply and the requirements of high reliability in the mission-critical Internet of Medical Things (IoMT), the efficient and reliable transmission of the sensing siganl of implantable medical devices (IMDs) is still a challenge. In order to improve the spectrum efficiency and transmission reliability, in this paper, a Generative Adversarial Network-enabled Sparse Compression and Recovery (GAN-SCR) scheme is proposed by exploiting the physical knowledge of sparsity, which compressively measures the sparse IMD sensing signal in the transmitter, and recovers the sensing signal in the receiver. In the stage of sparse measurement in the proposed GAN-SCR scheme, a pre-trained measurement discriminative network (MDN) is used to conduct signal compression at the transmitter, which enhances the restricted isometry property via learning. In the stage of sparse recovery, exploiting the temporal correlation and inherent sparsity of physiological signals, a pre-trained representation generative network (RGN) is used to map the sensing signal to a low-dimensional latent vector for sparse representation learning. Subsequently, the projection from the latent vector onto the measurement vector is structured by jointly training an RGN and an MDN, by which accurate signal recovery can be implemented via online optimization. Simulation results verify that the proposed GAN-SCR scheme outperforms other state-of-art sparse reconstruction algorithms in the accuracy of sensing signal recovery.

CCS CONCEPTS

• **Human-centered computing** → *Empirical studies in ubiquitous and mobile computing*; *Ubiquitous and mobile devices*; • **Networks** → *Mobile ad hoc networks.*

KEYWORDS

Generative Adversarial Network, compressed sensing, reprensentation learning, Internet of Medical Things, sparse deep learning

*Corresponding author.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.
UbiComp/ISWC '21 Adjunct, September 21–26, 2021, Virtual Event, Global
© 2021 Copyright held by the owner/author(s). Publication rights licensed to ACM.
ACM ISBN 978-1-4503-8461-2/21/09…$15.00
https://doi.org/10.1145/3460418.3480404

ACM Reference Format:
Tiankuo Wei, Danping Su, and Sicong Liu. 2021. Generative Adversarial Network Enabled Sparse Signal Compression and Recovery for Internet of Medical Things. In *Adjunct Proceedings of the 2021 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2021 ACM International Symposium on Wearable Computers (UbiComp/ISWC '21 Adjunct), September 21–26, 2021, Virtual Event, Global.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3460418.3480404

1 INTRODUCTION

In recent years, owing to the extension of human life expectancy and the acceleration of workforce aging, the risk of non-communicable diseases, such as heart disease, stroke and cancer, is continuously rising [14]. With the development of the Internet of Medical Things (IoMT), personalized and interconnected devices are commonly used in the area of healthcare [11]. Recently, the implantable medical device (IMD) has demonstrated its advantages in health monitoring and remote treatment with portability, proactivity, immediacy. An IMD is a medical device that works in/on the body, which can record and track the vital physiological data of the user and make it accessible to doctors, caregivers and relatives [18]. Timely and comprehensive treatment is enabled without the need for the disappointing long-term hospital staying, which is beneficial to patients. In order to enable doctors to remotely access medical data, wireless communication is used for the transmission of sensing signals. However, the IMD device is usually powered by a battery, and it is expected to work in the body for a long time because it is surgically inserted into the patient's body. Therefore, for such an energy-limited and long-term-intended device, it is necessary to adopt an efficient transmission system to improve the spectral efficiency and reduce the energy consumption.

Therefore, the flexible and efficient compressed sensing (CS) [5] technique can be considered, which can perform compression and sensing simultaneously by exploiting the sparse characteristics of the medical sensing signal. Utilizing the CS technology, high-dimensional sparse sensing signals can be measured and compressed into a vector with a much lower dimension in the IMD. Then, the original sensing signal can be approximately recovered at the receiver using sparse reconstruction algorithms. In the framework of CS, the spectrum efficiency can be improved and the energy consumption can be reduced [4, 7, 10], which is helpful to prolong the life of IMDs.

In the traditional CS framework, the measurement operation is generally implemented using a random matrix, such as Gaussian measurement matrix, and the reconstruction is usually performed by iterative sparse reconstruction algorithms, such as Orthogonal Matching Pursuit (OMP) [16], Subspace Pursuit (SP) [15] and

Approximate Message Passing (AMP) [1], etc. In order to further improve the reconstruction performance, many learning-based sparse recovery methods have been proposed [3, 8, 9], such as the generative model based methods [2], to learn about the inherent sparse features of the signals. Recently, the emerging Generative Adversarial Network (GAN) [6] is introduced into the framework of CS, which uses pre-trained generative and discriminative neural networks for the purpose of measurement and sparse representation, respectively [17]. The GAN-based framework can improve the recovery accuracy and accelerate the inference process compared with traditional iterative algorithms [12].

Therefore, an efficient and reliable sensing signal transmission scheme for IoMT is proposed in this paper, which uses the GAN-enabled CS architecture for measurement and representation learning of the IMD sensing signal to improve the spectral efficiency and transmission reliability. Specifically, a GAN enabled Sparse Compression and Reconstruction (GAN-SCR) scheme is proposed, in which a pre-trained neural network is used for compressive measurement to improve the spectrum efficiency and reduce the energy consumption. A representation generative network (RGN) and a measurement discriminative network (MDN) are jointly trained in the architecture of GAN, in which the RGN-based representation learning of the latent vector can further improve the recovery accuracy and transmission reliability.

The remainder of this paper is structured as follows. First, the system model of the IMD sensing signal transmission is presented in Section 2. Next, the proposed GAN-SCR scheme is proposed in Section 3. Then, we demonstrate the system performance with simulation results in Section 4, followed by the conclusion in Section 5.

2 SYSTEM MODEL

As illustrated in Figure 1, in this paper, an IMD sensing signal transmission system in a typical IoMT scenario is considered, in which the medical sensing signal is transmitted between the IMD and the programmer utilizing a sparse compression and recovery framework. During a typical sensing interval of the IMD, the physiological data of the patient is collected by the sensor and an N-length sensing signal is generated, which can be modeled as $\mathbf{s} = [s_1, s_2, \cdots, s_N]^T$. Due to the temporal correlation between many physiological signals, a non-sparse sensing signal $\mathbf{s}$ can usually be represented as a sparse vector $\mathbf{x}$ in a certain sparse basis, which can be expressed as

$$\mathbf{s} = \mathbf{\Psi}\mathbf{x}, \tag{1}$$

where $\mathbf{\Psi}$ denotes the $N \times N$ sparse basis matrix, which can be, for example, a discrete cosine transform (DCT) matrix, since it is a suitable basis for electrocardiogram (ECG) signals. Fully exploiting the sparsity of physiological signals, it can be compressed in the IMD and recovered in the programmer. Then, Using a certain measurement matrix $\mathbf{\Phi}$, the original sensing signal $\mathbf{s}$ is compressively measured in the IMD, where $\mathbf{\Phi}$ can be a randomly generated matrix, e.g., a Gaussian random matrix. The measurement matrix $\mathbf{\Phi}$ maps the original sensing signal $\mathbf{s}$ to the length-M measurement vector

$$\mathbf{y}_{\mathrm{t}} = \mathbf{\Phi}\mathbf{s}, \tag{2}$$

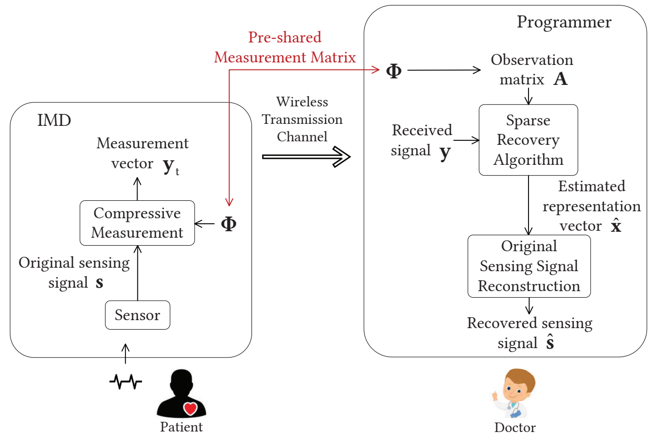

Figure 1: IMD sensing signal transmission system with a sparse compression and recovery framework.

where $M \ll N$. In this way, a compression from N-length to M-length is realized, where the signal compression ratio (CR) is defined as $\gamma = (1 - M/N) \times 100\%$.

Subsequently, the measurement vector $\mathbf{y}_{\mathrm{t}}$ is transmitted to the receiver equipped with a programmer through the wireless communication channel. After passing through the wireless channel with background noise, the received signal can be expressed as

$$\mathbf{y} = \mathbf{y}_{\mathrm{t}} + \mathbf{n}, \tag{3}$$

where $\mathbf{n}$ denotes the additive white Gaussian noise (AWGN). Then, the estimated representation vector $\hat{\mathbf{x}}$ of the original sensing signals in (1) can be calculated by solving the linear inverse problem given by

$$\mathbf{y} = \underbrace{\mathbf{\Phi}\mathbf{\Psi}}_{\mathbf{A}}\mathbf{x} + \mathbf{n}, \tag{4}$$

where $\mathbf{A}$ denotes an $M \times N$ under-determined observation matrix. In order to solve the under-determined linear inverse problem in (4), it is necessary to adopt sparse recovery algorithms, such as CS-based algorithms of OMP [16] and SP [15], and sparse approximation algorithms like AMP [1]. Recently, generative model based methods [2] have also been applied in sparse recovery, utilizing a trained neural network generator to provide a latent representation of the sparse representation vector $\mathbf{x}$, and then an optimization process is performed to solve the problem. After obtaining the estimated representation vector $\hat{\mathbf{x}}$, the recovered sensing signal $\hat{\mathbf{s}}$ can be derived from $\hat{\mathbf{x}}$ using (1).

To further improve the recovery accuracy and the efficiency of signal compression, in this paper, two GAN enabled networks are utilized, including a generative network to implement compressive measurement, and a discriminative network to map the original sensing signal $\mathbf{s}$ to a latent low-dimensional representation vector. The proposed GAN enabled sparse compression and recovery scheme is introduced in detail in the following section.

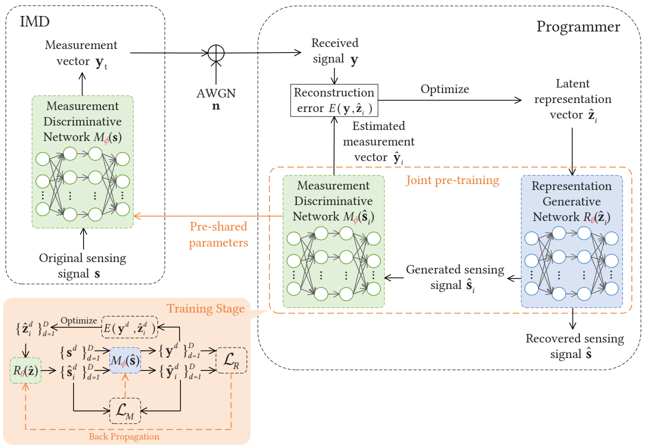

Figure 2: The block diagram of the proposed GAN-SCR scheme.

3 PROPOSED GAN ENABLED SPARSE COMPRESSION AND RECOVERY SCHEME

In this section, the proposed GAN-CSR scheme will be introduced in detail, starting from showing the structure and purpose of the networks of RGN and MDN, and then describing the compression measurement and sparse reconstruction procedure including both training and inference stages. The block diagram of the proposed GAN-SCR scheme is illustrated in Figure 2.

First, exploiting the sparsity of physiological signals, we use a generative network called RGN to build a mapping relation between an L-length latent representation vector $\mathbf{z}$ and the original IMD sensing signal $\mathbf{s}$, which can be expressed as

$$\mathbf{s} = R_{\boldsymbol{\theta}}(\mathbf{z}), \tag{5}$$

where $\boldsymbol{\theta}$ is the weight parameter of the RGN. It is worth noting that, compared with the traditional sparse representation based on a sparse basis or a linear dictionary, the latent representation implemented by the RGN introduces a nonlinear activation function instead of just a linear mapping, which enhances the learning ability of the neural network. Leveraging this superiority of the neural network, we can reduce the number of neurons while guaranteeing the sufficient representation ability of the RGN, to reduce the computational complexity and deal with the fact that IMD is lack of computational resources.

However, it has been found that only using the latent mapping relationship established by a generative network to minimize the measurement error for sparse recovery might get a trivial solution that contains no useful information [17]. Therefore, in the proposed GAN-SCR scheme, another network, i.e., the MDN, is introduced to replace the measurement matrix $\boldsymbol{\Phi}$ in (2) to achieve sparse measurement and compress the original IMD sensing signal $\mathbf{s}$ into a measurement vector $\mathbf{y}$, which can be expressed as

$$\mathbf{y} = M_{\boldsymbol{\phi}}(\mathbf{s}), \tag{6}$$

where $\boldsymbol{\phi}$ represents the weight parameter of the MDN. Different from the random measurement used for sparse compression in the traditional CS framework, the MDN is trained in advance to

Algorithm 1 The proposed GAN Enabled Sparse Compression and Recovery (GAN-SCR) Scheme: Training Stage

Input:
1) Minibatches of training data $\{\mathbf{s}^d\}_{d=1}^D$ of size-D
2) Learning rate α for training
3) Maximum number of iteration steps I and stepsize t of latent optimization

Initialize the RGN and MDN parameters $\boldsymbol{\theta}$ and $\boldsymbol{\phi}$
repeat
  for $d = 1$ **to** D **do**
    Measure the original sensing signal $\mathbf{y}^d = M_{\boldsymbol{\phi}}(\mathbf{s}^d)$
    Generate the latent representation $\hat{\mathbf{z}}_0^d \sim p_{\mathbf{z}}(\mathbf{z})$
    for $i = 0$ **to** $I - 1$ **do**
      Calculate the reconstruction error $E(\mathbf{y}^d, \hat{\mathbf{z}}_i^d)$ with (7) and optimize the latent representation in a gradient manner $\hat{\mathbf{z}}_{i+1}^d = \hat{\mathbf{z}}_i^d - t\frac{\partial}{\partial \hat{\mathbf{z}}_i^d} E(\mathbf{y}^d, \hat{\mathbf{z}}_i^d)$
    end for
  end for
  Evaluate the loss $\mathcal{L}_R$ and $\mathcal{L}_M$ of the RGN and MDN given by (8) and (9)
  Update the parameters of the both networks
$$\boldsymbol{\theta} = \boldsymbol{\theta} - \alpha\frac{\partial}{\partial \boldsymbol{\theta}}\mathcal{L}_R \qquad \boldsymbol{\phi} = \boldsymbol{\phi} - \alpha\frac{\partial}{\partial \boldsymbol{\phi}}\mathcal{L}_M$$
until reaching the maximum training steps

Output:
Trained parameters $\boldsymbol{\theta}$ and $\boldsymbol{\phi}$

enhance the restricted isometry property (RIP). RIP represents the similarity of the measurement vector $\mathbf{y}$ corresponding to different sensing signals $\mathbf{s}$, which is an important property to guarantee the feasibility of sparse reconstruction. Similar to the discriminative network in the original GAN network [6], the MDN is also used to discriminate the "realness" of the signal generated by the RGN, where the measurement error between the output $\hat{\mathbf{y}}$ of the MDN and the real measurement vector $\mathbf{y}$ can be used as the matrix of the generated $\hat{\mathbf{s}}$. Then, the RGN tries to generate a sensing signal $\hat{\mathbf{s}}$ that is close to the real sparse feature and reduce the measurement error. In contrast, the MDN attempts to improve its ability to distinguish between different sensing signals that are fed to it.

The RGN and MDN above are applied to the proposed GAN-SCR scheme to implement sparse compression and recovery, which can improve the compression rate and the accuracy of sparse recovery. The proposed GAN-SCR scheme is composed of two stages, i.e., the training stage and the inference (recovery) stage, as described in **Algorithm 1** and **Algorithm 2**, respectively, with the detailed procedures introduced as follows.

In the training stage, firstly, a second order optimization is implicitly performed in each iteration steps, where the latent vector optimization steps are implemented through back propagation. Using the projection from $\mathbf{z}^d$ onto $\mathbf{y}^d$ established by RGN and MDN, we can obtain the estimated measurement vector $\hat{\mathbf{y}}^d = M_{\boldsymbol{\phi}}(R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}^d))$ and use gradient descent with only a few steps to optimize the latent vector $\hat{\mathbf{z}}^d$ via minimizing the l_2-norm measurement error $E(\mathbf{y}^d, \hat{\mathbf{z}}^d)$ which can be calculated by

$$E(\mathbf{y}, \hat{\mathbf{z}}) = \|\mathbf{y} - \hat{\mathbf{y}}\|_2^2 = \left\|\mathbf{y} - M_{\boldsymbol{\phi}}(R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}))\right\|_2^2, \tag{7}$$

Algorithm 2 The proposed GAN Enabled Sparse Compression and Recovery (GAN-SCR) Scheme: Inference (Recovery) Stage

Input:
1) Sparse measurement vector $\mathbf{y}$
2) Maximum iteration number I for latent optimization
3) Trained parameters of $\boldsymbol{\theta}$ and $\boldsymbol{\phi}$ for RGN and MDN

Initialize the latent representation $\hat{\mathbf{z}}_0 \sim p_{\mathbf{z}}(\mathbf{z})$
for $i = 0$ **to** $I - 1$ **do**
  Perform a single-trip feedforward operation of RGN and MDN in turn to generate $\hat{\mathbf{y}}_i = M_{\boldsymbol{\phi}}(R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}_i))$
  Calculate the reconstruction error $E(\mathbf{y}, \hat{\mathbf{z}}_i)$ with (7), and optimize the latent representation $\hat{\mathbf{z}}_{i+1} = \hat{\mathbf{z}}_i - \frac{\partial}{\partial \hat{\mathbf{z}}_i} E(\mathbf{y}, \hat{\mathbf{z}}_i)$
end for
Perform a single-trip feedforward operation using RGN and obtain the final recovered sensing signal $\hat{\mathbf{s}} = R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}_I)$

Output:
Recovered original sensing signal $\hat{\mathbf{s}}$

where $\mathbf{y}^d$ and $\hat{\mathbf{y}}^d$ are the output of the MGN when the input is the original sensing signal $\mathbf{s}^d$ in the size-D training dataset $\{\mathbf{s}^d\}_{d=1}^D$ and the sparse sensing signal $\hat{\mathbf{s}}^d$ generated by RGN, respectively. Subsequently, the two networks of RGN and MDN are jointly trained in the architecture of GAN. The loss function of RGN is an average reconstruction error calculated by the estimated measurement vector $\hat{\mathbf{y}}^d$ generated by the MDN network, which is given by

$$\mathcal{L}_R = \mathbb{E}_{\hat{\mathbf{z}}^d \sim p_{\mathbf{z}}(\mathbf{z})} \left\| \mathbf{y}^d - M_{\boldsymbol{\phi}}(R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}^d)) \right\|_2^2, \tag{8}$$

where $\mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})}[f(\mathbf{z})]$ represents the expectation of $f(\mathbf{z})$ on the current distribution $p_{\mathbf{z}}(\mathbf{z})$ of the latent vector $\mathbf{z}$. The loss function of MGN is a counterpart of the RIP which is given by

$$\begin{aligned} \mathcal{L}_M = & \frac{1}{D} \sum_{d=1}^{D} \mathbb{E}_{\mathbf{s}^{d_1}, \mathbf{s}^{d_2}} \left[\left(\| M_{\boldsymbol{\phi}}(\mathbf{s}^{d_1} - \mathbf{s}^{d_2}) \|_2 - \| \mathbf{s}^{d_1} - \mathbf{s}^{d_2} \|_2 \right)^2 \right], \\ & \text{with } \mathbf{s}^{d_1}, \mathbf{s}^{d_2} \in \left\{ \mathbf{s}^d, R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}_0^d), R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}_I^d) \right\}, d = 1, 2, \ldots D, \end{aligned} \tag{9}$$

where $\hat{\mathbf{z}}_0^d$ and $\hat{\mathbf{z}}_I^d$ are the latent vector before and after the I-step latent vector optimization, respectively. It is worth noting that, in order to simultaneously enhance the RIP of the MDN on the training signals and the estimated sensing signals generated by the RGN, $\mathcal{L}_M$ is expressed as the average of three pairs of losses between an original sensing signal $\mathbf{s}^d$ and two estimated sensing signals $R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}_0^d)$ and $R_{\boldsymbol{\theta}}(\hat{\mathbf{z}}_I^d)$ generated by latent vectors before and after optimization. The parameters of both the RGN and MDN are updated by using the Adam optimizer and back propagation to minimize the loss $\mathcal{L}_R$ and $\mathcal{L}_M$, respectively. Note that after the training stage, the parameters of the MDN in the programmer are pre-shared with the MDN in the IMD.

In the inference stage, the well-trained networks of RGN and MDN are used to recover the original IMD sensing signal $\hat{\mathbf{s}}$. First, a latent representation vector $\hat{\mathbf{z}}_0$ is generated by a certain distribution $\hat{\mathbf{z}}_0 \sim p_{\mathbf{z}}(\mathbf{z})$, e.g., Gaussian distribution. Next, using the mapping relationship $\hat{\mathbf{z}} \rightarrow \hat{\mathbf{s}} \rightarrow \hat{\mathbf{y}}$ established by RGN and MDN, the error $E(\mathbf{y}, \hat{\mathbf{z}})$ of the estimated measurement vector can be obtained via (7). Then, online optimization for $\hat{\mathbf{z}}$ is implemented using gradient descent to minimize the measurement error $E(\mathbf{y}, \hat{\mathbf{z}})$. Finally, the optimal latent vector $\hat{\mathbf{z}_I}$ is substituted into the RGN network to derive the original sensing signal $\hat{\mathbf{s}}$.

4 SIMULATION RESULTS AND DISCUSSION

In this section, to validate the performance of the proposed GAN-SCR scheme, ECG record data with a sampling rate of 360 Hz in the MIT-BIH Arrhythmia Database [13] is used to implement the simulation. Specifically, we assume that the length of the medical sensing signal $\mathbf{s}$ generated in each sensing interval of IMD is $N = 500$. Therefore, the ECG experimental records are divided into several length-500 signals, which are prepared to generate the training and test datasets for simulation, with sizes of 1000 and 200, respectively. Some system parameters are set as follows. The compression rate is set to $\gamma = 50$, and thus the length of the measurement vector $\mathbf{y}$ is $M = 250$. We use a latent representation vector $\mathbf{z}$ of length 200, and use 3-step gradient descent with a stepsize of $t = 0.01$ for latent optimization. The Adam optimizer are used for the training of the neural networks with the learning rate $\alpha = 10^{-4}$.

In order to evaluate the reconstruction error of the proposed GAN-SCR scheme quantitatively, we use percentage root-mean square difference (PRD) as an evaluation metric, which is widely used to describe the recovery quality of ECG signals. For the original sensing signal $\mathbf{s}$ and the recovered sensing signal $\hat{\mathbf{s}}$, the PRD represented by λ is defined as

$$\lambda = \frac{\|\hat{\mathbf{s}} - \mathbf{s}\|_2}{\|\mathbf{s}\|_2} \times 100\%. \tag{10}$$

In addition, in order to objectively show the signal reconstruction quality, a PRD-based signal quality classification metric proposed by *Zigel* et al [19] is adopted, where $\lambda < 2$, $2 < \lambda < 9$ and $\lambda > 9$ are classified into "Very good", "Good" and "Bad" quality groups, respectively.

Firstly, a fragment of the IMD sensing signal $\mathbf{s}$ is shown in figure 3, which corresponds to the recovered sensing signal $\hat{\mathbf{s}}$ using the proposed GAN-SCR scheme for compressive measurement, wireless transmission and sparse recovery. The result in Figure 3 indicates that the IMD sensing signal is recovered with high accuracy. And from the numerical result point of view, The reconstruction error is $\lambda = 1.4011$, which is in the category of "Very Good" level. In order to verify the sparsity of the sensing signal and evaluate its corresponding reconstruction quality in the transform domain, the sparse representation of the above-mentioned sensing signal and the recovered signal in the DCT domain are shown in Figure 4. We can see that, as a typical physiological electrical signal, the ECG signal has significant sparsity in the DCT domain, and almost all of the sparse locations are included in the recovered sensing signal.

Subsequently, a comparative experiment is conducted for the GAN-SCR scheme and other benchmark schemes, including CS-based greedy algorithms of OMP [16] and SP [15] and the sparse approximation algorithm AMP [1] in a typical IoMT transmission system, to validate the effectiveness of the proposed GAN-SCR scheme. In addition, the influence of the background noise intensity on the accuracy of signal recovery is also considered. As illustrated in Figure 4, the results highlight that compared to the benchmark sparse reconstruction algorithms, the proposed GAN-SCR can achieve more accurate recovery results in the same channel conditions and with the same compression ratio. Moreover, with

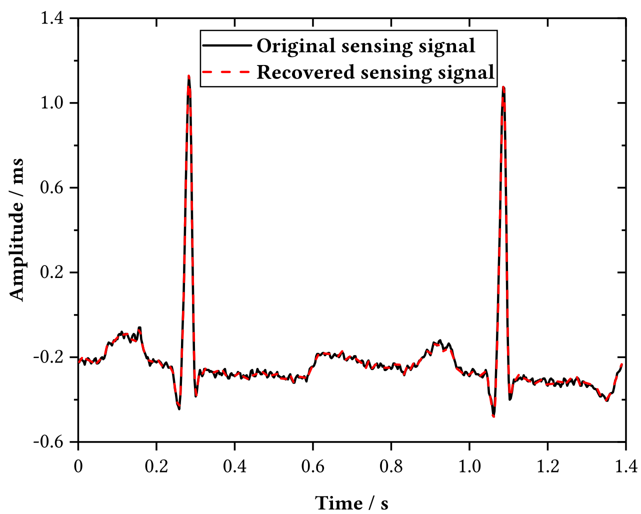

Figure 3: A Fragment of record 100 in the MIT-BIH Arrhythmia Database [13] and the recovered signal using the proposed GAN-SCR at SNR = 30dB.

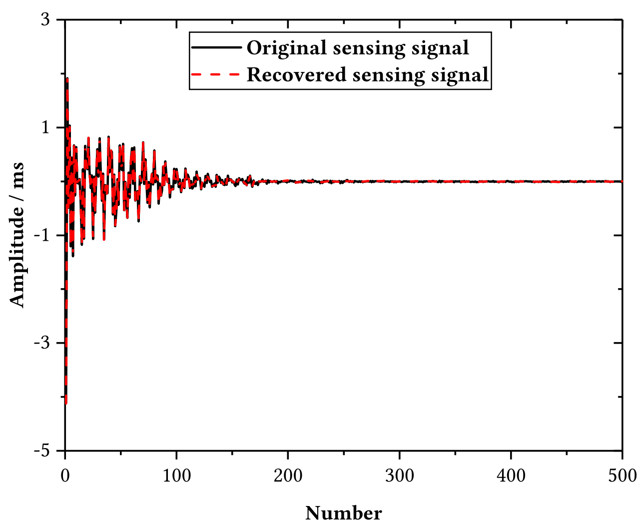

Figure 4: The sparse representation of the test signal and the recovered signal for ECG sensing signals in the DCT domain.

the increase of the noise intensity, although the reconstruction error of each scheme is continuously increasing, the accuracy of the GAN-SCR scheme is much higher than other methods, which can still reach the "Good" level even at SNR = 5dB. This shows that, exploiting the anti-noise capability of the proposed scheme, excellent reconstruction accuracy and high transmission reliability can be achieved to meet the requirements of critical missions in the IoMT scenarios.

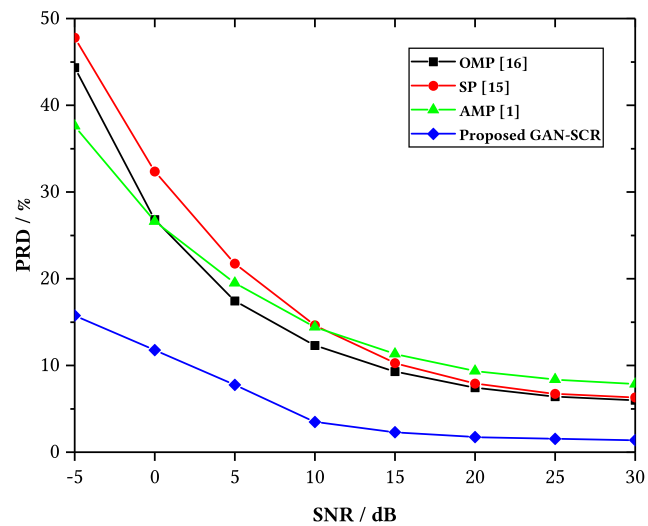

Figure 5: Reconstruction accuracy using the proposed GAN-SCR and other benchmark schemes for the IMD sensing signal recovery in IoMT transmission.

5 CONCLUSION

In this paper, a sparse compression and recovery scheme called GAN-SCR is proposed for efficient IoMT sensing and transmission, which significantly improves the spectral efficiency and transmission reliability by exploiting the inherent sparsity of the sensing signals. Two deep neural networks of RGN and MDN are used in the GAN-SCR scheme for representation learning and sparse measurement, which are jointly trained via a GAN-enabled framework to improve the sparse representation ability of the RGN and strengthen the RIP of the MDN. The simulation results show that the proposed GAN-SCR scheme has prominent performance in recovery reliability compared to the existing CS-based sparse reconstruction schemes, especially under the harsh condition of intensive background noise. Moreover, the proposed GAN-SCR scheme is also promising in other IoT sensing and transmission scenarios with stringent requirements of data reliability and transmission resource efficiency.

ACKNOWLEDGMENTS

This work is supported in part by the National Natural Science Foundation of China under grants 61901403, 61971366, and 61971365, in part by the Youth Innovation Fund of Xiamen under grant 3502Z20206039, and in part by the Natural Science Foundation of Fujian Province of China under grant 2019J05001.

REFERENCES

[1] Mohsen Bayati, Marc Lelarge, and Andrea Montanari. 2015. Universality in polytope phase transitions and message passing algorithms. *Annals of Applied Probability* 25, 2 (2015), 753–822.
[2] Ashish Bora, Ajil Jalal, Eric Price, and Alexandros G. Dimakis. 2017. Compressed Sensing Using Generative Models. In *Proceedings of the 34th International Conference on Machine Learning (ICML).* 537–546.
[3] Mark Borgerding, Philip Schniter, and Sundeep Rangan. 2017. AMP-inspired deep networks for sparse linear inverse problems. *IEEE Transactions on Signal Processing* 65, 16 (2017), 4293–4308.

[4] Jun Won Choi, Byonghyo Shim, Yacong Ding, Bhaskar Rao, and Dong In Kim. 2017. Compressed Sensing for Wireless Communications: Useful Tips and Tricks. *IEEE Communications Surveys and Tutorials* 19, 3 (2017), 1527–1550.

[5] David L. Donoho. 2006. Compressed sensing. *IEEE Transactions on Information Theory* 52, 4 (2006), 1289–1306.

[6] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Nets. In *Proceedings of the 27th International Conference on Neural Information Processing Systems (NIPS'14)*. 2672–2680.

[7] Zhicheng Li, Hong Huang, and Satyajayant Misra. 2017. Compressed Sensing via Dictionary Learning and Approximate Message Passing for Multimedia Internet of Things. *IEEE Internet of Things Journal* 4, 2 (2017), 505–512.

[8] Sicong Liu, Liang Xiao, Zhu Han, and Yuliang Tang. 2019. Eliminating NB-IoT Interference to LTE System: A Sparse Machine Learning-Based Approach. *IEEE Internet of Things Journal* 6, 4 (2019), 6919–6932.

[9] Sicong Liu, Liang Xiao, Lianfen Huang, and Xianbin Wang. 2019. Impulsive Noise Recovery and Elimination: A Sparse Machine Learning Based Approach. *IEEE Transactions on Vehicular Technology* 68, 3 (2019), 2306–2315.

[10] Sicong Liu, Fang Yang, Wenbo Ding, and Jian Song. 2016. Double Kill: Compressive-Sensing-Based Narrow-Band Interference and Impulsive Noise Mitigation for Vehicular Communications. *IEEE Transactions on Vehicular Technology* 65, 7 (2016), 5099–5109.

[11] Gunasekaran Manogaran, Naveen Chilamkurti, and Ching-Hsien Hsu. 2018. Emerging Trends, Issues, and Challenges in Internet of Medical Things and Wireless Networks. *Personal and Ubiquitous Computing* 22, 5–6 (2018), 879–882.

[12] Morteza Mardani, Enhao Gong, Joseph Y. Cheng, Shreyas S. Vasanawala, Greg Zaharchuk, Lei Xing, and John M. Pauly. 2019. Deep Generative Adversarial Neural Networks for Compressive Sensing MRI. *IEEE Transactions on Medical Imaging* 38, 1 (2019), 167–179.

[13] George B. Moody and Roger G. Mark. 2001. The impact of the MIT-BIH Arrhythmia Database. *IEEE Engineering in Medicine and Biology Magazine* 20, 3 (2001), 45–50.

[14] Christopher J L Murray, Cristiana Abbafati, Kaja M Abbas, Mohammad Abbasi, Mohsen Abbasi-Kangevari, et al. 2020. Five insights from the Global Burden of Disease Study 2019. *The Lancet* 396, 10258 (2020), 1135–1159.

[15] Chao-Bing Song, Shu-Tao Xia, and Xin-Ji Liu. 2014. Improved Analysis for Subspace Pursuit Algorithm in Terms of Restricted Isometry Constant. *IEEE Signal Processing Letters* 21, 11 (2014), 1365–1369.

[16] Jinming Wen, Zhengchun Zhou, Jian Wang, Xiaohu Tang, and Qun Mo. 2017. A Sharp Condition for Exact Support Recovery With Orthogonal Matching Pursuit. *IEEE Transactions on Signal Processing* 65, 6 (2017), 1370–1382.

[17] Yan Wu, Mihaela Rosca, and Timothy P. Lillicrap. 2019. Deep Compressed Sensing. In *Proceedings of the 36th International Conference on Machine Learning (ICML)*. 6850–6860.

[18] Tahreem Yaqoob, Haider Abbas, and Mohammed Atiquzzaman. 2019. Security Vulnerabilities, Attacks, Countermeasures, and Regulations of Networked Medical Devices—A Review. *IEEE Communications Surveys Tutorials* 21, 4 (2019), 3723–3768.

[19] Yaniv Zigel, Arnon Cohen, and Amos Katz. 2000. The weighted diagnostic distortion (WDD) measure for ECG signal compression. *IEEE Transactions on Biomedical Engineering* 47, 11 (2000), 1422–1430.