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Deep Multi-Channel Signal Decoding with Cascaded Latent-space Fidelity Boosting for Precision Medicine

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***Abstract*— Remote health monitoring is of great potential to bring long-term continuous big data for precision medicine. The challenge arises since the noise and interferences usually contaminate the signal significantly. In this study, to decode the medical insights from the rapidly decayed signal captured remotely, we propose a deep multi-channel signal decoding system with cascaded latent-space fidelity boosting. The system is composed of the multi-channel acoustic sensing device and the deep multi-channel signal decoding algorithm. The device can be placed on the bedframe to capture the spatial dynamics of the acoustic information during breathing. The deep learning framework with cascaded latent-space fidelity boosting before inference, can suppress noise and interferences hidden in the signal, through multiple iterations of space transformation and signal reconstruction. We take the sleep apnea as the real-world study, to demonstrate the promise of the proposed system. Our experiments have demonstrated the effectiveness of the system, superior to state-of-the-art. This study will promisingly advance remote signal perception and mining for precision medicine.**

Keywords—Array Sensor, Multi-channel Signal Processing, Deep Learning, Remote Health Monitoring

I. Introduction

Advanced electronics and computing technologies are advancing health monitoring in daily scenarios [1, 2]. Remote health monitoring is of great potential to bring long-term continuous big data for precision medicine [3-6]. The nature of contactlessness, unobtrusiveness, and convenience makes remote health monitoring highly promising for different kinds of vital sign monitoring.

We take a special interest in array-based multi-channel signal perception and decoding, for complementary pattern capturing considering the rapid decaying of the signal. Previous studies usually target the direct signal decoding. Decoding can leverage sophisticated artificial intelligence to understand the hidden patterns. The long short-term memory has been leveraged for contact-free heart rate estimation [7]. The recurrent network has been designed for risk prediction for patients [8]. The transformer-based method has been designed for heart rate and blood pressure forecasting [9]. The BreathTrack system [10] has been developed with the smartphone for breathing sound capturing and the deep learning for sleeping phase analysis. Chen *et al.* developed the passive radio sensing system and the deep transfer network for respiration analysis [11]. The convolutional neural network has been developed for acoustic sleep apnea detection [12].

However, the remote signal is usually highly noisy and of heavy interferences, posing a great challenge for data mining [13-16]. Therefore, we propose to leverage the array signal sensing and the deep learning for robust data mining. We take the sleep apnea as the real-world study, to demonstrate the promise of the proposed system.

More specifically, the system is composed of the multi-channel acoustic sensing device and the deep multi-channel signal decoding algorithm. The device can be placed on the bedframe to capture the spatial dynamics of the acoustic information during breathing. The deep learning is leveraging the cascaded latent-space fidelity boosting before inference, which is achieved through multiple deep autoencoders stacked for noise and interference suppression. Each autoencoder compresses the input to the latent-space where the critical patterns are maintained and irrelevant signal characteristics are suppressed. Our experiments have demonstrated the great promise of the proposed novel system. The major contributions are summarized as below:

(1) The multi-channel acoustic signal sensing and learning system, for sleep apnea detection;

(2) The deep learning framework with cascaded latent-space fidelity boosting before inference, thereby suppressing noise and interferences hidden in the signal;

(3) The cascaded structure with multiple iterations of latent-space transformation and signal reconstruction, thereby boosting the fidelity gradually.

II. Approach

A. System Diagram

As shown in Fig. 1, the system is composed of the on-bedframe acoustic sensing device and the deep learning framework. The device captures multi-channel acoustic signal during breathing, and the deep learning leverages the stacked autoencoder to iteratively suppress the noise and interferences in the latent-space.

B. Cascaded Latent-Space Noise/Interference Suppression

The deep learning framework leverages the cascaded latent-space fidelity boosting before inference, thereby suppressing

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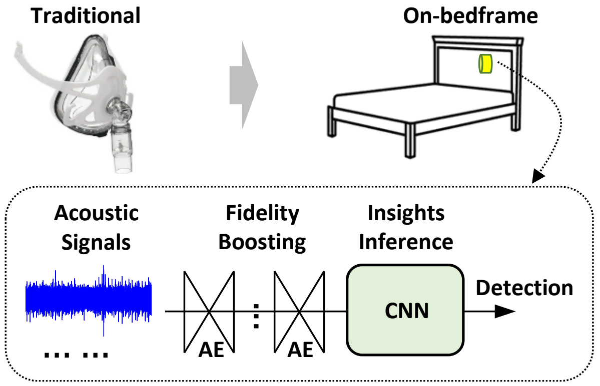

Fig. 1. The proposed deep multi-channel signal decoding framework with cascaded latent-space fidelity boosting, towards remote health big data. (Notes) AE: Autoencoder; CNN: Convolutional Neural Network.

noise and interferences hidden in the signal. For each iteration of the boosting, as (1-2), the encoder D_{ψ}^{e} transforms the signal $\mathcal{X}$ to the latent-space representation $\mathcal{C}$, and then the decoder D_{ω}^{d} reconstructs the input achieving the estimate $\widehat{\mathcal{X}}$. ψ and ω correspond to the parameters of the encoder and the decoder, respectively.

$$D_{\psi}^{e}: \mathcal{X} \to \mathcal{C} \tag{1}$$

$$D_{\omega}^{d}: \mathcal{C} \to \widehat{\mathcal{X}} \tag{2}$$

The learning process is as (3), where, $D_{\psi}^{e} \circ D_{\omega}^{d}$ denotes the combined process that includes the encoding and decoding steps. The process optimizes the parameters ψ and ω, to minimize the square loss between the input and the reconstructed input.

$$\psi, \omega = \underset{\psi,\omega}{\operatorname{argmin}} \left\| \mathcal{X} - \left(D_{\psi}^{e} \circ D_{\omega}^{d}\right)\mathcal{X} \right\|^{2} \tag{3}$$

The cascaded fidelity boosting is as (4), where, Ω is the depth of the cascaded architecture, and $\mathcal{O}$ is the final output. Ω is selected as 3 in our study, with a cascaded training strategy, meaning that the earlier autoencoder is trained and afterwards the next autoencoder gets trained.

$$\mathcal{O} = \left(D_{\psi}^{e} \circ D_{\omega}^{d}\right)^{\Omega} \mathcal{X} \tag{4}$$

C. *Detection and Evaluation*

The array signal after the cascaded fidelity boosting is then learned by the convolutional neural network, for non-breath event detection. Multiple criteria have been used for evaluation including accuracy, precision, recall, specificity, and f1-score.

III. Results

A. *Experiments*

The experiments have been conducted on the acoustic signal acquired with the on-bedframe monitor customized. With the IRB approval, four subjects participated in the data collection, and the corresponding signals have been processed to extract the signal envelope considering the acoustic signal is highly noisy.

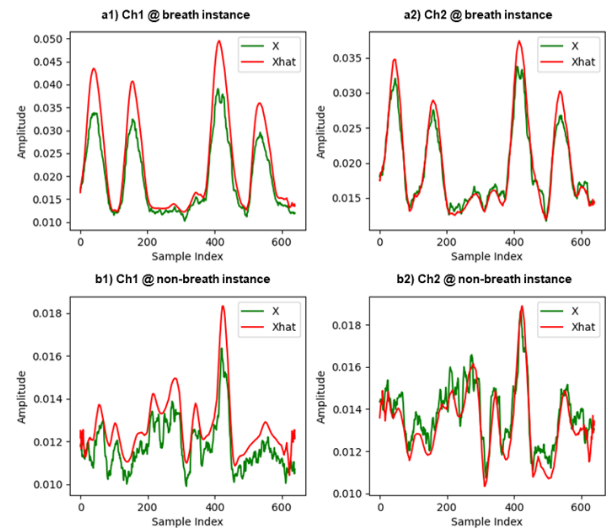

Fig. 2. The boosted signal with the high fidelity, through the cascaded latent-space suppression process proposed.

B. *Cascaded Latent-Space Noise/Interference Suppression*

Fig. 2 shows the boosted signal with the high fidelity, through the cascaded latent-space suppression process. Two channels out of four are selected in the visualization. a1) illustrates the channel-1 signal segment for the breath instance, and a2) corresponds to the channel-2 segment. As indicated, the proposed novel deep learning framework can effectively suppress the noise and interferences, thereby yielding the boosted signal with better morphologies.

In b1), the channel-1 segment for the non-breath instance has been visualized, and the channel-2 segment is given in b2). With a lower signal strength during the non-breath instance, the signal is pretty noisy but also carries high spikes. The proposed approach can also enhance the signal fidelity effectively with major characteristics revealed.

C. *Performance Summary and Comparison*

Fig. 3 shows the performance summary with the five criteria introduced previously. Further, the state-of-the-art methods

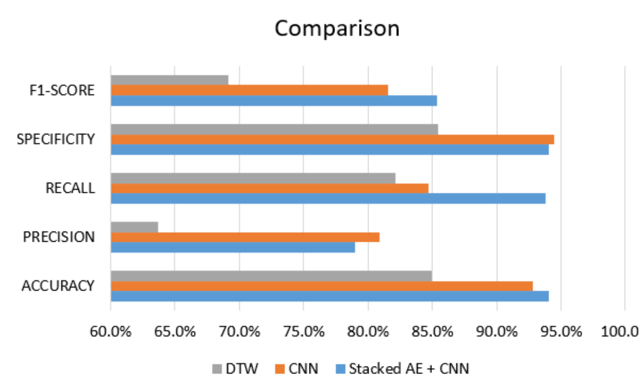

Fig. 3. The performance summary for the proposed system, and the comparison with state-of-the-art.

including the convolutional neural network and the dynamic time warping [12] have been considered in the comparison.

The results promisingly demonstrate that the proposed novel deep learning framework has the highest accuracy (94%). The recall and specificity are also much higher than state-of-the-art, indicating the effectiveness regarding non-breath events detection.

IV. Conclusion

In this study, we have designed and validated a deep multi-channel signal decoding system with cascaded latent-space fidelity boosting, aiming to decode the medical insights from the rapidly decayed signal captured remotely. The multi-channel acoustic signal sensing and learning system has been built to capture the breath sound dynamics. The deep learning framework with cascaded latent-space fidelity boosting before inference, has been designed to suppress the noise and interferences hidden in the signal. The cascaded structure owns multiple iterations of transformation and signal reconstruction, for gradual fidelity boosting. Evaluated on the sleep apnea experiments, our system has demonstrated great promise, compared with state-of-the-art. This study will greatly contribute to remote health big data through innovations on robust signal perception and mining.

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