SDEMG

SCORE-BASED DIFFUSION MODEL FOR SURFACE ELECTROMYOGRAPHIC SIGNAL DENOISING

ICASSP 2024 KOREA

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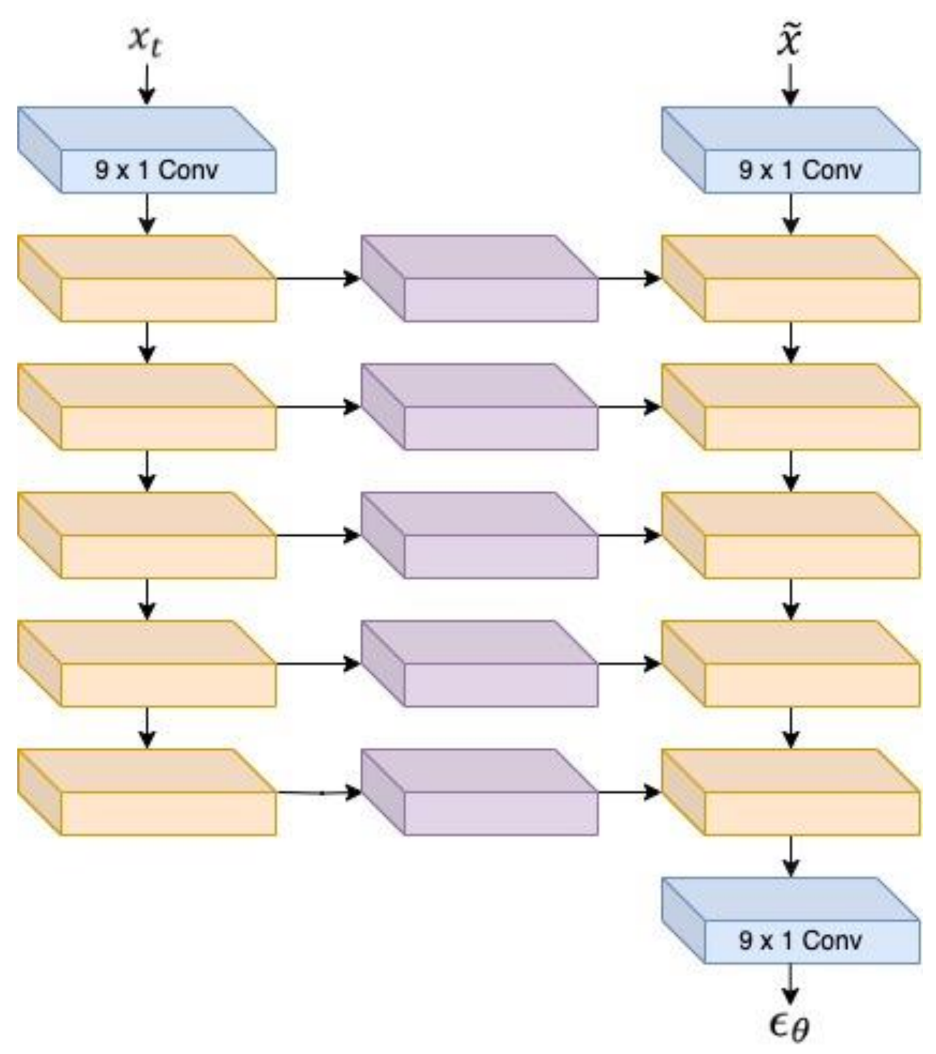
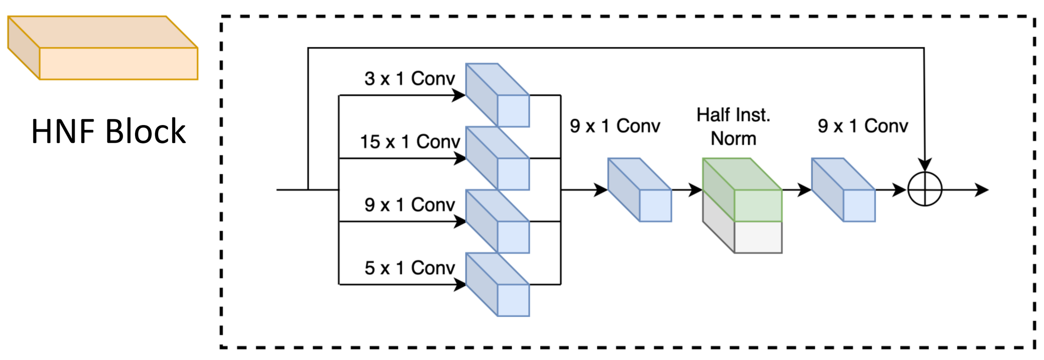
Abstract

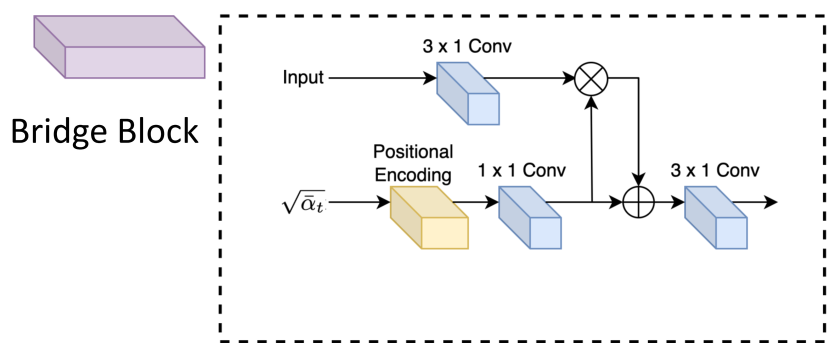
- Surface electromyography (sEMG) recordings can be influenced by electrocardiogram (ECG) signals when the muscle being monitored is close to the heart

- Signal enhancement methods based on neural network (NN) have achieved extraordinary results in improving signal quality, few studies have explored the feasibility of neural network for ECG contamination removal in sEMG
- Distortion can be observed in the denoise result or previous methods such as high-pass filter (HP) , template subtraction (TS) , and fully convolutional network (FCN)
- Score-based diffusion models are a category of deep generative models that generates high quality and high fidelity samples
- This study proposed SDEMG, a score-based diffusion model, to reconstruct high-quality and high-fidelity sEMG samples from ECG-interfered sEMG signals

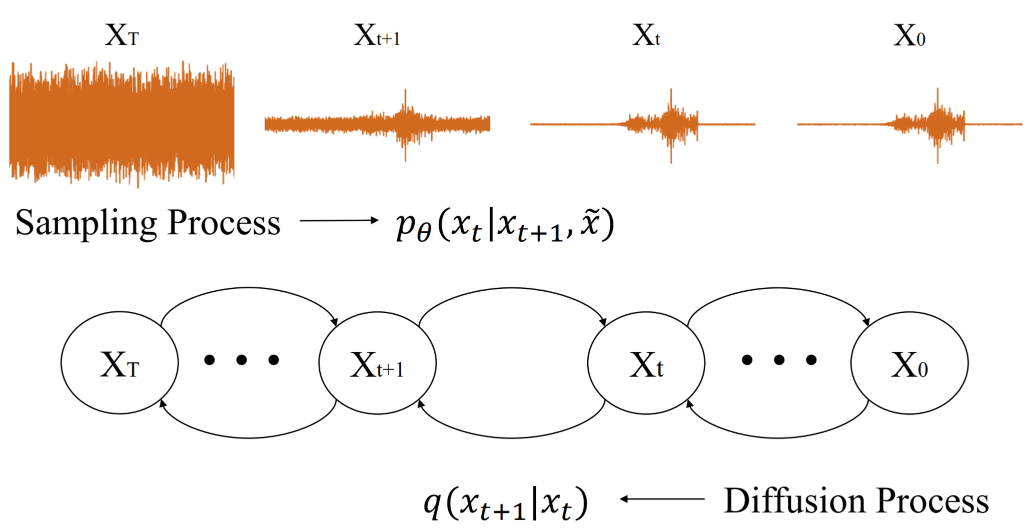
Model Architecture







Proposed Method



- The figure above concludes our method to incorporate diffusion model to sEMG denoising
- Noisy (Contaminated) signal is used as condition to avoid signal distortion and generate high quality signal
- The algorithms below show the training and sampling process of SDEMG

Algorithm 1 Training

1: **repeat**
2: $x_0, \tilde{x} \sim q(x_0, \tilde{x})$
3: $t \sim Uniform(\{1, \ldots, T\})$
4: $\bar{\alpha} \sim Uniform(\gamma_{t-1}, \gamma)$
5: $\epsilon \sim \mathcal{N}(0, I)$
6: Take gradient descent step on

$$\nabla_\theta ||\epsilon - \epsilon_\theta(\sqrt{\bar{\alpha}}x_0 + \sqrt{1-\bar{\alpha}}\epsilon, \tilde{x}, \bar{\alpha})||^2$$

7: **until** Converged

Algorithm 2 Sampling

1: $x_T \sim \mathcal{N}(0, I)$
2: **for** $t = T, \ldots, 1$ **do**
3: $z \sim \mathcal{N}(0, I)$ **if** $z > 1$ **else** $z = 0$
4: $x_{t-1} = \frac{1}{\alpha_t}\left(x_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\epsilon_\theta(x_t, \tilde{x}, \sqrt{\bar{\alpha}_t})\right) + \sigma_t z$
5: **end for**
6: **return** x_0

Dataset

- The 12-channel clean sEMG data of the NINAPro database were measured by electrodes on the upper arm. This work uses data in DB2, including sEMG from 40 subjects

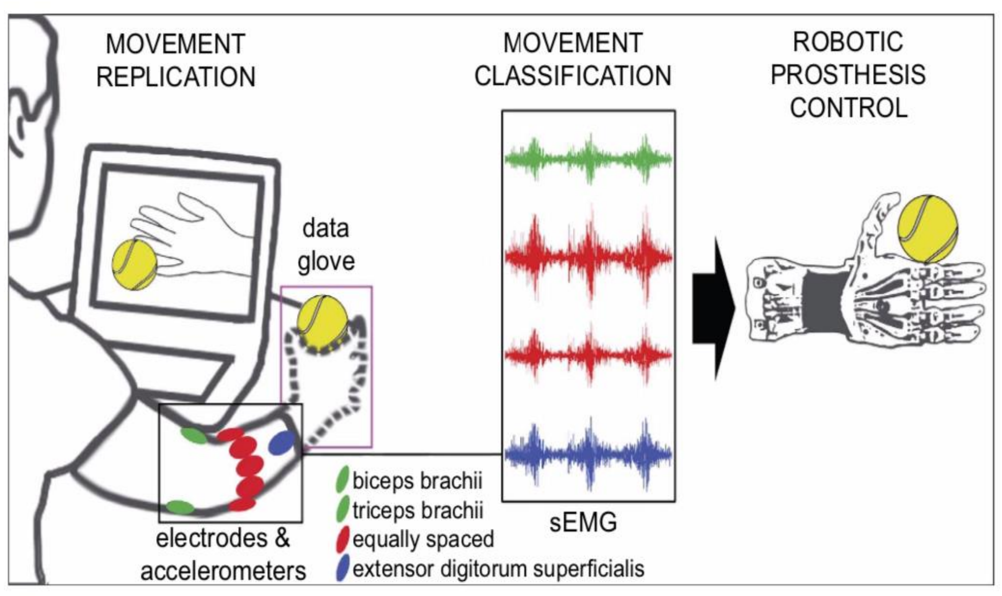


Fig . The setting of sEMG measurement in NINPro database[1]

- For **ECG artifacts**, this study employs the **MIT-BIH NSRD** from the Physionet data bank[2]. There are 2 ECG channels collected from 18 healthy individuals
- Mismatch conditions between training and testing datasets

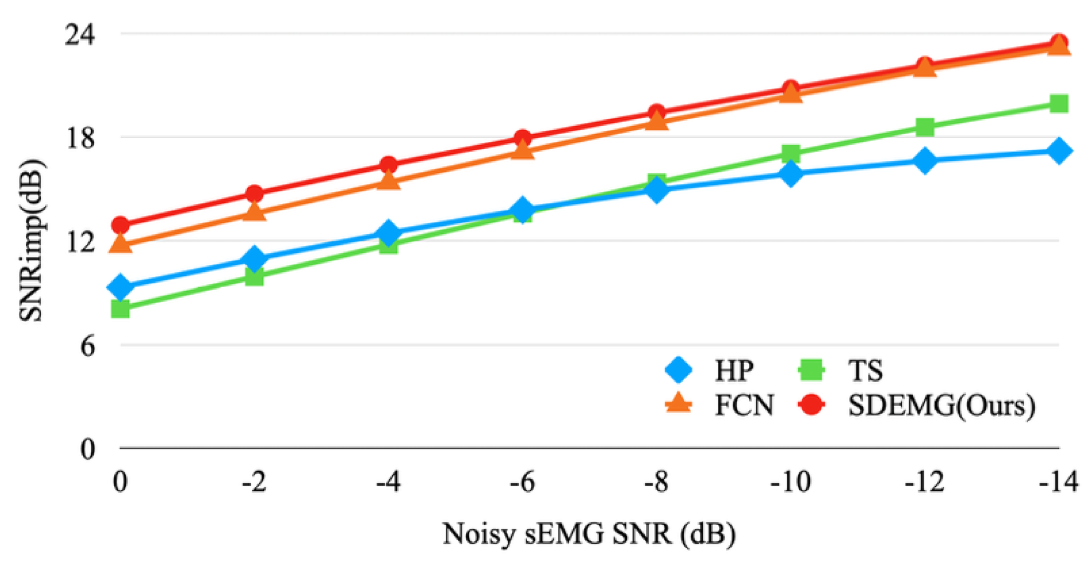
Dataset	sEMG	ECG	SNR (dB)
Train	Channel 2, Exercise 1, 30 subjects	14 Subjects	-5, -7, -9, -11, -13, and -15
Test	Channels 9 to 12, Exercise 2, 10 subjects	4 Subjects	-14 - 0 with a step of 2

Results

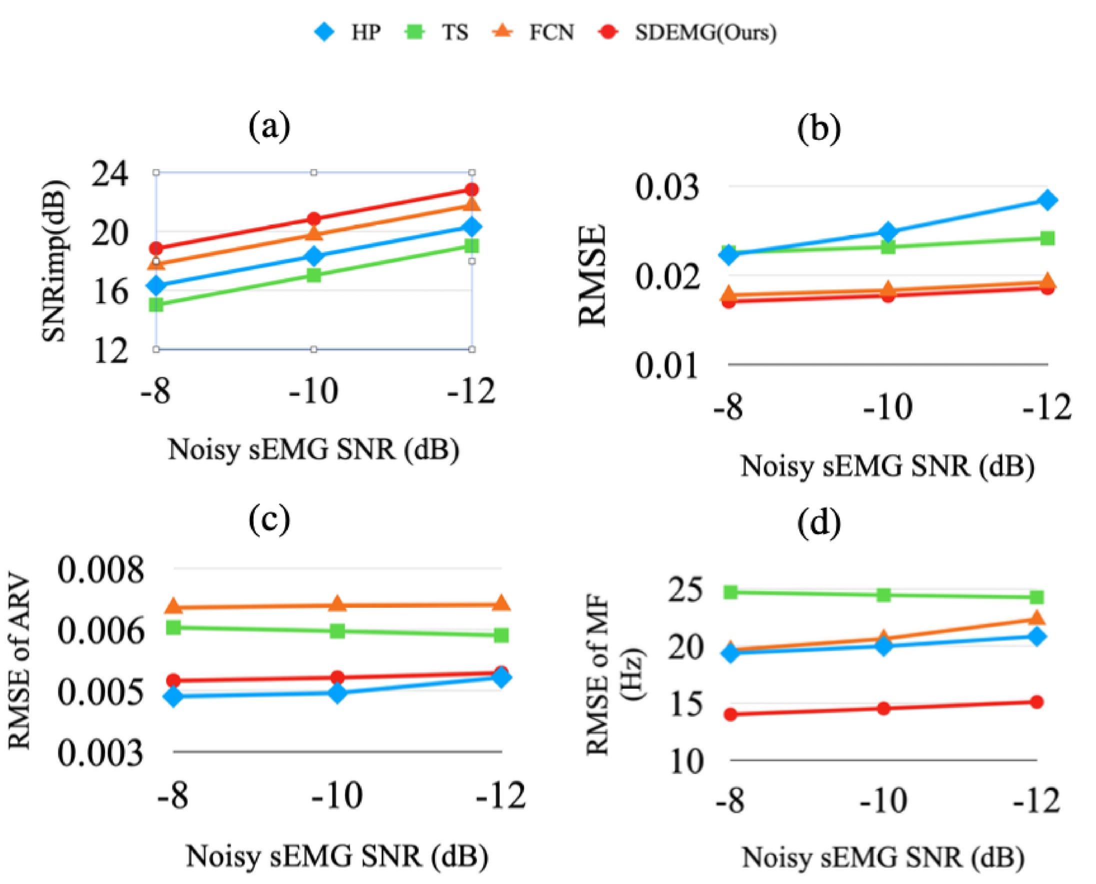
Table 1. Overall performance of HP, TS, FCN, and SDEMG.

	SNR_{imp} (dB)	RMSE	$RMSE_{ARV}$	$RMSE_{MF}$ (Hz)
HP	13.885	1.735e-2	3.06e-3	17.688
TS	14.279	1.626e-2	3.86e-3	23.149
FCN	17.758	1.178e-2	3.86e-3	18.038
SDEMG(Ours)	**18.467**	**1.138e-2**	**2.81e-3**	**14.435**

- Compared with high-pass filter (HP) , template subtraction (TS) , and fully convolutional network (FCN)
- SDEMG outperforms all other methods in every metric
- Denoise result evaluated by SNR_{imp}



- SDEMG remains the preferred method under the specific condition simulating trunk sEMG with ECG contamination (i.e. SNR_{in} = -10 dB with biceps brachii sEMG from channel 11.)



Evaluation Metric

- SNR_{imp}, RMSE, and RMSE of two sEMG features, average rectified value (ARV) and mean frequency (MF)

$$ARV = \frac{\sum_{n=1}^{L}|x[n]|}{L}, \qquad MF = \frac{\sum_{n=N_1}^{N_2} f_n \cdot S_n}{\sum_{n=N_1}^{N_2} S_n}.$$

References

1. Manfredo Atzori, et al., "Electromyography data for non-invasive naturally-controlled robotic hand prostheses," Scientific data, vol. 1, no. 1, pp. 1–13, 2014.
2. Ary L Goldberger, et al., "Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals," circulation, vol. 101, no. 23, pp. e215–e220, 2000.

For More Information

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