Joint Attention Mechanism Learning to Facilitate Opto-physiological Monitoring during Physical Activity

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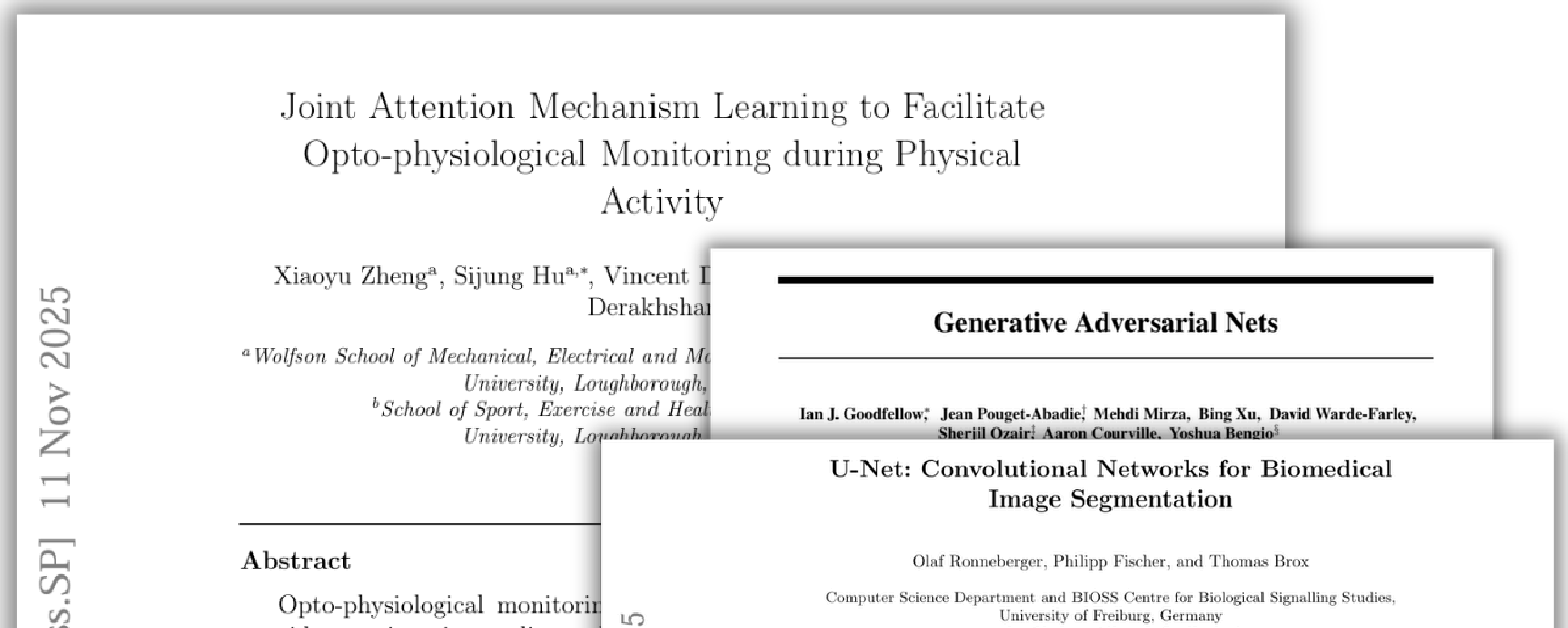
Joint Attention Mechanism Learning to Facilitate Opto-physiological Monitoring during Physical Activity

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Abstract

Opto-physiological monitorin

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Generative Adversarial Nets

Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio

U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, and Thomas Brox

Computer Science Department and BIOSS Centre for Biological Signalling Studies, University of Freiburg, Germany

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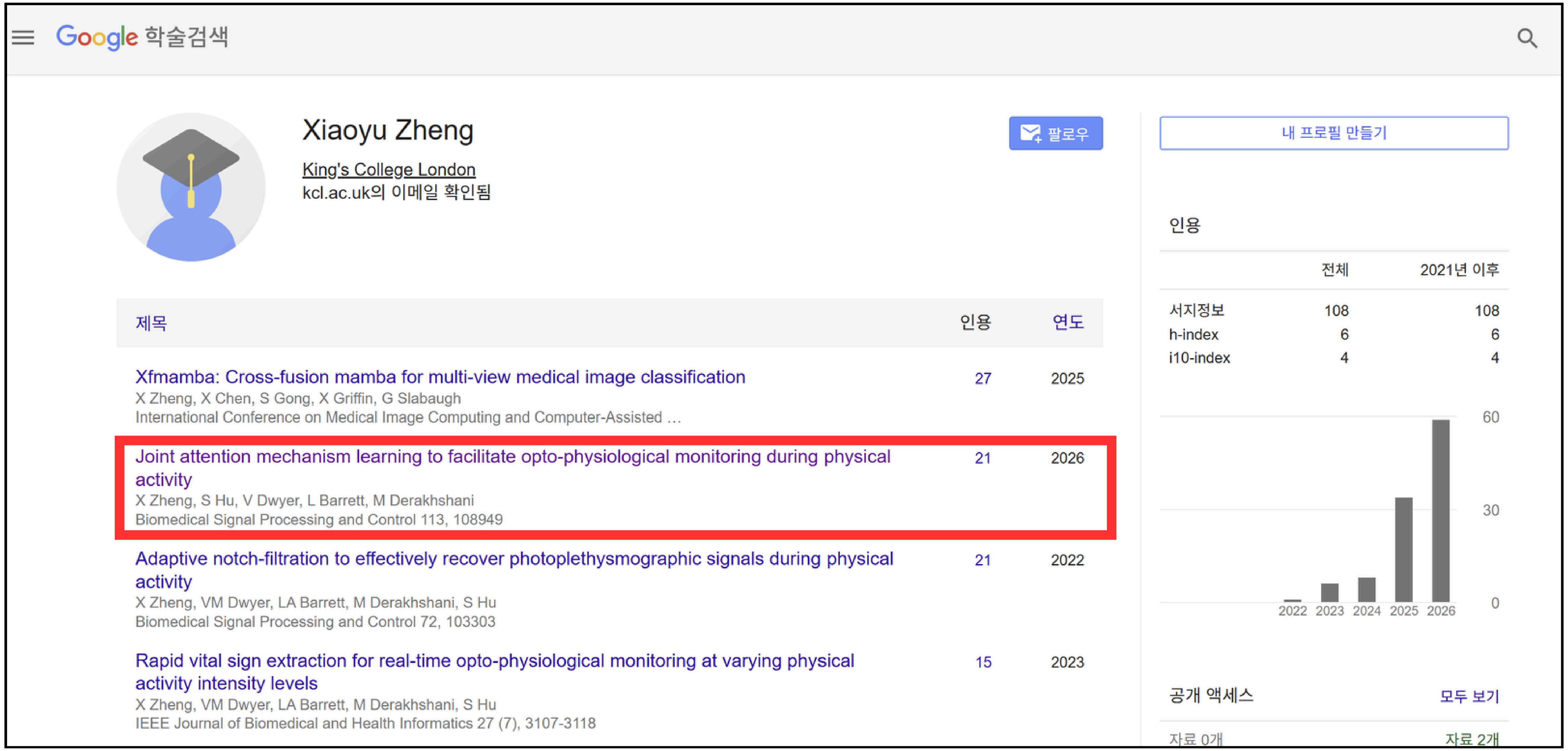
Overview

01 Author & Journal



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- **Biomedical Signal Processing and Control**
- School of Sport, Exercise and Health Sciences, Loughborough University

Introduction 운동 환경에서 PPG 신호의 Motion Artifact 제거 필요성

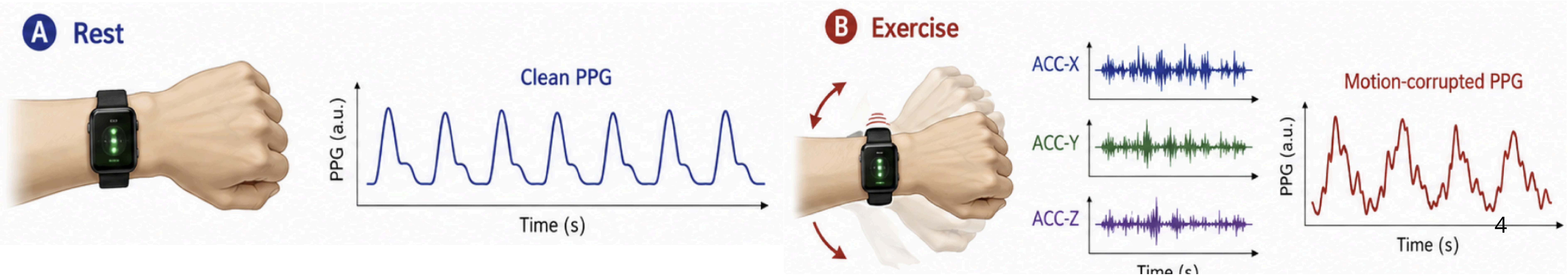
Keywords: photoplethysmography(PPG), generative adversarial network(GAN), motion artefacts(MAs), attention mechanism, opto-physiological monitoring

1. Background

- PPG는 HR, RR, SpO_2 추정에 활용
- 운동 중 Motion Artifact → waveform 왜곡

2. Research Motivation

- **Traditional MA Removal:** 높은 연산 복잡도로 임베디드/웨어러블 적용 불리
- **Existing Deep Learning:** 단순 심박수 추정에 치중(End-to-End 수치 예측 위주)
- **Existing GAN / Attention:** Motion Reference 활용 부재



목표: 동잡음이 포함된 PPG를 깨끗한 PPG waveform으로 복원

- **Generator**
  - PPG+ACC →Generator→Denoised PPG
- **Motion Removal algorithm**
  - during training
- **Discriminator**
  - Generated PPG↔Reference PPG

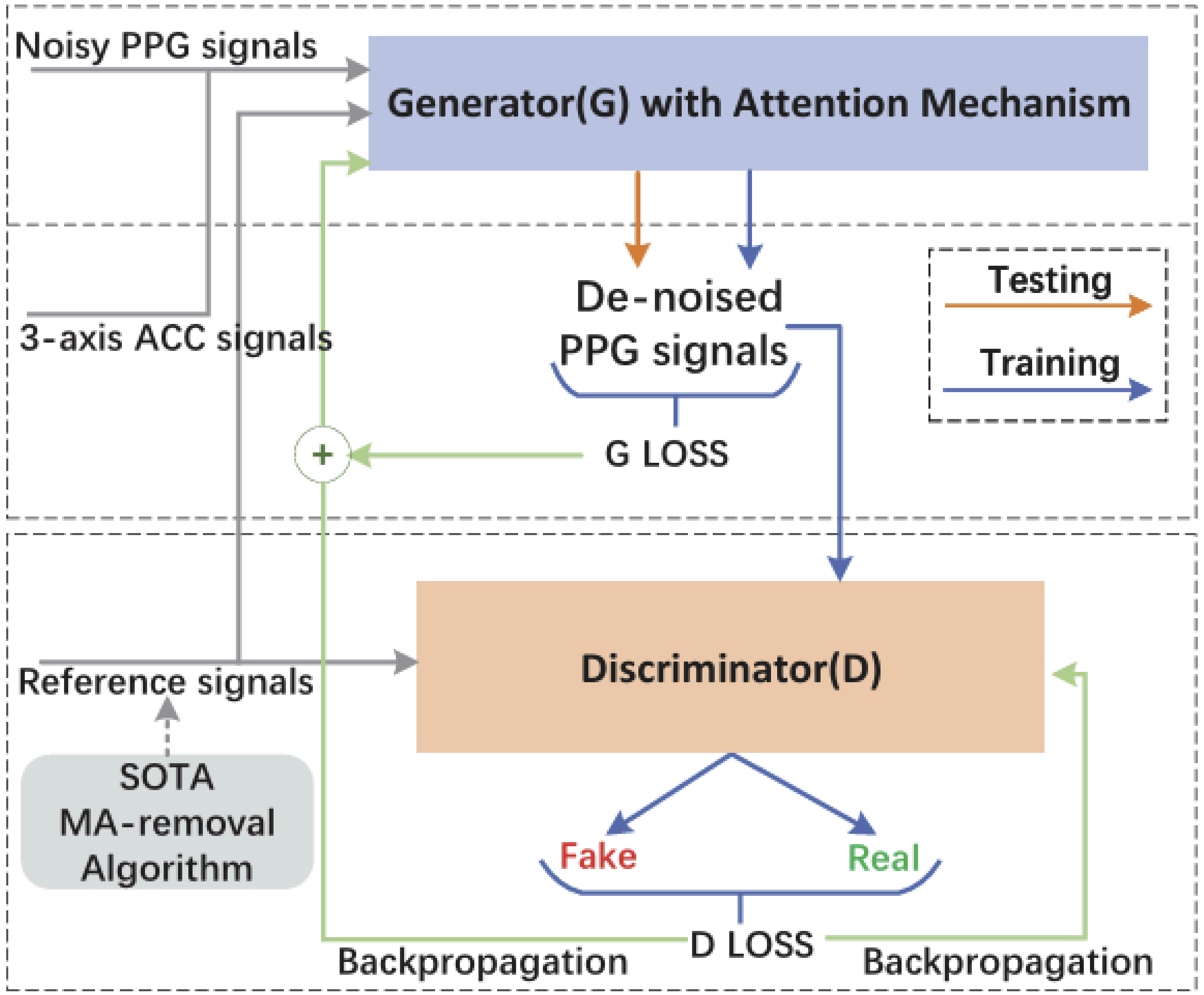


Fig. 1. The proposed AM-GAN comprising a joint attention mechanism together with a GAN.

목표: 동잡음이 포함된 PPG를 깨끗한 PPG waveform으로 변환하는 것

Generator backbone: U-Net (1D)

- signal-to-signal reconstruction
- Skip Connection
  - low-level feature
  - central bottleneck

2.1. U-Net Generator Aligned with Attention Mechanism

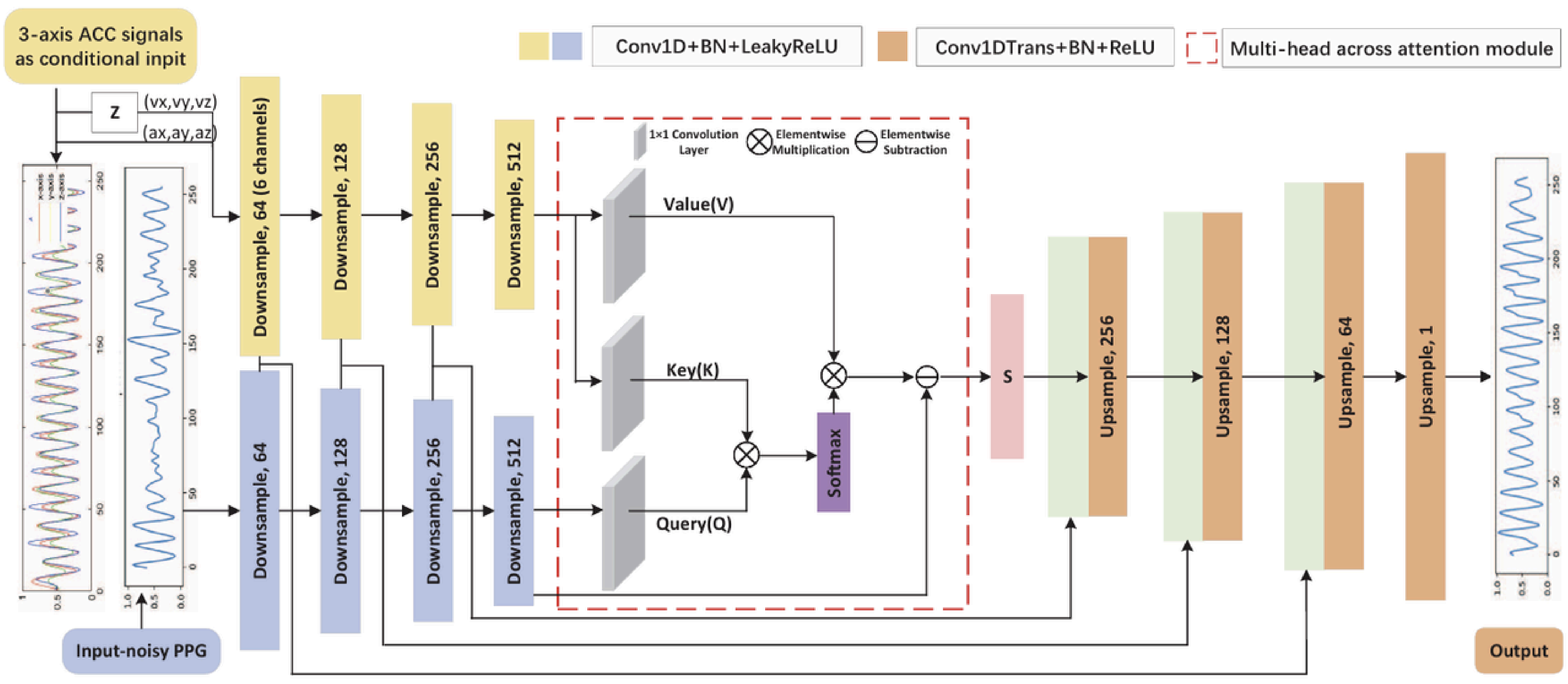


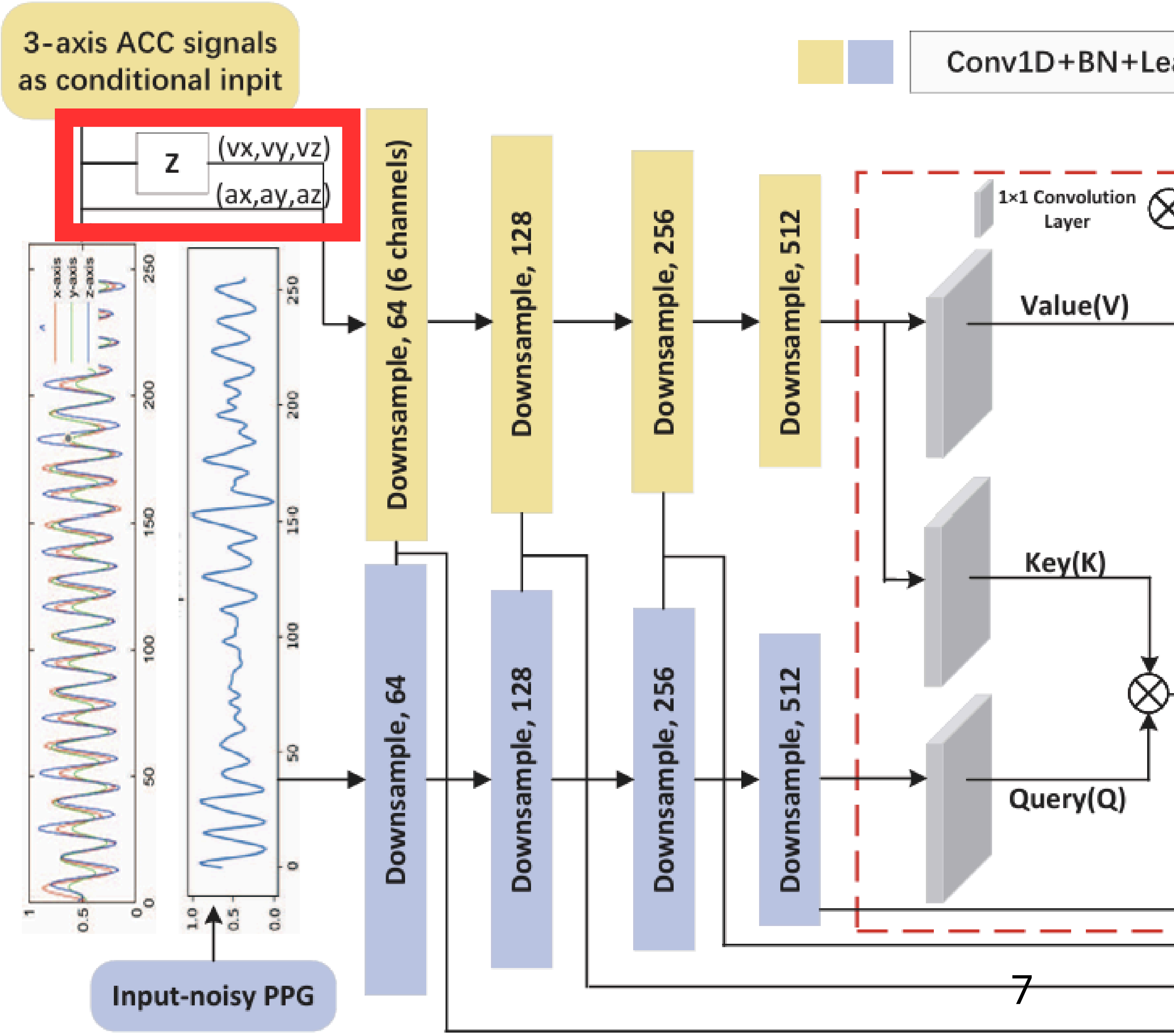
Fig. 2. The generator network aligned with the attention mechanism. In the cross-attention mechanism, the noisy PPG (P) feature map is set as the *Query* tensor, while the combined feature maps for the triaxial ACC and VEL are set as *Key* and *Value* tensors.

U-Net에 noisy PPG만 넣으면 모델은 PPG 안에서
'이 부분이 실제 심박 성분인지, 아니면 Motion Artifact인지' 스스로 구분하기 어려움.

motion-related signal

$$a_x[i], a_y[i], a_z[i] \quad v_x[i], v_y[i]\ v_z[i]$$

$$v_x = \frac{1}{f_s} Z[a_x]$$



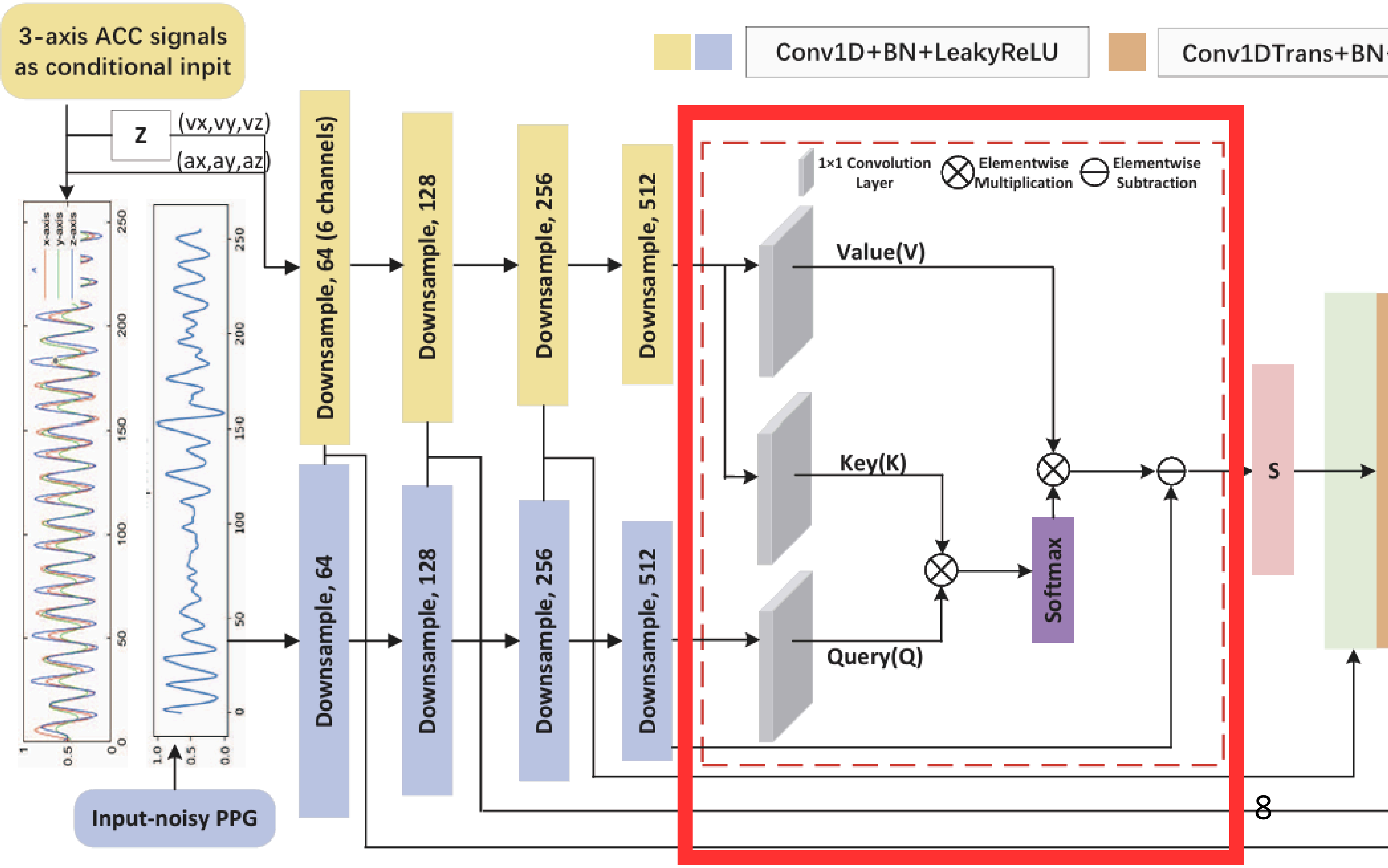
AM-GAN: Attention-mechanism-based Generative Adversarial Network

'PPG feature 중에서 ACC의 움직임 정보와 가장 관련 있는 부분이 어디인가?'

- **Cross-Attention**

$$S = P \ominus softmax((QK^T)/\sqrt{d_k})V$$

- **Multi-Head Attention**



'어떤 PPG가 깨끗한 PPG인가?'

Motion Removal algorithm (during training)

Reference PPG, p = s + n

- p: noisy PPG
- **s: clean PPG**
- n: Motion Artifact
  - 3축 ACC와 ACC를 적분한 velocity
  - motion subspace를 만들고, PPG에서 그 공간과 관련된 성분을 Motion Artifact로 추정

$$\boldsymbol{s} = \boldsymbol{p} - \boldsymbol{\Phi}\boldsymbol{\Phi}^{\top}\boldsymbol{p}$$

$$S = P - \underbrace{\mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V}_{\text{Motion-related feature}}$$

Motion Removal algorithm **Cross-Attention**

Discriminator: Generated PPG↔Reference PPG

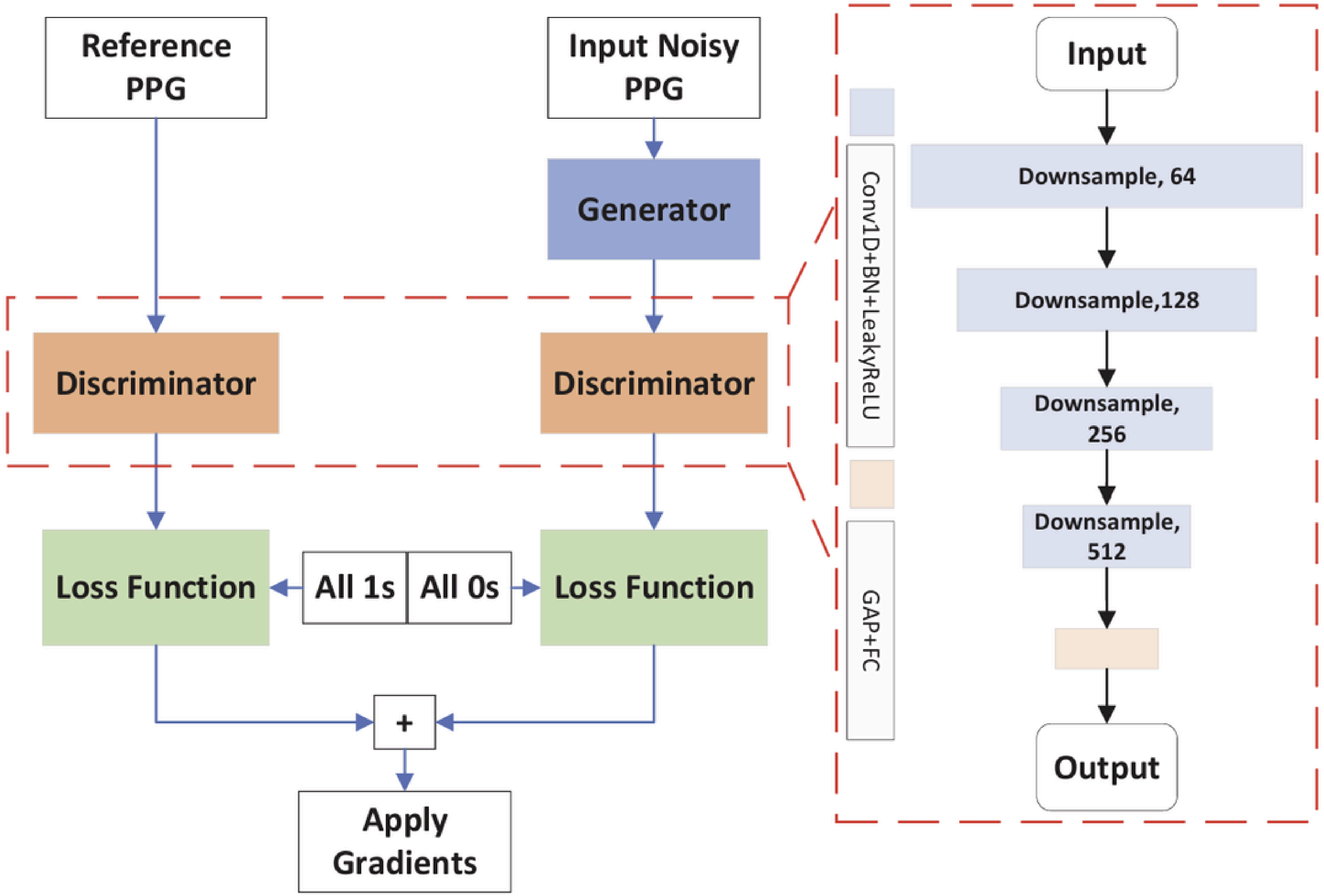
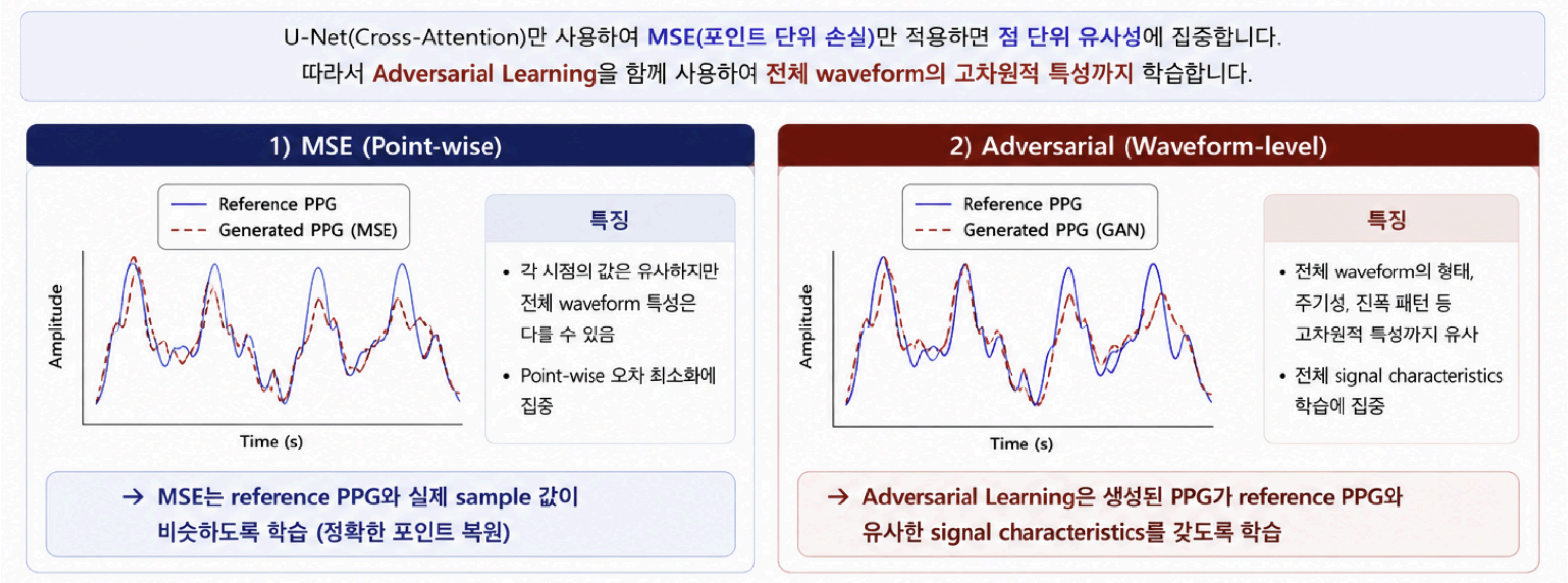


Fig. 3. The discriminator structure.

03 Methods AM-GAN: Attention-mechanism-based Generative Adversarial Network

1. **MSE:** reference PPG와 실제 sample 값이 비슷하도록 학습
2. **Adversarial learning:** 생성된 PPG가 reference PPG와 유사한 signal characteristics를 갖도록 학습

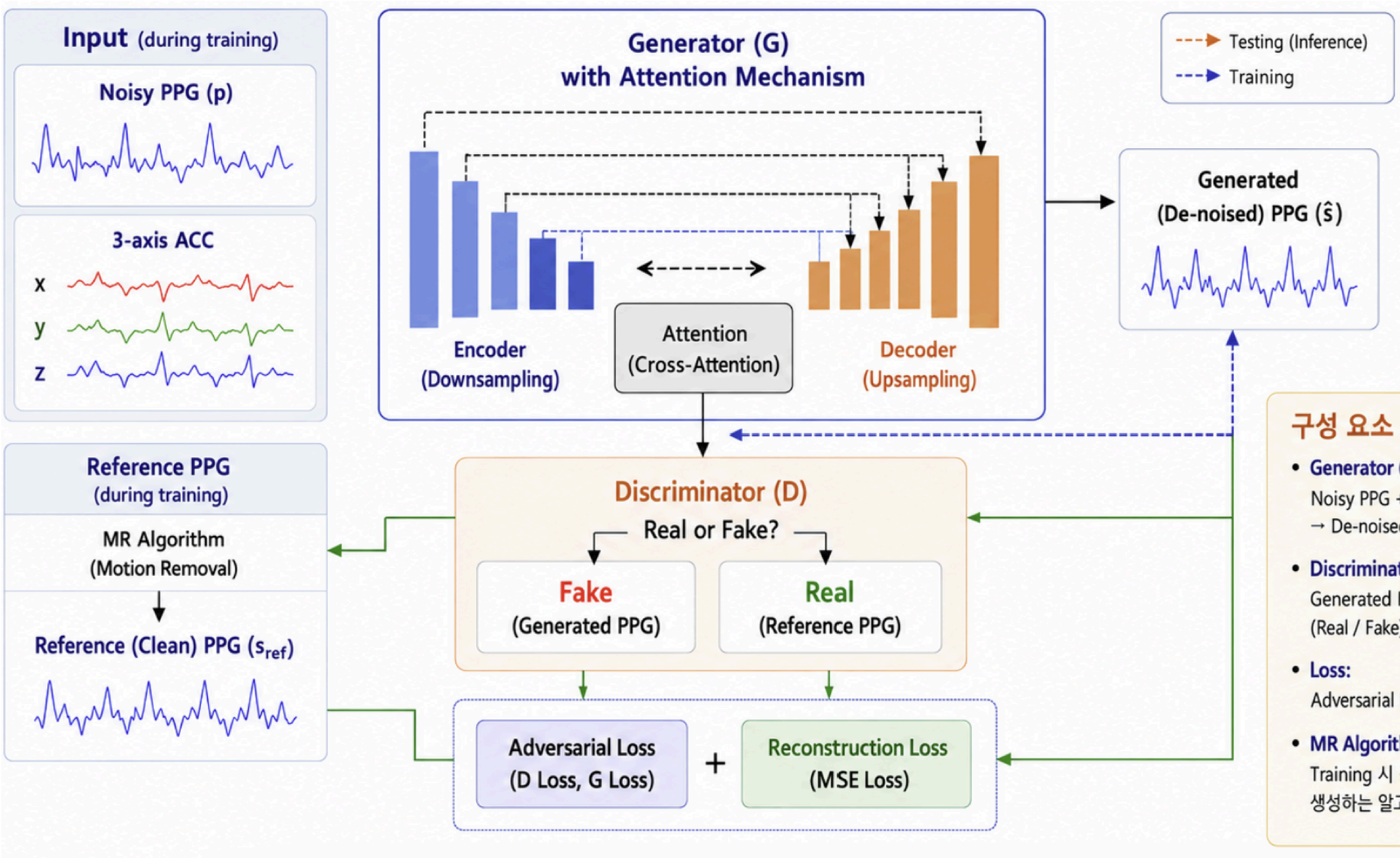


$$L_{MSE} = \frac{1}{n}\sum_{i=1}^{n} \|\boldsymbol{s}_{ref} - G(\boldsymbol{p}, \boldsymbol{a}_{x,y,z})\|_2 \tag{4}$$

$$L_G = \log(1 - D(G(\boldsymbol{p}, \boldsymbol{a}_{\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}})) + \lambda L_{MSE} \tag{5}$$

$$L_D = \log(D(\boldsymbol{s}_{ref})) + \log(1 - D(G(\boldsymbol{p}, \boldsymbol{a}_{\boldsymbol{x},\boldsymbol{y},\boldsymbol{z}}))) \tag{6}$$

AM-GAN: Attention-mechanism-based Generative Adversarial Network



구성 요소

- **Generator (G):** Noisy PPG + ACC → Attention 기반 U-Net → De-noised PPG 생성
- **Discriminator (D):** Generated PPG와 Reference PPG를 구분 (Real / Fake)
- **Loss:** Adversarial Loss + Reconstruction Loss(MSE)
- **MR Algorithm:** Training 시 정한(Reference) PPG를 생성하는 알고리즘

04 Results 시간 영역에서의 PPG 파형 복원 시각화 결과

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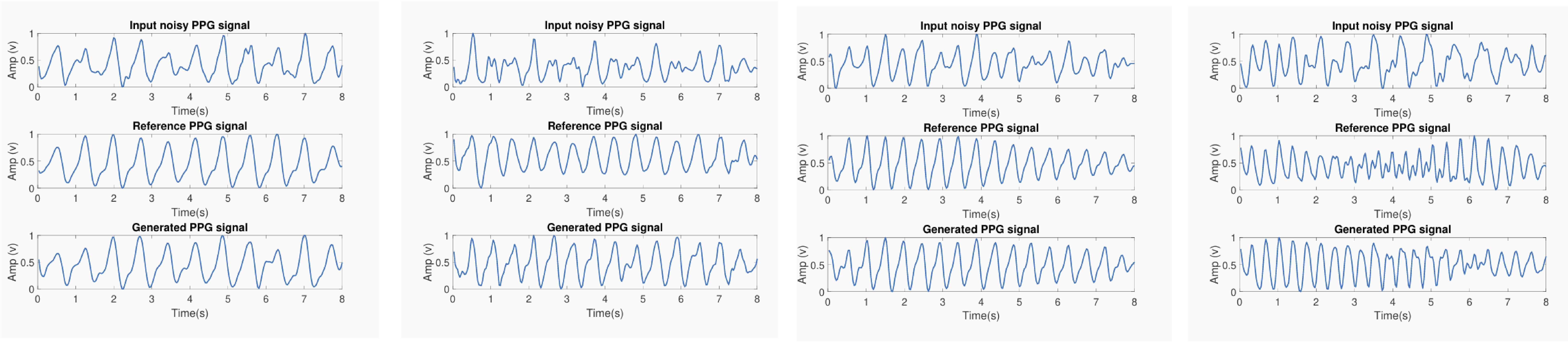
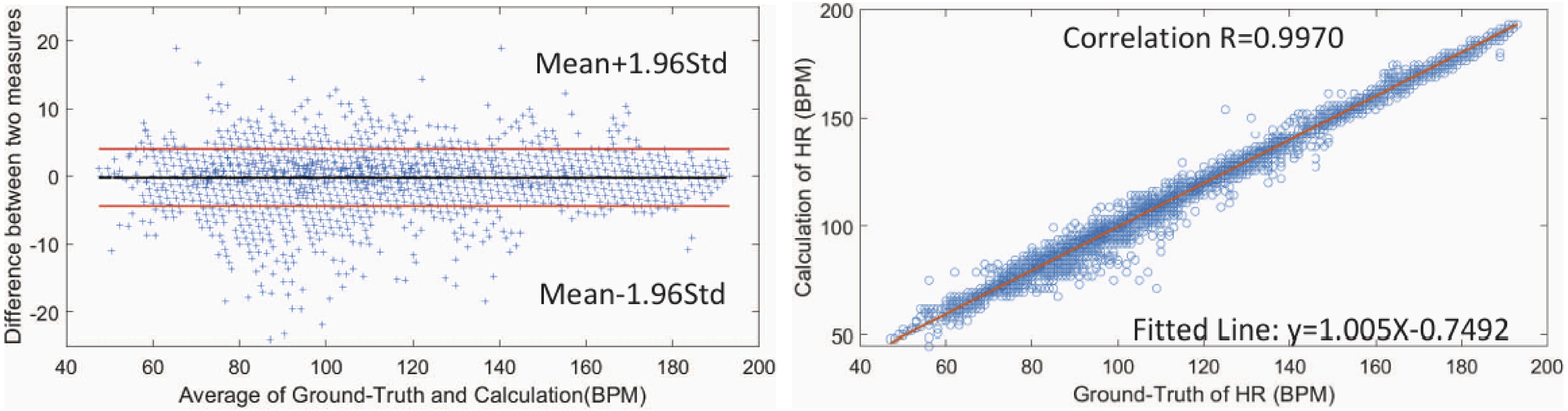


(a) (b) (c) (d)

- Input noisy PPG
- Reference PPG
- Generated PPG

Fig. 4. A representative example for the waveform comparison of the original noisy signal, the reference signal and the generated signal at different physical activity intensities; i.e., (a) at rest, (b) low-intensity activity ($6km/h$), (c) medium-intensity activity ($9km/h$), and (d) high-intensity activity ($12km/h$).

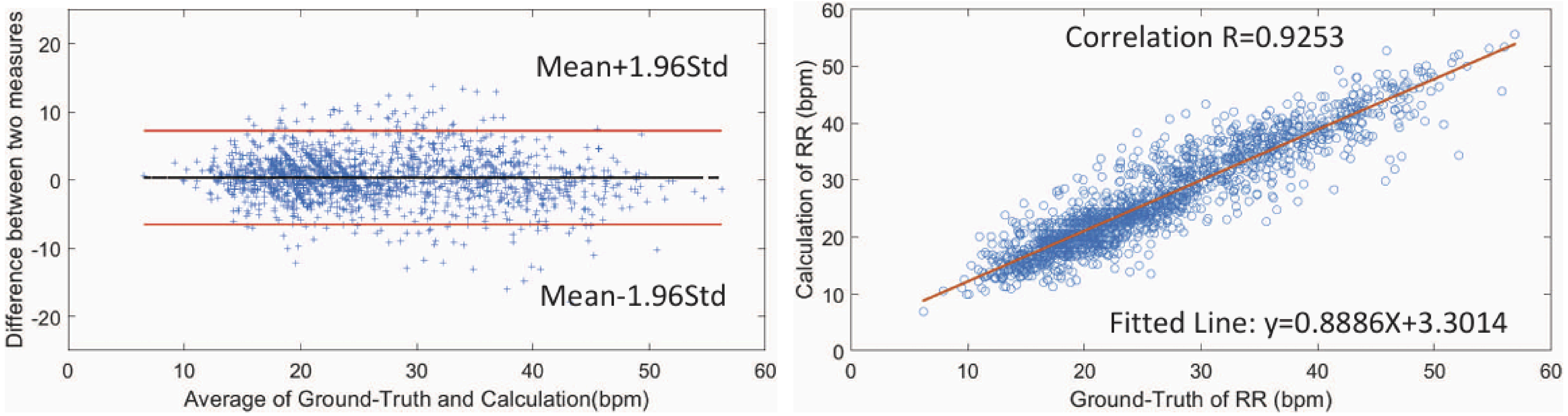
심박수(HR) 추정 성능 평가 — Bland–Altman 및 Pearson 상관분석



(a) (b)

Fig. 7. HR results calculated from the 16 testing subject datasets (in BPM: beats/min) in the cycling and treadmill exercises. (a) Bland-Altman plot. (b) Scatter plot of Pearson correlation.

04 Results 호흡수(RR) 추정 성능 평가 — Bland–Altman 및 Pearson 상관분석



(a) (b)

Fig. 9. RR results, measured in breaths/minute (bpm), were derived from the datasets of 16 test subjects during cycling and treadmill exercises. Displayed are (a) a Bland-Altman plot and (b) a scatter plot illustrating the Pearson correlation.

04 Results 산소 농도별 사이클링 운동에서의 SpO_2 추정 결과

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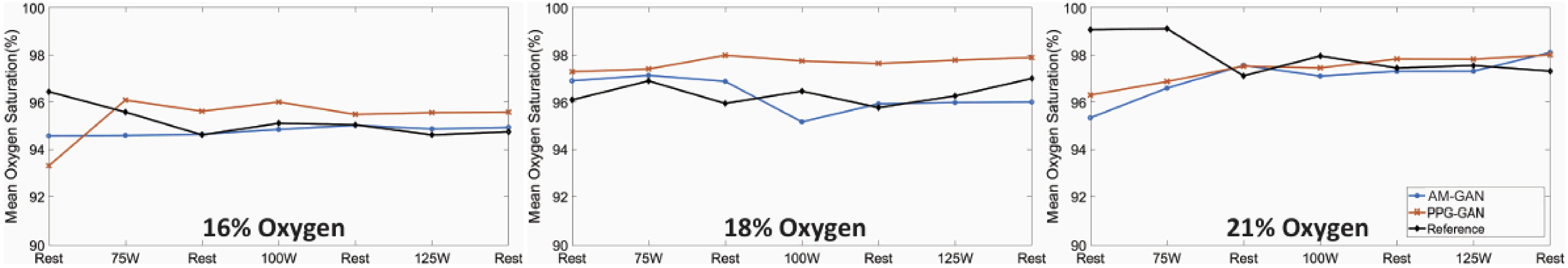
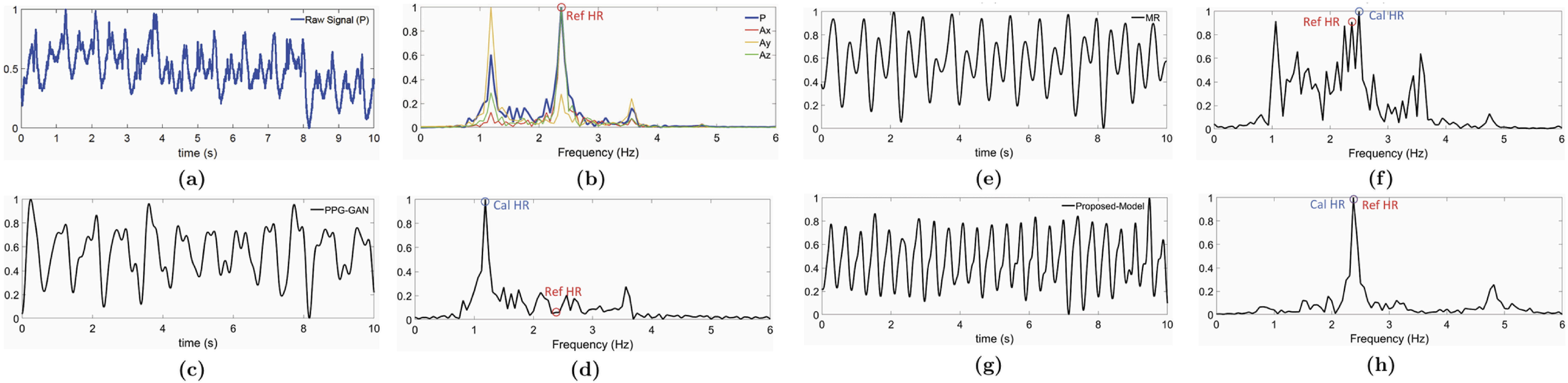


Fig. 10. SpO_2 calculation results from C2 subject 4 (three oxygen levels) in cycling exercise. The X-axis illustrates the cycling activity intensities.

04 Results PPG 잡음 제거 방법별 시간·주파수 영역 비교



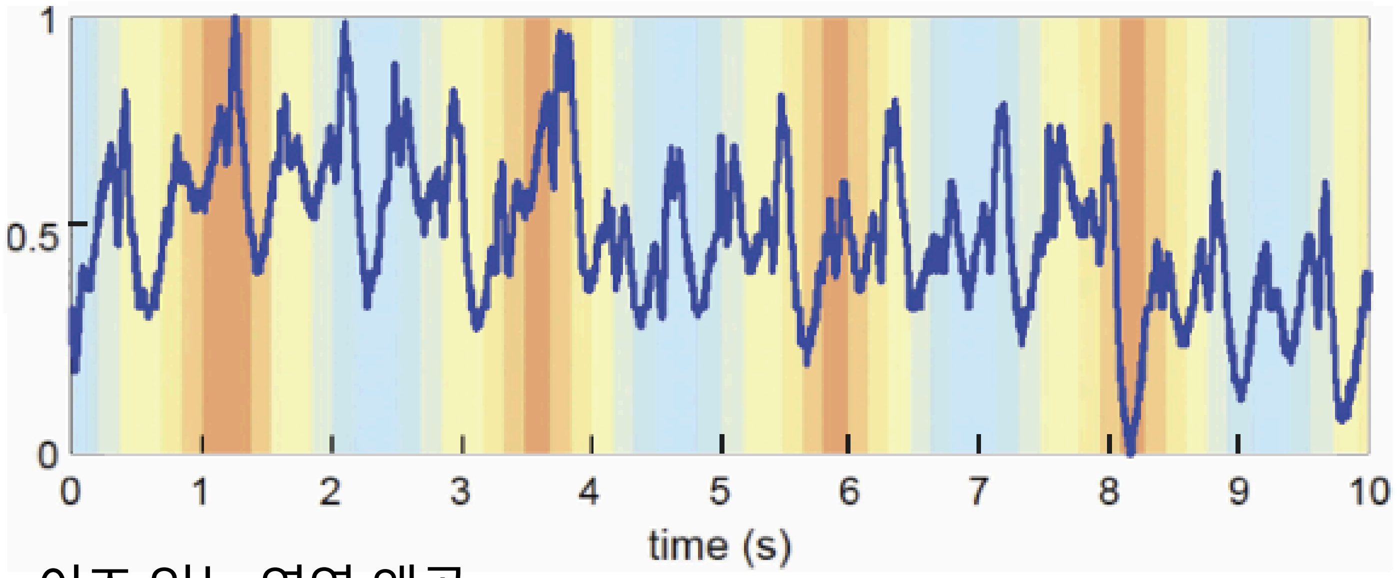
- (a,b) Raw PPG + ACC
- (c,d) PPG-GAN
- (e,f) MR Algorithm
- (g,h) AM-GAN

Fig. 11. Raw signal and de-noised PPG signals in time and frequency domains. (a) Time-domain raw PPG signal. (b) Frequency-domain raw PPG signal (P) and triaxial ACC signals (Ax, Ay and Az). (c,d) Time and frequency-domain generated de-noised PPG signal from PPG-GAN [30]. (e,f) Time and frequency-domain de-noised PPG signal from MR [22]. (g,h) Time and frequency-domain generated de-noised PPG signal from AM-GAN.

AM-GAN Attention Map 시각화

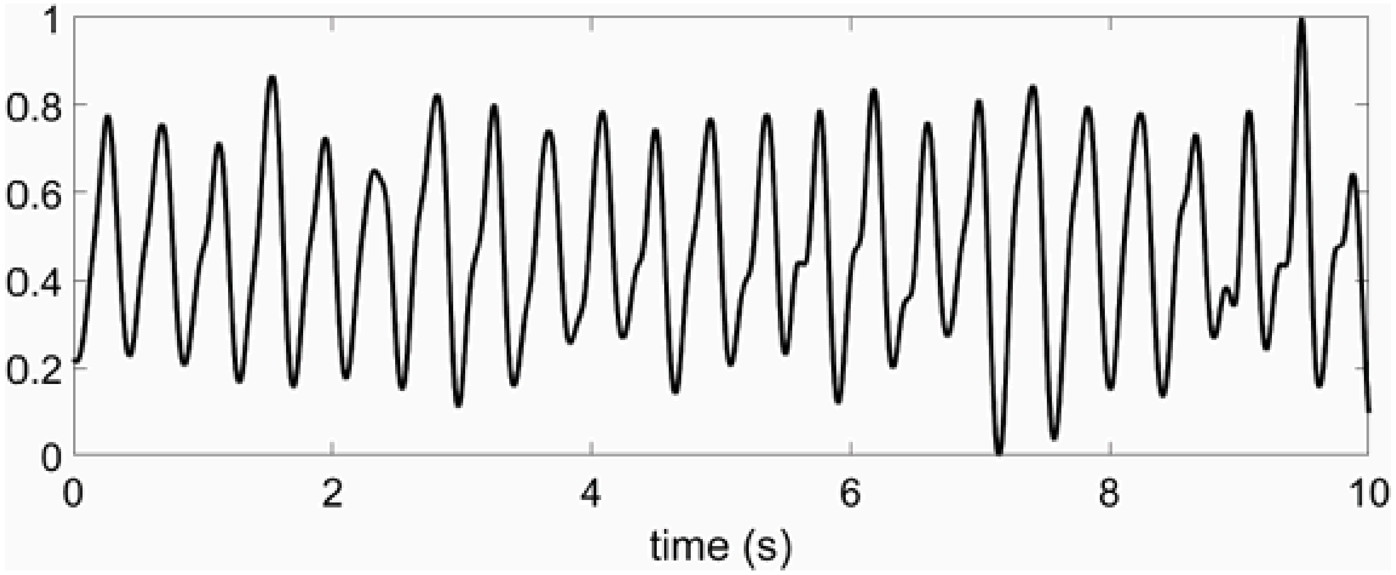
원시 신호 위에 겹쳐진 어텐션 맵

최종 재건된 깨끗한 PPG



주황 부분: 노이즈 있는 영역 왜곡

(a)



(b)

Fig. 12. Visualisation of attention maps is presented where the brighter parts indicate regions to which the generator pays more attention. (a) The attention map overlays highlight the raw PPG signal segments. (b) Reconstructed PPG signal from AM-GAN.

Thank You

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