Application of Deep Hierarchical VAE for ECG Reconstruction

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July 9th, 2025

Clinical Problem: Sleep-Cardiac Monitoring Gap

The Hidden Crisis in Sleep Medicine

Sleep-Cardiac Comorbidity Crisis

- **80%** of sleep apnea patients have undiagnosed cardiac arrhythmias
- **45%** increase in cardiac events during specific sleep stages
- **$15B** annual healthcare cost from undetected interactions

Current Diagnostic Limitations

- PSG studies lack continuous cardiac monitoring
- Separate cardiac & sleep studies = **2x** patient visits

Treatment Optimization Barriers

- CPAP therapy cardiac impact poorly quantified
- Sleep medication cardiac effects undermonitored
- Individual treatment response highly variable
- No personalized risk stratification tools

Workflow Inefficiencies

- Limited simultaneous PSG-ECG monitoring
- Physician expertise gap in cross-modal interpretation

Technical Challenges in Cross-Modal Modeling

Why PSG-to-ECG Reconstruction is Challenging

Signal Processing Challenges

- **Temporal Misalignment:** PSG-ECG signals have different temporal dynamics during sleep transitions
- **Signal Quality Issues:** Sleep study artifacts not present in controlled ECG recordings
- **Multi-Scale Dependencies:** Sleep phenomena span microseconds to hours
- **Domain Shift:** Laboratory vs. home sleep study differences

Individual Variability

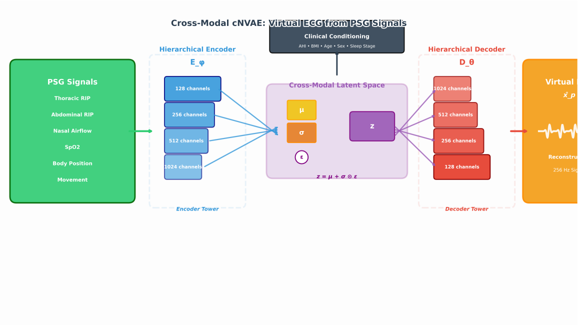
- **Physiological Coupling:** Respiratory-cardiac relationships vary dramatically between patients
- **Comorbidity Effects:** Diabetes, hypertension, obesity alter baseline patterns
- **Medication Interactions:** Sleep drugs, cardiac medications modify signal relationships
- **Demographic Factors:** Age, sex,

Novel Cross-Modal Adaptation of Existing cNVAE-ECG

- Building on Established **cNVAE-ECG** (Sviridov & Egorov, 2025)
- 488M parameters, **12-lead ECG generation**
- Validated class conditioning framework for **cardiac pathologies**

Proposed Approach

- Polysomnography (PSG) signals replace noise input
- **Sleep Clinical Conditioning:** 47 sleep variables + AHI, sleep stages
- **Cross-Domain Feasibility Study:**



Proposed Architecture:
PSG Input → Clinical Conditioning → ECG Reconstruction

488M parameters | 4-scale hierarchical VAE |

Comprehensive Dataset & Cross-Modal Framework

Multi-Modal Sleep Dataset

- **63** 63 sleep study participants (Aug–Oct 2024)
- 103,705 synchronized 30-second **windows**
- 8 channels (EEG, EOG, EMG, respiratory, ECG)
- **Clinical Variables:** 47 sleep architecture & physiological metrics
- 256 Hz sampling, SNR > 15 dB preprocessing

Data Splits (Patient-Level)

- **Train:** 56,919 windows (AHI-stratified)

Clinical Conditioning Framework

Tier 1 - Primary Conditioners:
AHI, Sleep Efficiency, REM%, BMI, Age, O2 Saturation

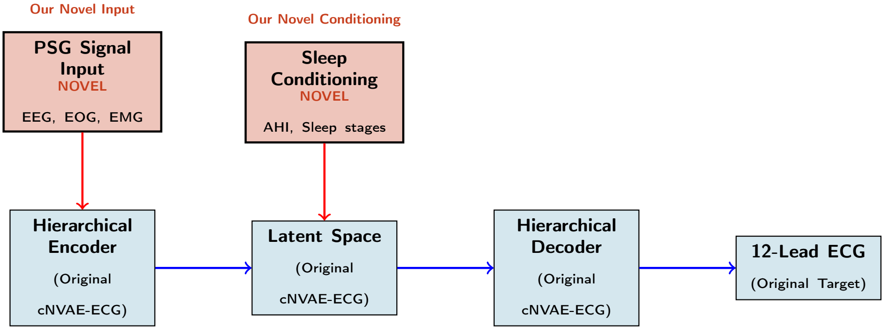
Tier 2 - Sleep Architecture:
N1%, N2%, N3%, REM Latency, Arousal Index, PLM Index

Tier 3 - Individual Factors:
Comorbidities, Medications, Sleep Questionnaires (PSQI, ESS)

Cross-Modal Innovation

- Sleep stage-aware attention mechanisms
- Respiratory-cardiac coupling modeling
- Individual-specific adaptation
- Multi-scale temporal relationships

Architecture: Original cNVAE-ECG + Novel PSG Conditioning



Original cNVAE-ECG Framework

- Hierarchical VAE architecture (Sviridov & Egorov)
- Noise-to-ECG generation with class conditioning
- 12-lead ECG output with cardiac pathology labels
- Proven superior performance vs. GAN methods

Our Novel Contributions

- PSG signal input instead of random noise
- Sleep clinical variable conditioning framework
- Cross-modal PSG-to-ECG reconstruction paradigm
- Feasibility study for sleep-cardiac monitoring

Simple, Achievable Metrics for Phase 1-2

Basic Success Criteria

- **Proof of concept:** Any correlation $r > 0.3$ between reconstructed and actual ECG
- **Heart rate extraction:** Basic heart rate tracking accuracy ± 5 BPM
- **Sleep conditioning benefit:** 10-15% improvement when adding AHI + sleep stage

What We'll Actually Measure

- **Signal correlation:** Overall ECG waveform similarity (Pearson r)
- **Heart rate accuracy:** Mean absolute error in beats per minute
- **Model convergence:** Does training actually work and stabilize?
- **Sleep stage impact:** Performance difference across N1, N2, N3, REM

Technical Limitations & Constraints

Fundamental Technical Challenges

Fundamental Constraints

- **Information bottleneck:** PSG may lack sufficient info for full ECG reconstruction
- **Non-invertible mappings:** Multiple PSG patterns $\rightarrow$ same ECG morphology
- **Temporal causality:** ECG-PSG relationships may be bidirectional, not unidirectional
- **Individual variability ceiling:** Some patients may be inherently unpredictable

Failure Mode Analysis

- **Signal Quality Failures:** Poor PSG $\rightarrow$ unreliable ECG reconstruction
- **Domain Shift Failures:** Lab-trained model fails in home sleep studies
- **Rare Event Failures:** Model misses infrequent but critical arrhythmias

Risk Mitigation & Clinical Challenges

Risk Mitigation Strategies

- **Uncertainty-Aware Inference:** Flag low-confidence reconstructions
- **Multi-Model Ensembles:** Combine predictions from diverse architectures
- **Active Learning:** Continuously improve with physician feedback
- **Fallback Mechanisms:** Revert to conventional monitoring when AI fails

Clinical Adoption Barriers

- **Physician trust:** Skepticism about AI-generated cardiac data
- **Workflow integration:** Disruption of established clinical procedures
- **Training requirements:** Staff education on AI system capabilities/limitations
- **Cost justification:** ROI unclear for healthcare systems

Realistic Success Assessment

Worst-Case Scenarios

- **False Security:** Physicians over-rely on AI, miss critical findings
- **Diagnostic Cascade:** AI errors propagate through clinical decision chain
- **Litigation Risk:** Malpractice liability when AI-assisted diagnosis fails
- **Health Disparities:** AI exacerbates existing healthcare inequalities

Success Probability Assessment

- **Technical Feasibility:** 70% - Challenging but achievable
- **Clinical Validation:** 60% - Requires extensive multi-site studies
- **Regulatory Approval:** 50% - Novel AI/ML pathway uncertainty
- **Clinical Adoption:** 40% - Significant workflow barriers

Realistic Implementation Plan

Focus on Phase 1-2: Proof of Concept

Phase 1: Basic Adaptation (Months 1-2)

- Get PSG signals feeding into cNVAE-ECG architecture
- Replace noise input with simple PSG signal encoder
- See if the model can train without crashing
- **Success:** Any positive correlation ($r > 0.2$) between output and real ECG

Phase 2: Add Sleep Variables (Months 3-4)

- Add AHI and basic sleep stage information as conditioning
- Test if sleep context helps reconstruction quality
- Analyze which sleep variables matter most

What We Hope to Learn

Realistic Expectations for Phase 1-2

Technical Insights

- **Is it even possible?** Can PSG signals contain enough info for basic ECG reconstruction?
- **What are the bottlenecks?** Where does the approach fail and why?
- **Which sleep variables help?** Does AHI or sleep stage improve results?

Practical Outcomes

- **Proof of concept** (or proof it doesn't work)
- **Technical roadmap** for future research directions
- **Realistic assessment** of clinical potential

Acknowledgements

Special Thanks

Dr. Christopher Cheung

Principal Investigator & Research Supervisor

Schulich Heart Program, Sunnybrook Health Sciences Centre

T-CAIREM

Funding & institutional support for advancing AI-driven sleep-cardiac research

Sleep Laboratory Team @ Sunnybrook

Collaborative support for cross-modal dataset development

Thank You

Questions & Discussion

Cross-Modal Sleep-Cardiac Monitoring
Advancing precision medicine through AI-driven
PSG-to-ECG reconstruction with clinical conditioning

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