A Cross-Modal ECG–SQUID MCG Representation Learning Framework

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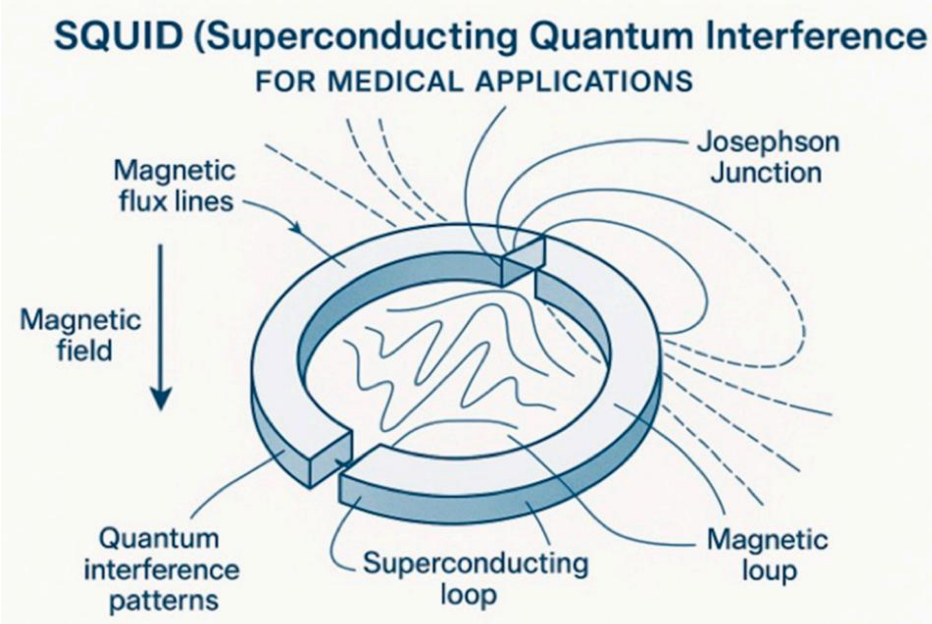
What is SQUID Magnetocardiography (MCG)

MCG = Magnetic ECG measured using SQUID devices

- SQUID = **Superconducting Quantum Interference Device**
- Most sensitive magnetic sensor in the world
- Detects magnetic fields produced by the heart
- Unlike ECG, magnetic fields **aren’t distorted** by body tissues
- Can reveal cardiac abnormalities that ECG may miss
- Used today mainly in research centers (rare & expensive)



- *Fenici et al., European Heart Journal, 2020*
- *Park et al., Sensors, 2020*
- *Koch et al., Biomedical Engineering Online, 2011*

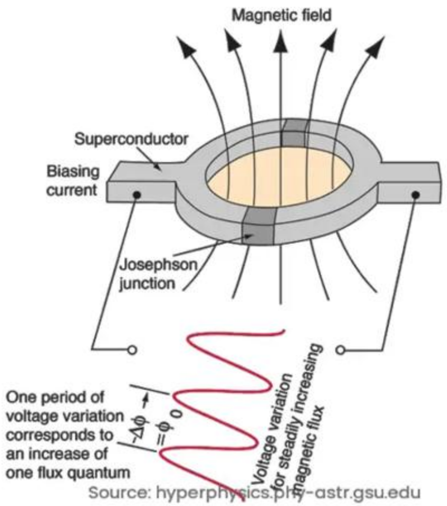
Why MCG matters (Clinical motivation)

MCG can detect:

- Ischemia earlier than ECG
- Conduction abnormalities
- Fetal arrhythmias (when ECG is unreliable)
- Subtle repolarization changes
- Spatial current distribution of the heart

Problem:

- Almost no hospitals use MCG — devices are rare, expensive, and datasets are tiny.
- This makes AI or deep-learning on MCG nearly impossible.



The Current Gap

Gap 1 – MCG Technology Is Underutilized in Clinical Practice

- SQUID-MCG can detect ischemia, fetal arrhythmia, and subtle conduction delays
- But MCG is rare, expensive(***cost $1M+***), and only available in research centers

Gap 2 – ECG Alone Cannot Capture Everything

- ECG signals get distorted by tissue, muscle, fat
- MCG is cleaner, but too rare
- Clinicians lack a unified view combining both modalities

Gap 3 – There Are Almost No MCG Datasets for AI

- Only one open-access dataset contains real SQUID-MCG: Koch et al. (2011)
- It is extremely small (127 beats)
- Makes modern AI training impossible without new methods

Gap 4 – No way to help hospitals without SQUID machines

- If we could use ECG to approximate MCG
- Many hospitals could benefit from MCG insights
- But no such system exists today

Probable Solution

We need a way to learn MCG representations without needing thousands of MCG recordings.

ECG and MCG measure the same heart activity, but each sees a DIFFERENT part of the truth.

- ECG beat → vector (electrical potential ON the skin)
- MCG beat → vector (magnetic field generated by the SAME currents INSIDE the heart)
- Both vectors are close if they come from the same heartbeat.

Simple Word:
ECG and MCG are like two cameras taking a picture of the same object from different angles.

→ Both capture the heartbeat.
→ Both look at the same depolarization/repolarization.
→ Both detect conduction abnormalities.

BUT they see different distortions and different hidden details.

ECG → foundational cardiac patterns
MCG → rare, high-value complementary info

Core Research Idea

This study proposed: A model connects electrical and magnetic views of the same heartbeat to provide a more complete cardiac understanding.

The input to the trained model can be either an ECG alone, an MCG alone, or both — because the model learns a shared representation for both modalities. A shared latent heartbeat representation for clinical use.

Dataset

PTB Diagnostic ECG Dataset
Source: PhysioNet / PTB Diagnostic ECG Database
Signals: 12-lead ECG
Sampling Rate: 1000 Hz
Subjects: 290+
Conditions: Myocardial infarction, arrhythmia, block, hypertrophy, healthy controls
Size: Thousands of heartbeats (large dataset)

PTB gives us a strong, robust ECG understanding before we try to align ECG with MCG.

Koch ECG–MCG (SQUID) Paired Dataset
Source: Koch et al., Biomedical Engineering Online (2011)
Modalities:

BSPM (Body Surface Potential Mapping) → electrical activity
- 32 channels
- 1000 Hz

MCG (Magnetocardiography) using SQUID
- 100 channels
- 1000 Hz
- Femto-Tesla units (fT)

MRI torso scans

Methodology Overview

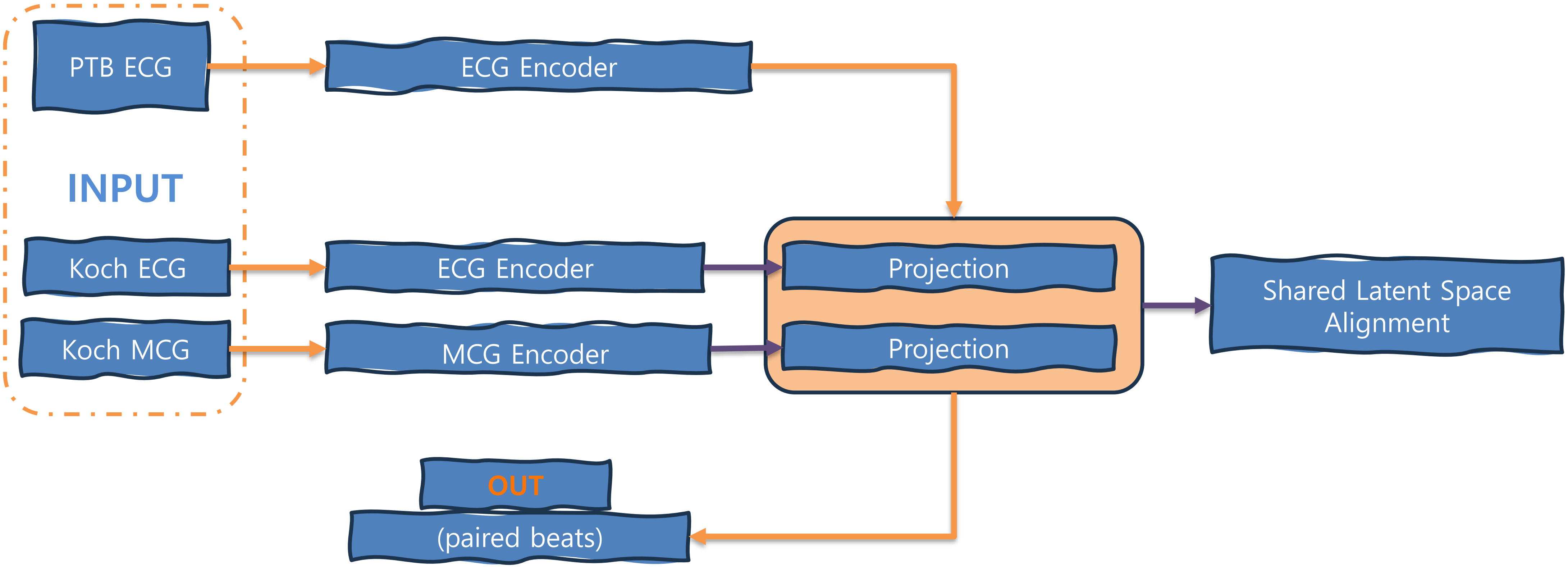
Stage 1 – Learn ECG features from a large dataset (PTB Diagnostic ECG)

- Self-supervised learning (no labels needed)
- Model learns patterns of electrical activity

Stage 2 – Align ECG with MCG using paired data (Koch dataset)

- For each heartbeat: ECG signal ↔ MCG signal
- Use contrastive learning to match them in a shared space

Stage 3 – Align ECG with MCG using paired data (Koch dataset)



Conclusion

In this project we propose to:

Self-supervised learning (no labels needed)

- **Build the first cross-modal representation between ECG and MCG**
- **Overcome MCG data scarcity using contrastive learning**
- **Explore a new direction for cardiac AI research**
- **Enable practical future applications like virtual MCG, enhanced diagnosis, and multimodal fusion**

Status:

- Dataset (ready)
- Preprocessing complete (initially done)
- Model design complete (0n progress: experimented with 1d CNN)
- Training (Next Step)
- Evaluation (Next Step)

Thank You