Continual Adaptive Control for Pediatric Myoelectric Prostheses Using Single-Channel EMG and On-Device Learning

Armelle Varillas[1,2], John Sparkman[1], Damla Turgut[1], Albert Manero[1]

[1]Limbitless Solutions, University of Central Florida, Orlando, FL

[2]Johns Hopkins University, Baltimore, MD

Motivation

How to reduce the current~40% pediatric prosthetic abandonment[1]

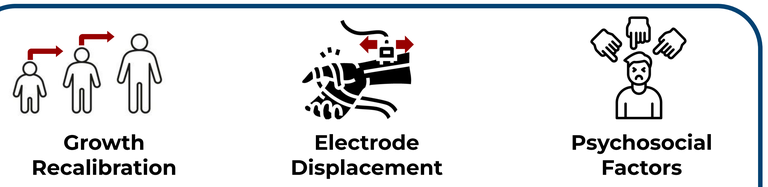


Figure 1: Pediatric prosthetic abandonment is driven by recalibration burden, electrode displacement failures, and psychosocial factors.[2,7]

Background

The Challenge[3]

- **Prosthetic Control Problem**
- **Traditional Approach**
- **Catastrophic Forgetting**

Why Continual Learning?[4]

✓ Adapt to new motor patterns
✓ Retain previously learned gestures
✓ Personalize to individual users
✓ Reduce recalibration burden

Digital Signal Processing[5]

- 2000 Hz sampling rate
- 20 - 450 Hz bandpass filter
- 200 ms windows (50% overlap)

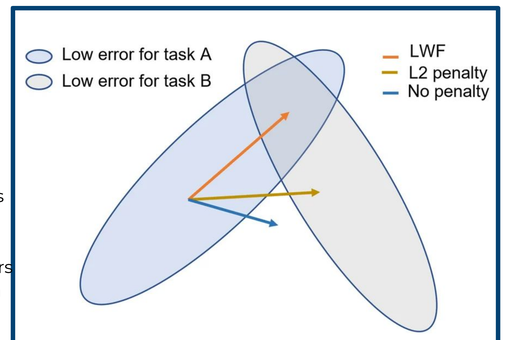


Figure 2: Elastic Weight Consolidation

Research Question

Can neural networks continuously adapt to changing EMG patterns while preserving previously learned gestures?

Dataset

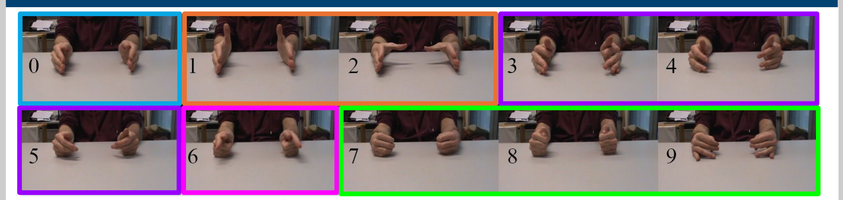
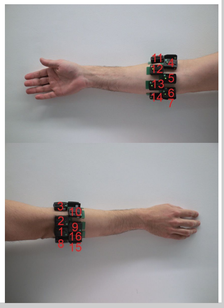


Figure 3: Ninapro DB8[8]

- **Subjects**: 10 able-bodied, 2 amputees
- **Gestures**: 10 hand movements → 5 classes
- **Rest**, **Thumb** (up/extension), **Digits** (flexion), **Pointing** (index point/extension), **Grips** (cylindrical, lateral, and tripod grips)
- **Sensors**: 16 EMG channels with 9-axis IMUs (accelerometer, gyroscope, magnetometer)
- **Sessions**: 3 acquisition sessions (A1, A2, A3) per subject (10 reps, 10 reps, 2 reps)



Methods

Model Architecture: built on a TCN framework[9]

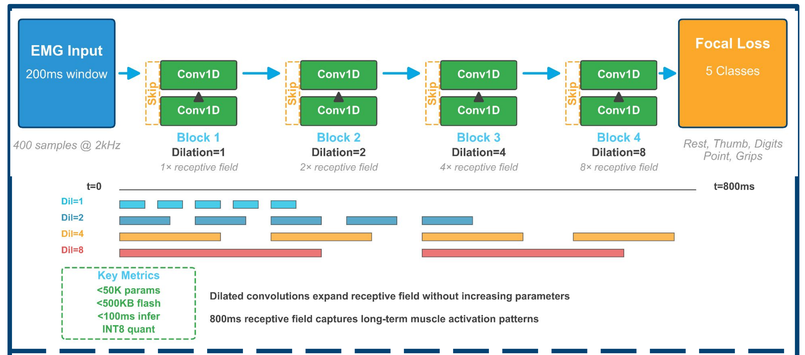


Figure 4: Temporal Convolutional Network (TCN)

KEY INNOVATIONS

1. **Class-Specific EWC Regularization**
   • Targeted regularization → better stability-plasticity balance
2. **Stratified Fisher Computation**
   • Acc. importance weighting without overfitting
3. **Focal Loss Integration**
   • 86.5% peak accuracy



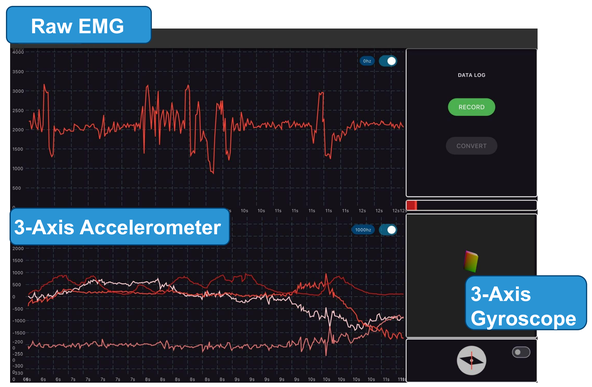


Figure 5: Data collection and sensors

Discussion

Why EWC Works for EMG

1. **Parameter Protection:** Fisher matrix identifies gesture-critical weights → prevents overwriting
2. **Balanced Learning:** λ = 5000 provides stability without over-rigidity
3. **Stratified Fisher:** Class-balanced sampling → fair importance estimation
4. **Focal Loss Synergy:** Hard example focus + catastrophic forgetting prevention

Limitations of Offline Approach

1. **Fixed Model Post-Training:** Cannot adapt to within-session changes (fatigue, electrode shift)
2. **Generalization Gap:** 20.6% performance drop from training → test sessions
3. **Uniform Lambda:** Same regularization for all classes ignores task-specific difficulty
4. **Computational Cost:** 50 total epochs (30 + 20) → not real-time capable

Clinical Implications

Current State: Proof-of-concept for continual learning feasibility in EMG

Translation Barriers:

- Offline training requires supervised data collection (user burden)
- No adaptation during actual prosthetic use
- Generalization gap → performance degrades in real-world deployment

Path Forward: Hybrid architecture combining offline initialization + online adaptation

Results

Success: Negative Forgetting

- All 12 subjects showed improvement (not degradation)
- Mean +20.9% accuracy gain from A1 → A2
- EWC successfully preserved A1 knowledge while learning A2

Challenge 1: Generalization Gap (20.6%)

- Training (A2): 73.2% → Test (A3): 52.6%
- Subject-specific factors (electrode position, muscle fatigue)
- Indicates need for online adaptation (motivation for future work)

Challenge 2: Rest Class Instability

- 31-85% accuracy range across subjects
- Most variable gesture class
- Hypothesis: Rest lacks discriminative features → needs lower λ

Future Work

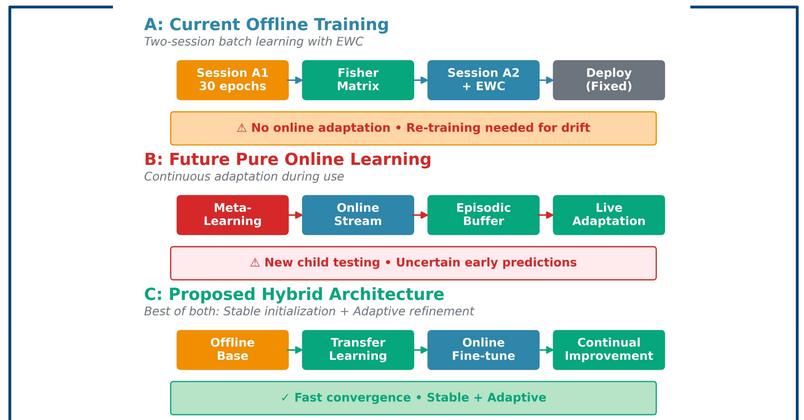


Figure 6: Current model architecture and proposed future architectures

Conclusions

Key Findings

1. **EWC successfully prevents catastrophic forgetting**
2. **73.2% mean accuracy achieved**
3. **20.6% generalization gap identified**
4. **Rest class instability**

Scientific Contributions

- First application of stratified Fisher computation to EMG data
- Demonstration of negative forgetting (learning gains) in sequential gesture adaptation
- Identification of class-specific EWC optimization as critical direction

Acknowledgments & References

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