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EEG-BASED USER IDENTIFICATION SYSTEM USING 1D-CONVOLUTIONAL LONG SHORT-TERM MEMORY NEURAL NETWORKS WITH WAVELET TRANSFORM

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Outline

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- Datasets
- Methodology
- Proposed Enhancement
- Results
- Conclusion

Introduction

- **Problem Statement**: Traditional user identification systems, such as passwords and fingerprints, have vulnerabilities to theft and forgery.

- **EEG as Biometrics**: EEG signals are unique and difficult to mimic, offering a more secure biometric solution.

- **Objective**: Propose a novel 1D-Convolutional LSTM neural network to enhance EEG-based user identification with wavelet transform

Datasets

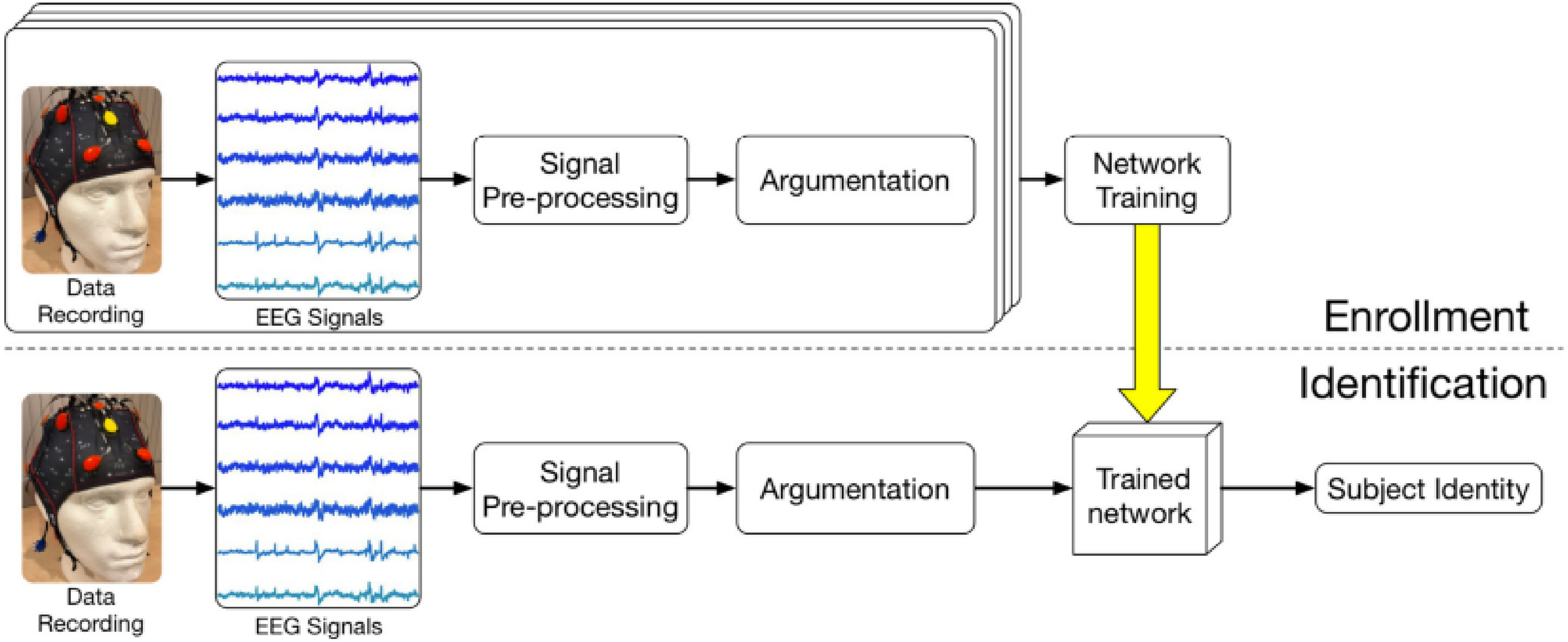
Physionet EEG Motor Movement/Imagery Dataset

- **Subjects**: 109 individuals performing physical and imaginary tasks.
- **Channels**: 64 EEG channels with sampling frequency of 160 Hz.
- **Preprocessing**: Normalization and segmentation into 1-second windows (160 × 64 samples).

Experimental Settings:

- Different experiments with 4, 16, 32, and 64 EEG channels.

Overview of the proposed EEG-based biometric identification system



Experiment Methodology

Preprocessing:

- Normalize EEG signals across time.
- Segment into 1-second epochs with 160×64 samples.

Model Training:

- **Data split:** 90% for training/validation (3:1 ratio), 10% for testing.
- **Optimization:** Adam optimizer, dropout for regularization.
- **Comparison Models**: CNN, LSTM, and 1D-Convolutional LSTM.
- **Evaluation Metrics:** Rank-1 accuracy

Proposed Enhancements

Improving Signal Processing:

- Implemented advanced feature extraction method called wavelet transform to handle non-stationary signals.

Implemented Models:

- Comparison of CNN, LSTM, and CNN-LSTM hybrid approaches with wavelet transform and without wavelet transform.
- Demonstrate improvements from CNN-LSTM over standalone CNN and LSTM.

What is Wavelet Transform?

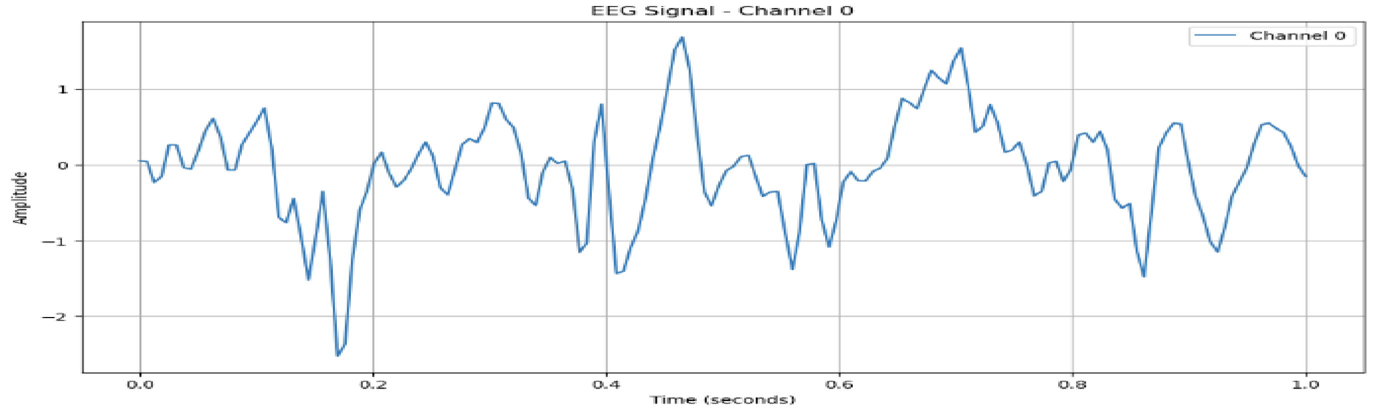
Wavelet Transform:

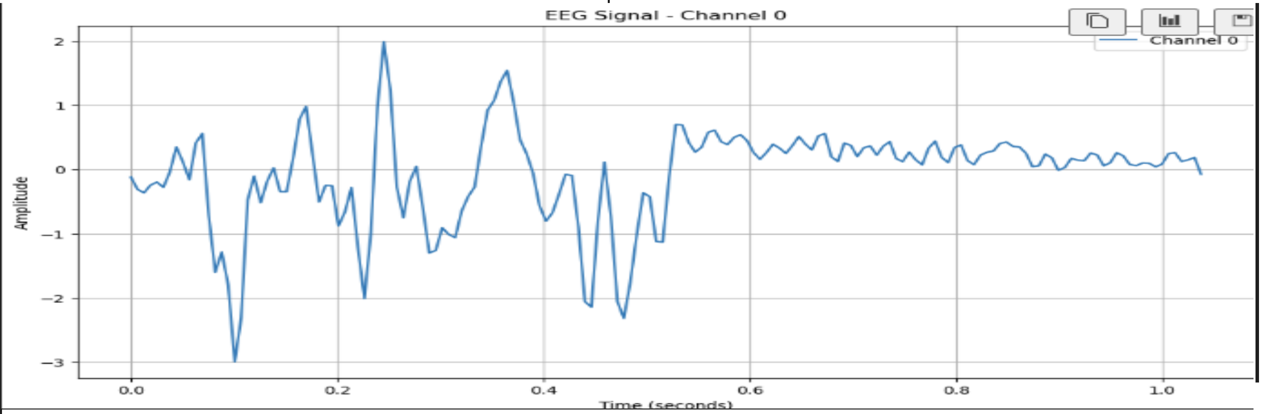
- Breaks down a time-domain signal into smaller frequency components.
- Keeps both **time** and **frequency** information for each part of the signal.
- It is especially useful for non-stationary signals like EEG, where frequency characteristics change over time.

Wavelet Function:

- A wavelet transform decomposes a signal into **approximate coefficients** and **detailed coefficients** for multiple frequency bands (scales).
- For a 1D signal of length N, the wavelet transform might output fewer or more coefficients than the original signal length
- Different wavelets (e.g., Daubechies) have different lengths and overlaps.
- The overlap extends the signal during decomposition.
- **Libraries:** Pywt

DWT


EEG Signal - Channel 0
Channel 0
Amplitude
Time (seconds)


EEG Signal - Channel 0
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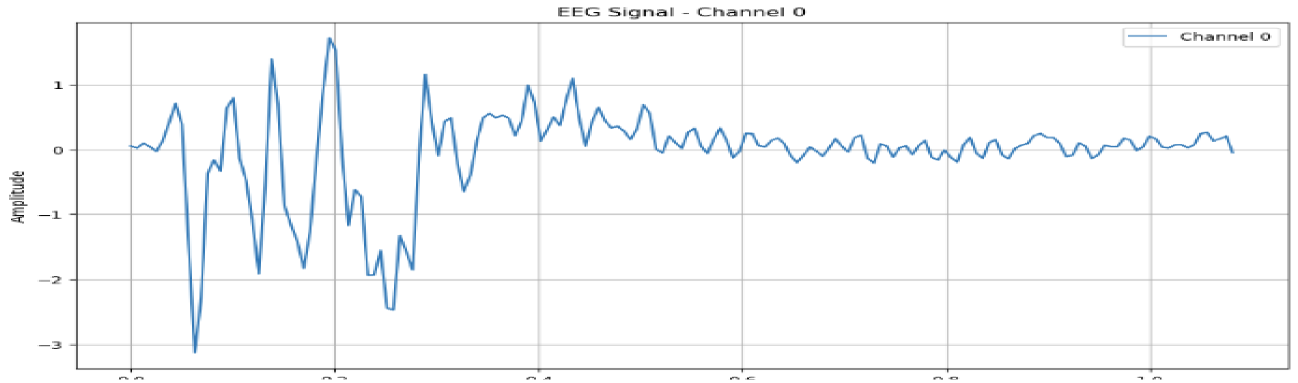
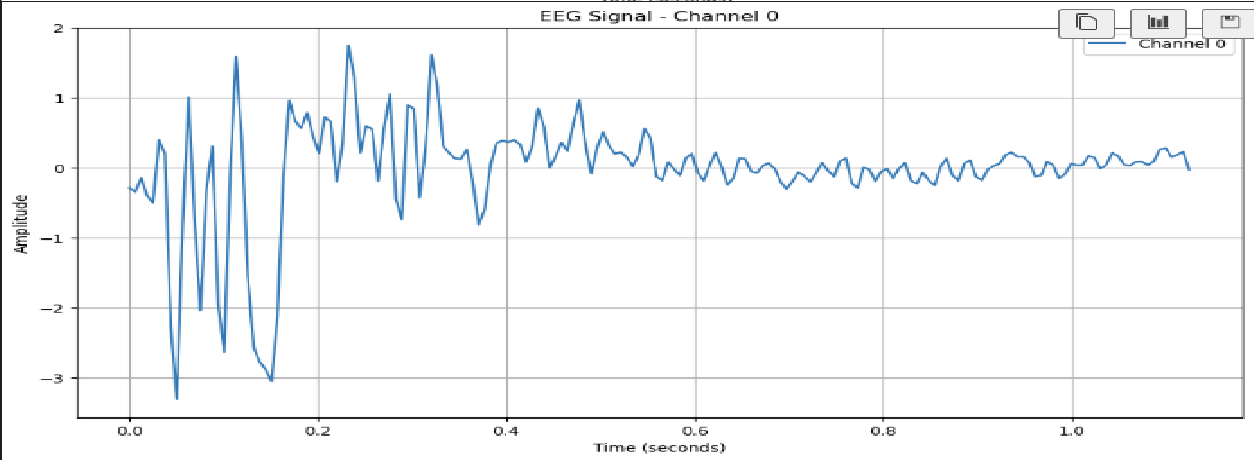
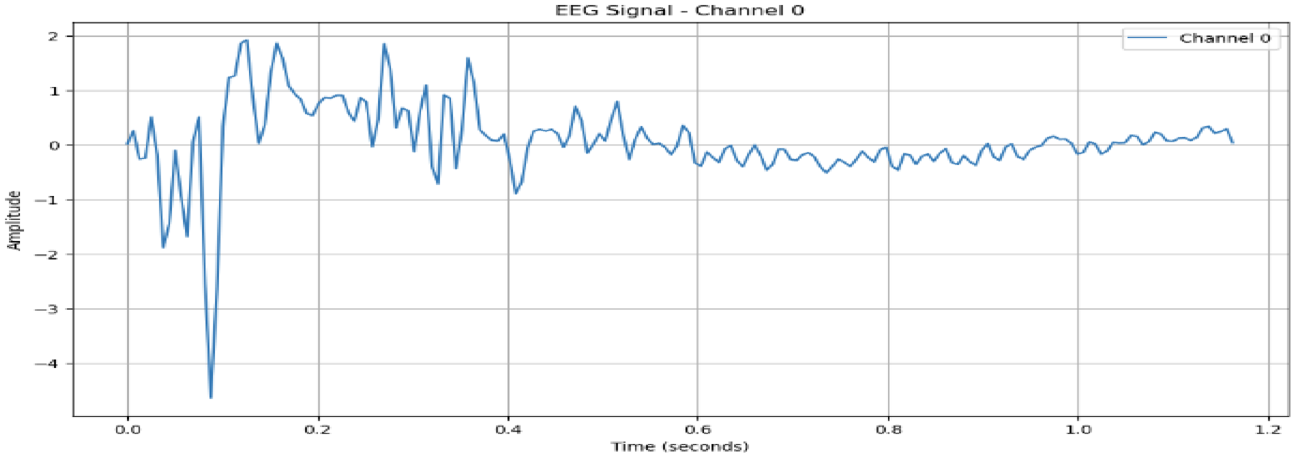
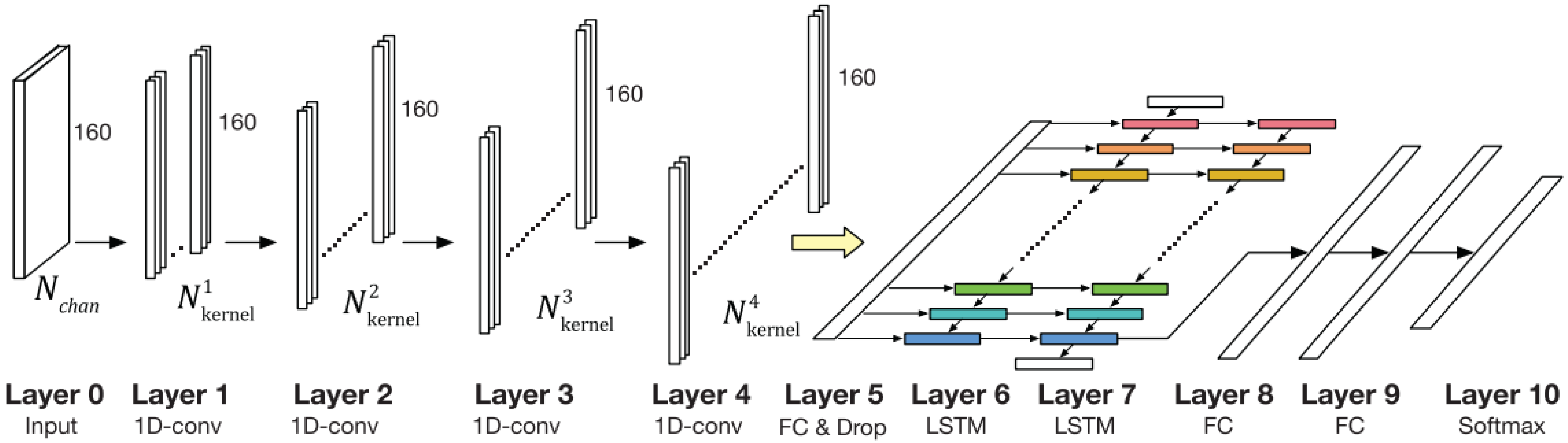

EEG Signal - Channel 0
Channel 0
Amplitude

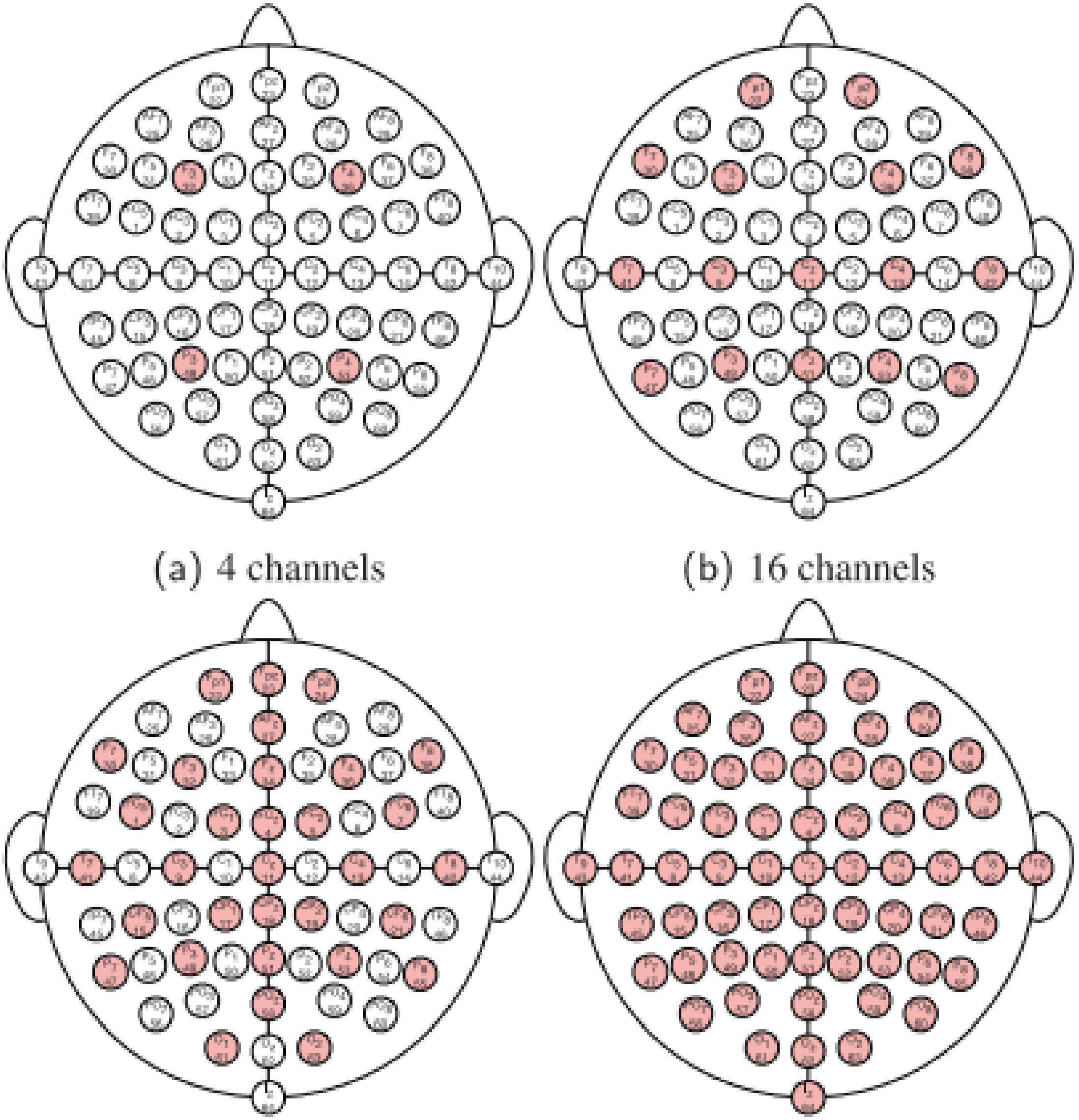

EEG Signal - Channel 0
Channel 0
Amplitude
Time (seconds)


EEG Signal - Channel 0
Channel 0
Amplitude
Time (seconds)

Model Architecture



Channels



(a) 4 channels

(b) 16 channels

(c) 32 channels

(d) 64 channels

Results

Performance Comparison:

Results without Wavelet Transform		
Model	No of Channels	Rank-1 Accuracy
CNN_LSTM	64	0.9641
	32	0.9382
	16	0.9582
	4	0.9352
CNN	64	0.9641
	32	0.9382
	16	0.9835
	4	0.9611
LSTM	64	0.666
	32	0.577
	16	0.6642
	4	0.6582

Results with Wavelet Transform		
Model	No of Channels	Rank-1 Accuracy
CNN_LSTM	64	0.9964
	32	0.9929
	16	0.9888
	4	0.9823
CNN	64	0.9988
	32	0.997
	16	0.9935
	4	0.9829
LSTM	64	0.9594
	32	0.877
	16	0.8111
	4	0.6582

Effectiveness of Reduced Channels:

- 64-channel proposed approach achieves the highest accuracy.

Conclusion

- The 1D-Convolutional LSTM model improves upon existing EEG-based identification systems.
- Achieves high accuracy with fewer channels, reducing system cost and complexity.

Thank You