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Advances toward Realizing an Intelligent and Robust Control Scheme for Limb Rehabilitation Robots

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University of Derby, Derby, DE22 3AW, United Kingdom

(25.07.2023)

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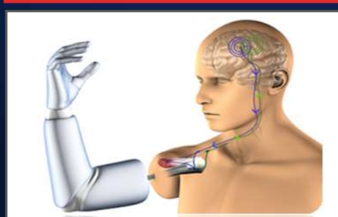

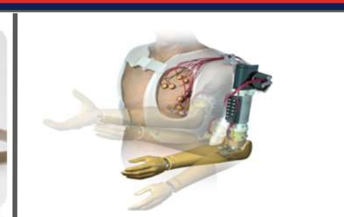

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PRESENTATION OUTLINE

1. Education and Work Experience
2. Overview of Research
3. Research Progress 1
4. Research Progress 2
5. Scholarly Contributions
6. Discussion Session

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EDUCATIONAL & PROFESSIONAL QUALIFICATION

2022

2022
University of Colorado, Boulder
Certification (Researcher Management & Leadership)

2022

2021 - 2022
Massachusetts Institute of Technology (MIT), Cambridge
Certification (Data Science & Machine Learning)

2018

2014 - 2018
University of Chinese Academy of Science, Beijing
PhD (Pattern Recognition and Intelligent Systems)

2014

2011 - 2014
Federal University of Technology, Akure
Master of Technology (Computer Science)

2013

2013
Oracle University, California
Certification (Oracle Database Administrator Certified Associate)
Certification (Oracle Database SQL Certified Expert)

2009

2004 - 2009
Kogi Stage University, Anyigba
Bachelor of Science (Computer Science)

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WORK EXPERIENCE (ACADEMIA & INDUSTRY)

2023 — **2023 – To Date**
University of Derby, Derby, UK
Position – Senior Lecturer

2018 — **2018 – 2023**
Shenzhen Institute of Advanced Technology, CAS
Position1 – Associate Professor (2020-2023)
Position2 – Postdoctoral Research Fellow (2018-2020)

2014 — **2014**
State Information Technology Agency
Position – Program Analyst

2010 — **2010 – 2014**
High Technology Research and Development Group (HTRDG)
Position – Systems Analyst/Senior Software Engineer

2010 — **2010**
Hands on Institute of Information Technology (HiiT)
Position – Faculty/Resource Person

2009 — **2009 - 2010**
APTECH (Applied Technology) Computer Education
Position – Faculty/Resource Person

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Location

*A home to the first factory in the world

*Birthplace of the Industrial Revolution (in early 1717)

*Rail, Aerospace, & Automotive industries. E.g.: Rolls-Royce , Alstom, Toyota.

* Beautiful tourist attraction sites.

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RESEARCH VISION

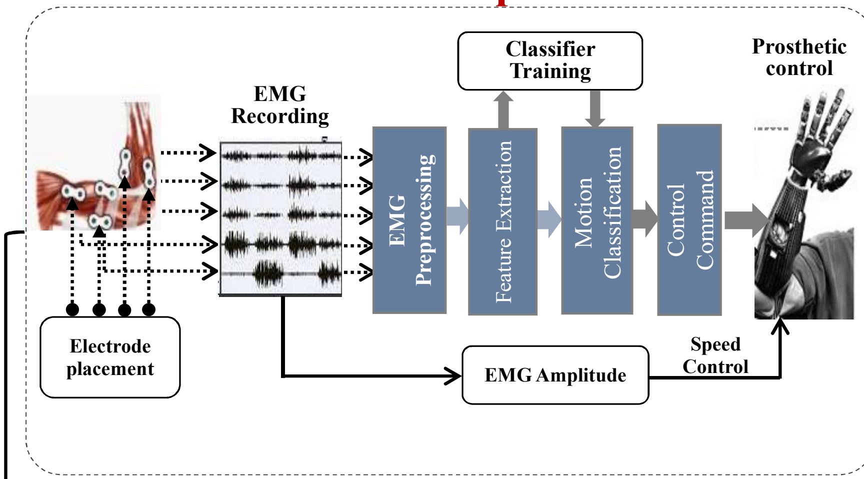
To constantly innovate **AI-based** technologies through **cutting-edge** research that addresses ***critical problems*** in the field of **Cyber-physical Systems**:

- **Intelligent Rehabilitation Robotic Systems**
- **Intelligent Decision Support Systems**

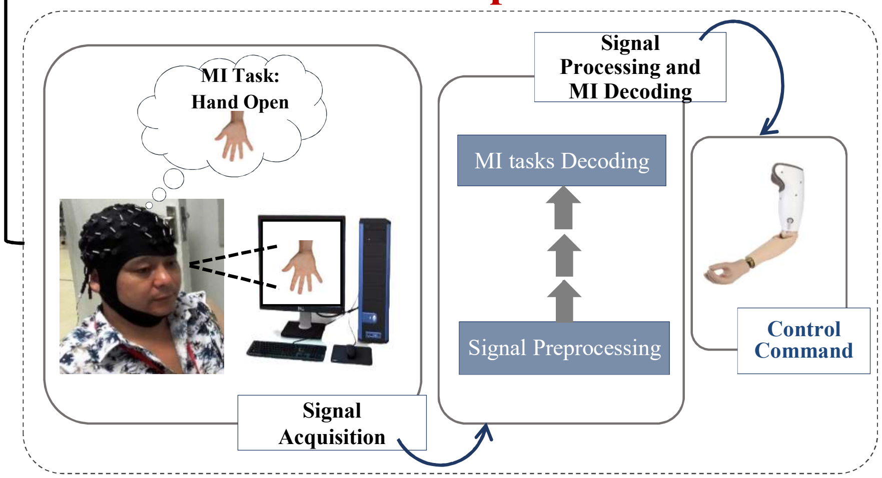
***Intelligent Rehabilitation Robotic Systems: IRRS**

***Intelligent Decision Support Systems: IDSS**

IRRS: Muscle-computer Interface



IRRS: Brain-computer Interface



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An Enhanced Deep Transfer Learning Model based on Spatial-Temporal driven Scalograms for Precise Decoding of Motor Intent in Stroke Survivors

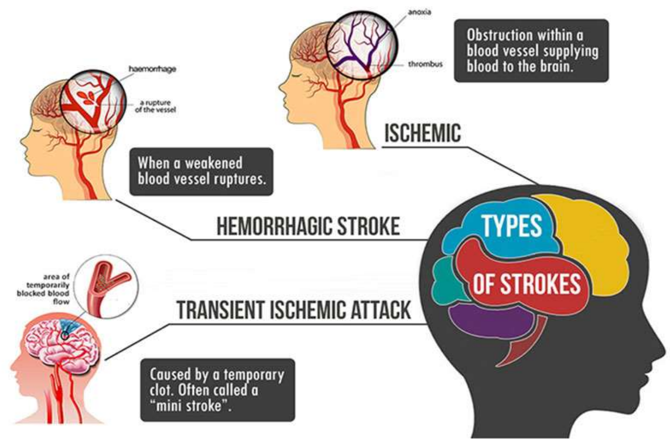
INTRODUCTION

Limb Dysfunction:

- Stroke is identified as the second cause of disability and death *(Giada Milani et al., 2022).*
- It significantly influences the quality of life of patients and relatives *(Guzik and Bushnell 2017).*

Impacts on Limb Function:

- Loss of grasping function
- Loss of sensation (a feel of touch)
- Inability to cope with daily activities
- A sense of incomplete body part



Rehabilitation Approaches:

- Restoration of lost limb function (s)
- Re-integrate survivors into the society

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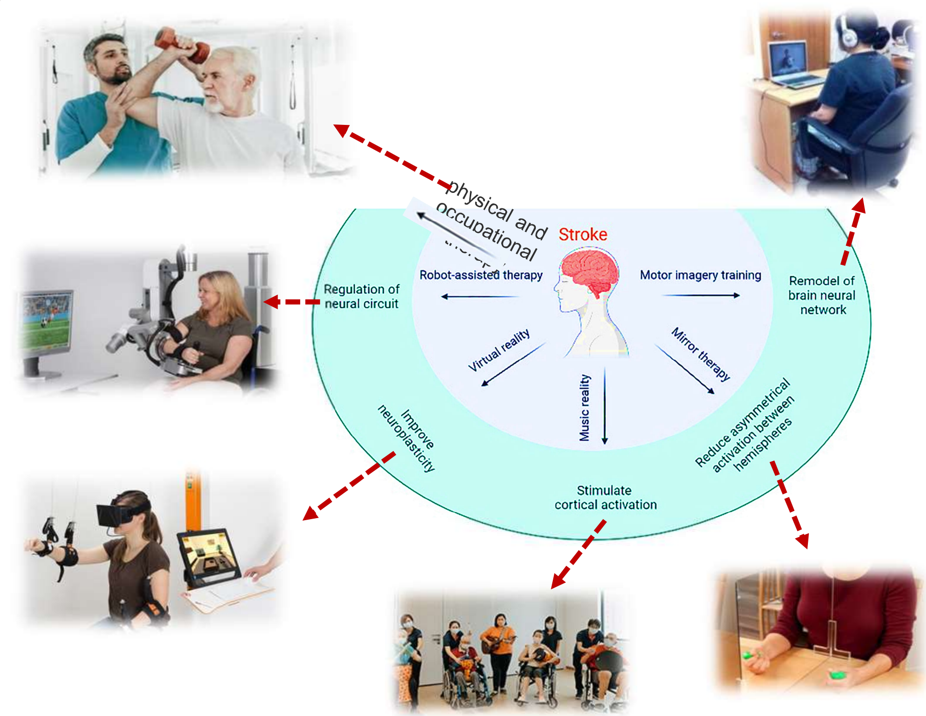
Limb Rehab Strategies:

- Physiotherapy based approach
  Driven by physical exercise
- **Robot-assisted therapy**
  Regulation of neural circuit
- Virtual reality based approach
  Improve neuroplasticity
- Mirror therapy
  Minimize asymmetrical activation btw cortical hemisphere
- Motor imagery training
  Remodel of brain neural network



Intelligent Rehab Robots: Decode motor intention of patient (s), Initiate intuitive/ active motor training, and Foster neural plasticity, leading to motor function restoration. **Such Robots require a <u>Robust Pattern Recognition Scheme.</u>**

***Myo-signals are captured 20-200milliseconds before initiation of limb motion**

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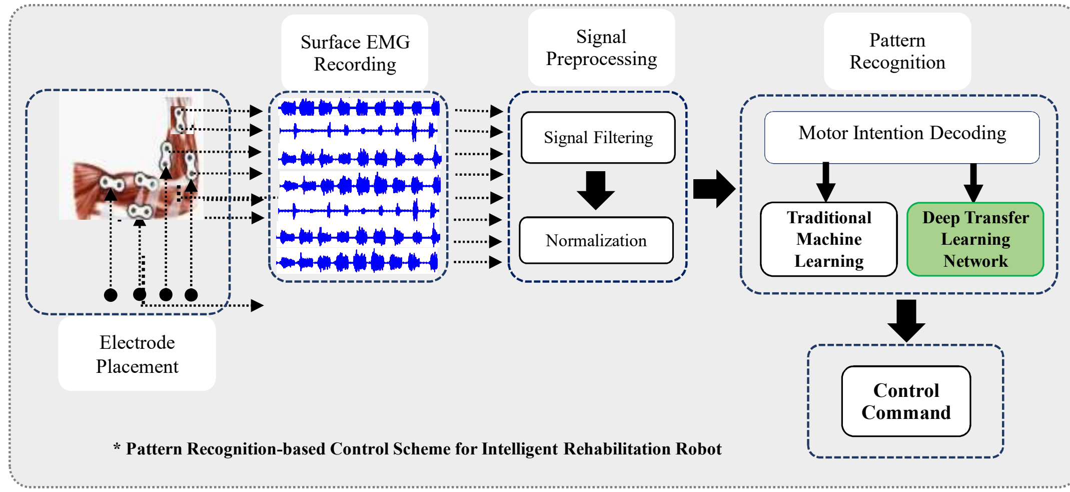
Pattern Recognition Scheme

❖ Deep Transfer Learning Network:

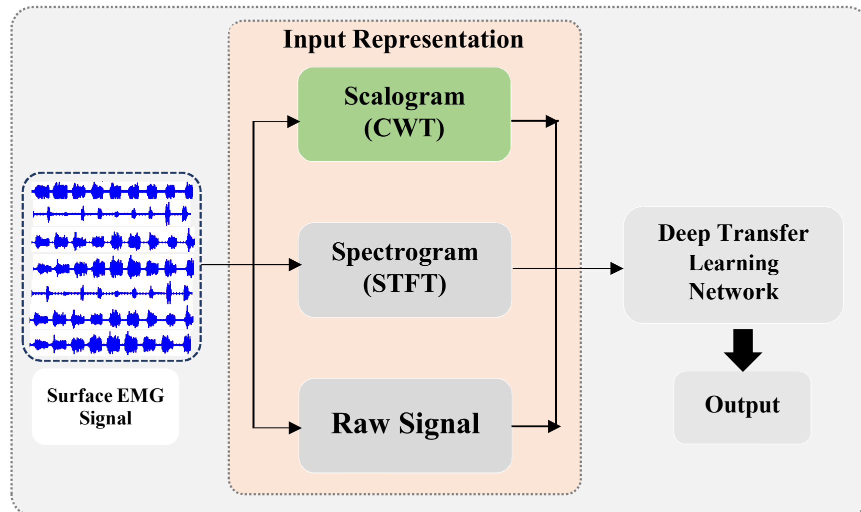
- Incremental learning
- Lesser amount of efforts and data
- Extraction of high/low level features
- Weights are not learned from scratch
- Easy adaptation



* Pattern Recognition-based Control Scheme for Intelligent Rehabilitation Robot

❖ Input Representation

- Scalograms-based on **CWT** have been widely recommended
- Have high time-frequency characteristics, yielding inputs with high-resolution
- **However, they lack the integration of spatial-temporal information, necessary for constructing rich set of motor information via EMG signals.**



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RESEARCH OBJECTIVE

To optimally characterize the motor intent of especially severely impaired stroke patients from multi-channel sEMG signals for intuitive robotic training, this study is aimed at:

- Developing a spatial-temporal based Scalograms as inputs to a deep Transfer Learning Convolutional Neural Network (TL-CNN).
- The approach is implemented across three variants of wavelet functions (including Morse, Amor, and Bump), employed by the CWT algorithm
- Each variant is used to decode the limb motion intentions of the severely impaired stroke patients from multi-channel sEMG and compared to conventional methods under various experimental settings.

METHODOLOGY

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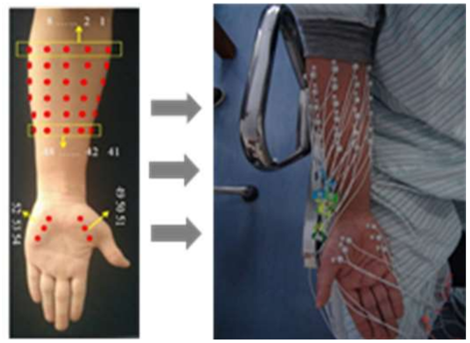
Data Collection

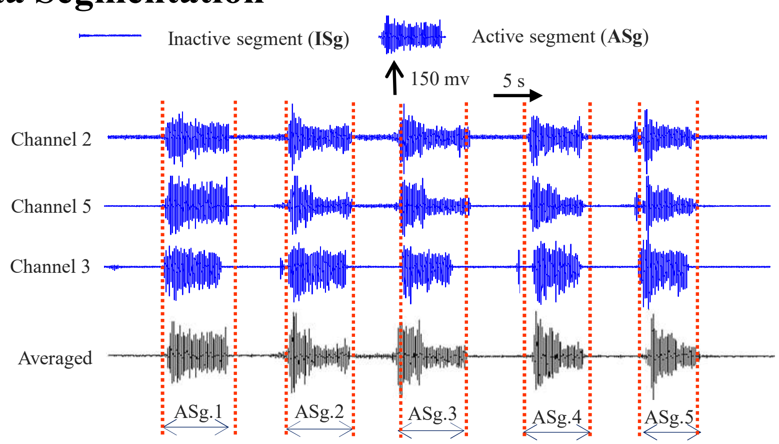
- ❖ HD-sEMG recording system
- ❖ 56 Monopolar electrodes
- ❖ Sampling frequency: 1024Hz
- ❖ 5 Subs/Up to 22 limb motions
- ❖ 6 sec. per motion & 6 trials
- ❖ Signal filtering (Notch/Bandpass)



Electrode configuration for sEMG recordings

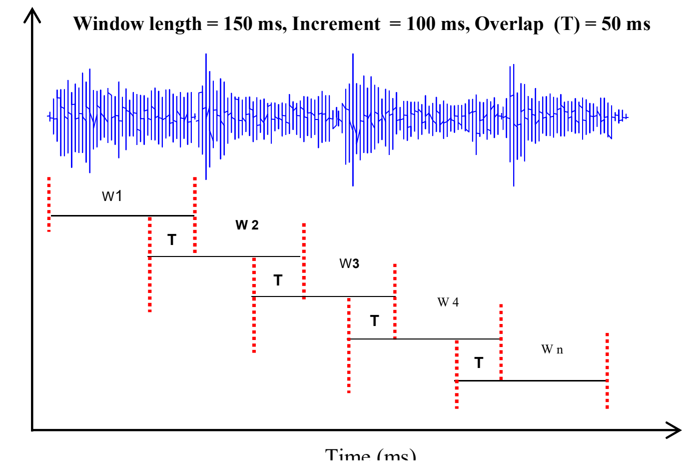
Fugl-Meyer scale: 35-61; Brunnstrom scale: 4-5

Data Segmentation



Segmentation of EMG recordings of active limb motions

Data Windowing



Sliding window scheme for data preprocessing

STD Construction & Performance Analysis

- ❖ The STD was obtained based on the framework in the next slide.
- ❖ $ACC = \frac{\text{No.of correctly classified samples}}{\text{Total number of samples}} * 100\%$
- ❖ Analysis of variance with a confidence level set to $p<0.05$

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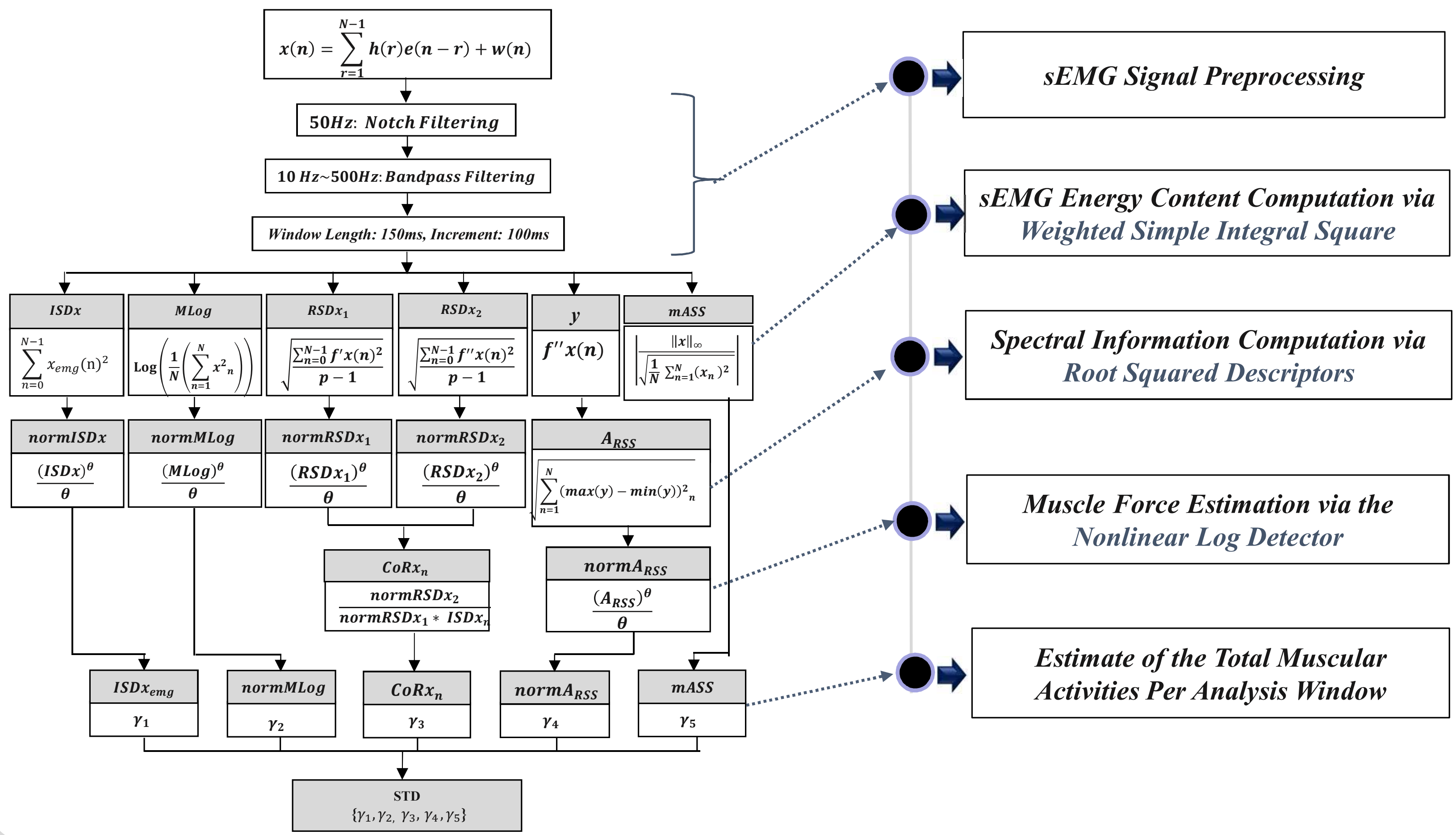
Spatial-Temporal Descriptor Construction



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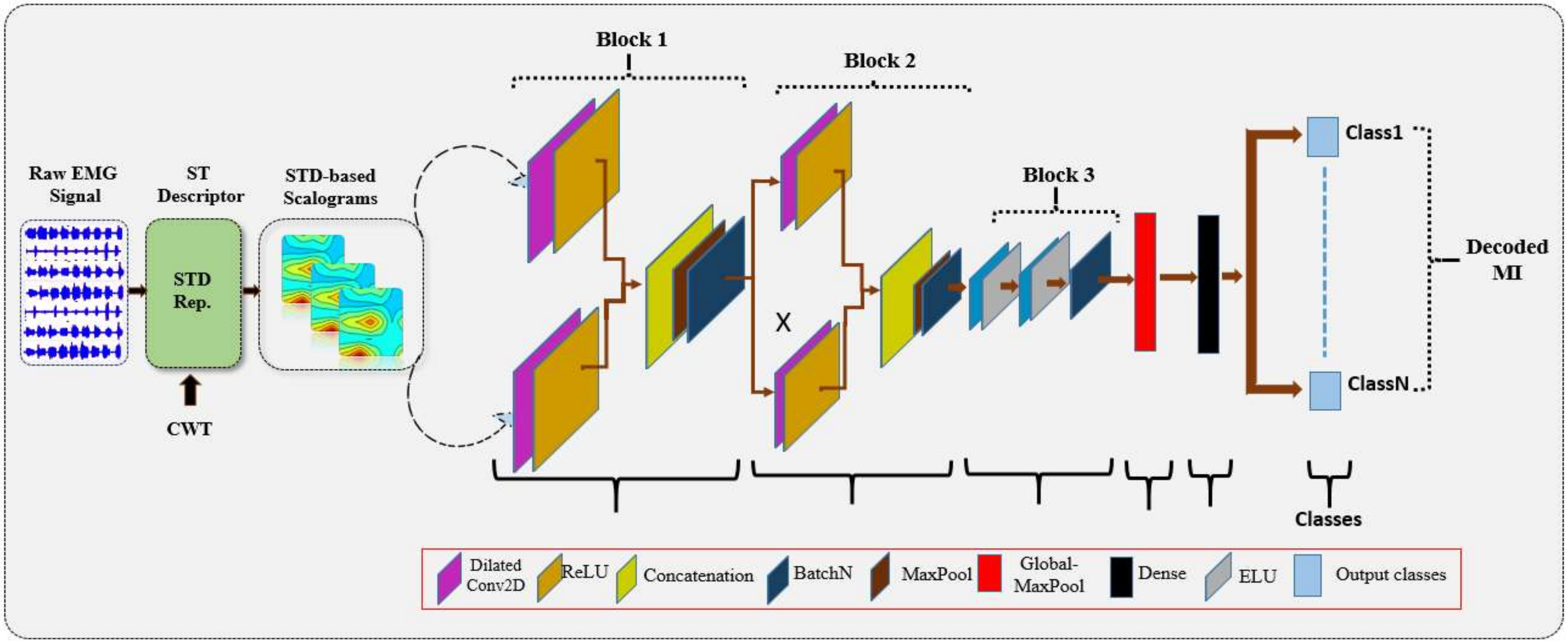
METHODOLOGY



Variants of Scalograms Generated

- ❖ STD_CWT_{morse}
- ❖ STD_CWT_{amor}
- ❖ STD_CWT_{bump}

TL-CNN Model (GoogleNet)

- ❖ 144 layers in all
- ❖ Requires RGB images as input
- ❖ Input dimension: 224x224x3

Training Parameters

- ❖ Train/Test data ratio: 80%/20%
- ❖ MiniBatchSize/MaxEpoch: 20/10
- ❖ LearningRate: 0.0001
- ❖ Loss Function: SGD

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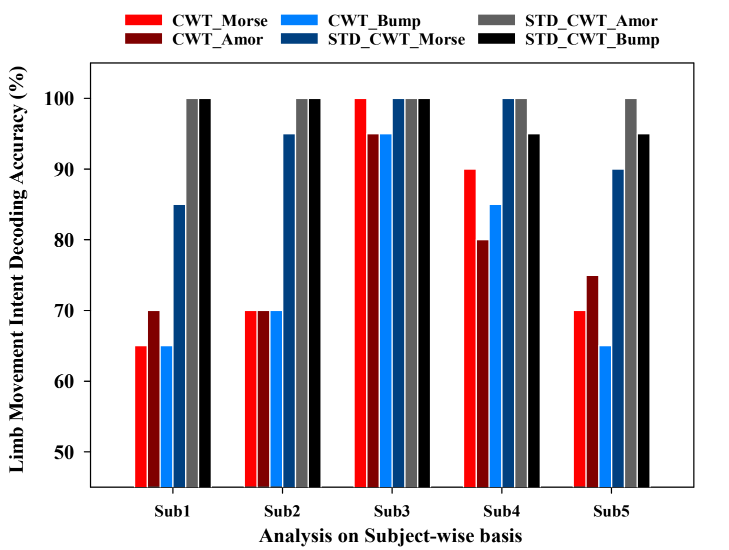
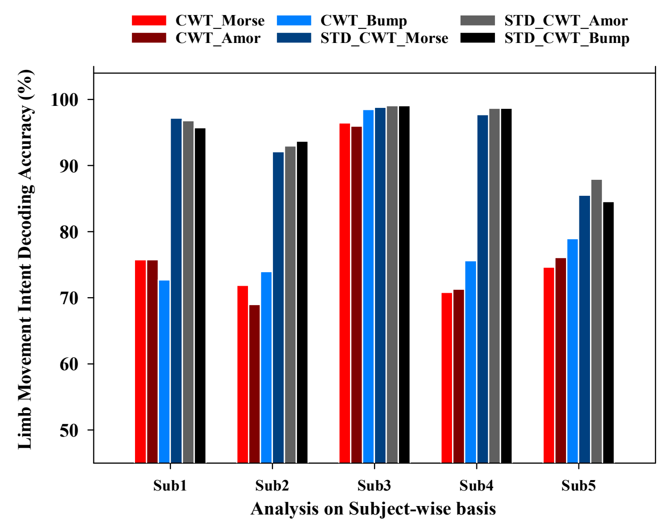
Individual Subject Analysis

- The three variants of the proposed method (STD_CWT$_{morse,}$ STD_CWT$_{amor,}$ and STD_CWT$_{bumb}$) enabled the TL-CNN model to achieve significantly higher decoding across subjects compared to existing methods (CWT$_{morse,}$ CWT$_{amor,}$ and CWT$_{bumb}$).

- During the TL-CNN model training, the **STD_CWT$_{morse}$** variant recorded the **<u>least decoding accuracies</u>** across subjects compared to the STD_CWT$_{amor}$ and STD_CWT$_{bumb}$ while there is no significant different amongst the three variants for the tested models.



The TL-CNN model training results for the proposed and existing methods with the three distinct wavelets (Morse, Amor, and Bulp)



The TL-CNN model testing results for the proposed and existing methods with the three distinct wavelets (Morse, Amor, and Bulp).

- Overall, the proposed approach's decoding outcomes are consistent and higher for both **Training** and **Testing** sessions across **motion classes** and **subjects.**

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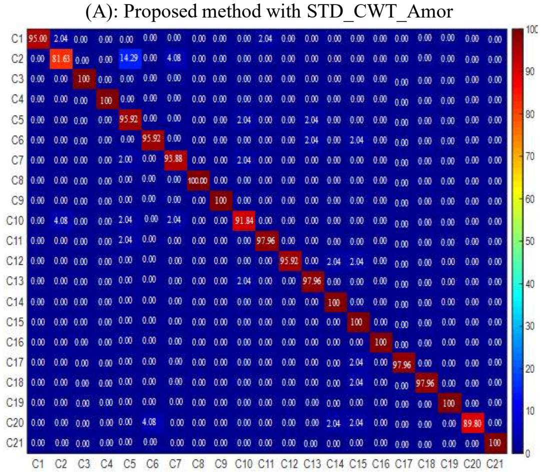
RESULT & DISCUSSION

Across Subjects: Average MI decoding performance of the TL-CNN model across subjects for the proposed and the existing methods.

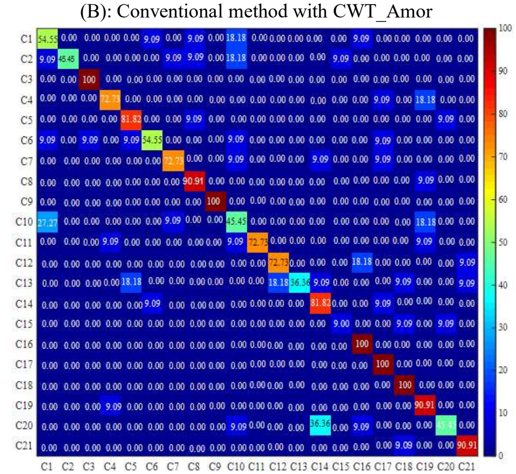
	TL-CNN's Training Result		TL-CNN's Test Result	
	ACC (%)	**STD (%)**	**ACC (%)**	**STD (%)**
CWT_Morse	79.00	15.17	77.91	10.56
STD_CWT_Morse	**94.00**	**6.52**	**94.28**	**5.53**
CWT_Amor	78.00	10.37	77.62	10.68
STD_CWT_Amor	**100.00**	**0.00**	**95.07**	**4.67**
CWT_Bump	76.00	13.42	79.95	8.56
STD_CWT_Bump	**98.00**	**2.74**	**94.34**	**10.62**

Individual Limb Movement Analysis

(A): Proposed method with STD_CWT_Amor



(B): Conventional method with CWT_Amor



Analyzing TL-CNN model for individual motion decoding

Summary of Findings:

- **STD_CWT$_{Amor}$** achieved the best performance (ACC/STD) across subjects.
- On the other hand, **STD_CWT$_{Morse}$** recorded the least performance

Findings:

- The **STD_CWT$_{Amor}$** achieved consistently higher performance for individual limb gesture decoding
- This trend can be observed in the diagonal entries of both confusion matrices.

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Conclusion & Future Work

Conclusion

- ❖ The use of spatial-temporal based Scalograms as inputs to deep transfer learning networks is proposed to efficiently characterize limb motor intention, that could aid intuitive and adaptive robotic training for stroke patients.
- ❖ Compared to existing methods, the proposed approach achieved significant improvement in decoding accuracy (**14.39% ~ 17.45%),** and has the capability to adequately characterize individual motor task.
- ❖ This suggest that the proposed method may facilitate the practical deployment of accurate and robust clinically relevant control scheme for rehabilitation robots.

Future Work

- ❖ Future work will focus on further investigating the proposed method with experimental design that involve:
  - ✓ Additional datasets with various characteristics (TBI patients and Amputees as well)
  - ✓ Other deep transfer learning models (NASNetLarge, AlexNet, ResNet, VGG-16, and VGG-19, etc.)
  - ✓ Spatial-temporal Scalograms based on the combination of two or more wavelet functions
  - ✓ Real time evaluation metrics

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❖ Upper Limb Amputation:

- Limb amputation imposes severe burden on affected individuals.
- More than five million individuals leave with upper limb amputation globally.
- Prostheses have been built to restore their lost limb functions.

Myoelectric Prostheses

❖ Myo-prostheses' Limitations:

- Lack intuitive control scheme
- Lack sensory feedback mechanism
- Can't be worn for long time
- Latency issue

→ **Limiting Factor** → **Success?**

MOTIVATION

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❖ Goal

- Investigate confounding factors that degrade the prostheses performance.
- Develop a simple yet efficient AI-based solutions to resolve identified issues.
- Conduct extensive experimentation to proof the potential of the solutions.

Effect of Co-existing Dynamic Factors on the Performance of Myoelectric Prostheses

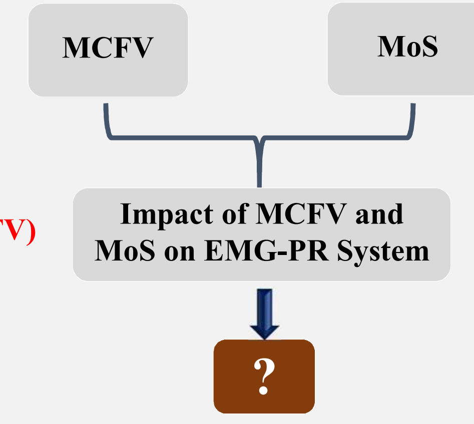
Related Literature

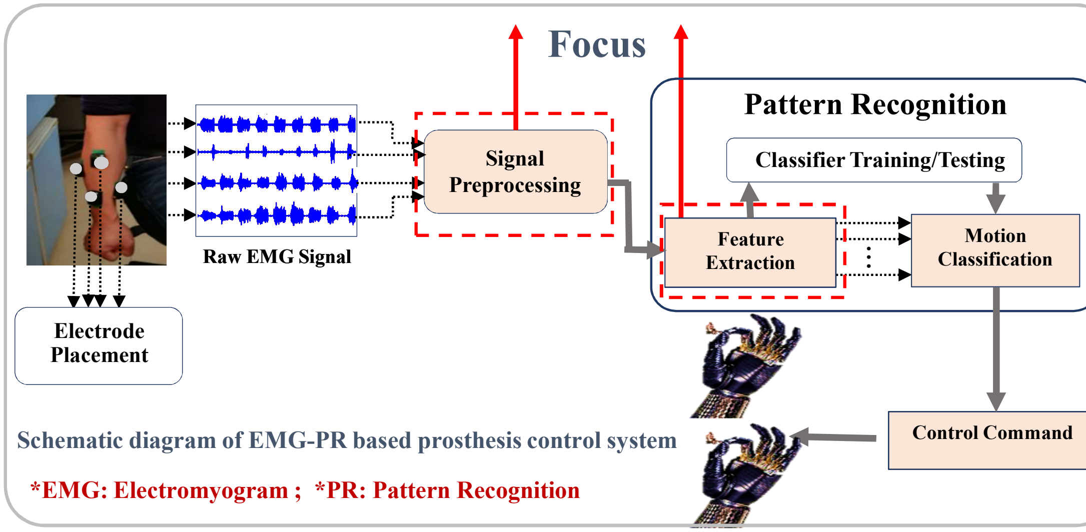
"Improving the performance against force variation of EMG controlled multifunctional upper-limb prostheses for transradial amputees," *IEEE TNSRE*, 24(6) (2016) 650–661.

"Resolving the adverse impact of mobility on myoelectric pattern recognition in upper-limb multifunctional prostheses," *CMB, Elsevier.* 90 (2017) 76–87.

❖ Key Confounding Factors:

- Electrode Shift
- **Cross-user model (Adaptation)**
- **Muscle Contraction Force Variation (MCFV)**
- Arm Posture Changes
- **Mobility of Subject (MoS)**
- Electrode-skin Contact Impedance





Schematic diagram of EMG-PR based prosthesis control system

*EMG: Electromyogram ; *PR: Pattern Recognition

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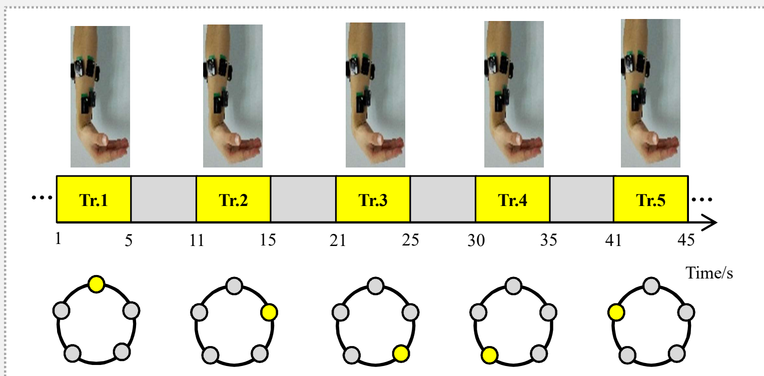
❖ Hypothesis:

Alterations in EMG signal patterns from the dual impact of **MCFV** and **MoS** may influence the decoding rate of individual targeted limb movement.

❖ Solution:

Systematically investigated the co-existing impact of both factors on EMG-PR control system's performance.

❖ Sequence and Duration of Limb Motion Tasks

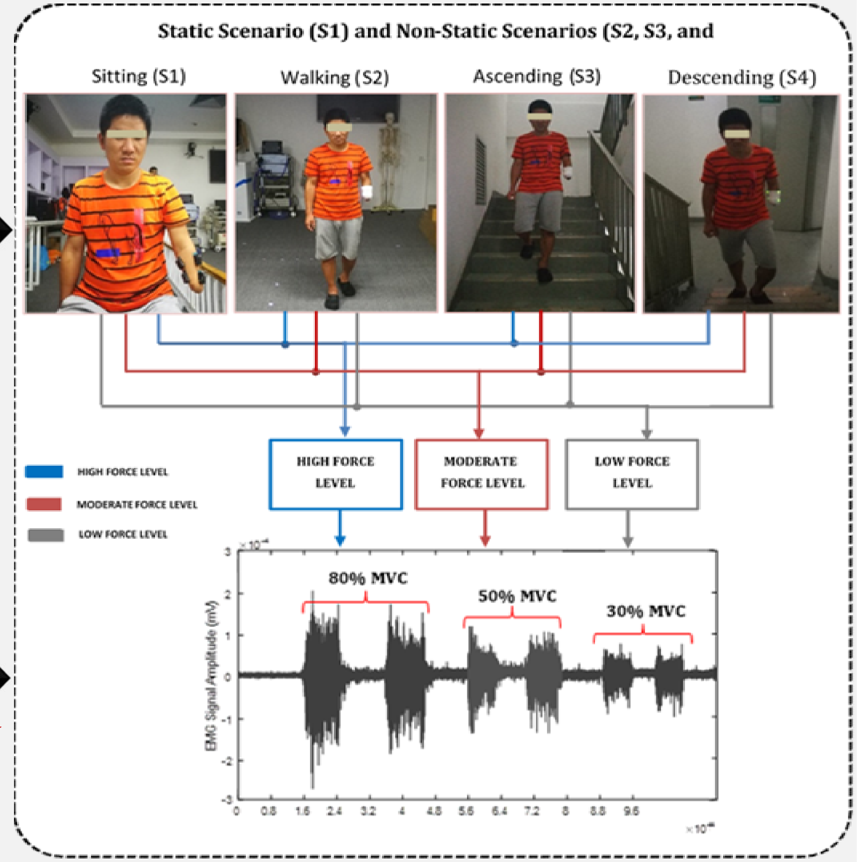


A representation of number of trials and duration per limb motion

MoS

MCFV

❖ Experimental Procedure for EMG Data Acquisition



A representation of the experimental settings for surface EMG recordings

* 8 Subjects and 7 Classes of Limb Motions

* 4-6 Trigno Wireless EMG Sensors for the Data Collection

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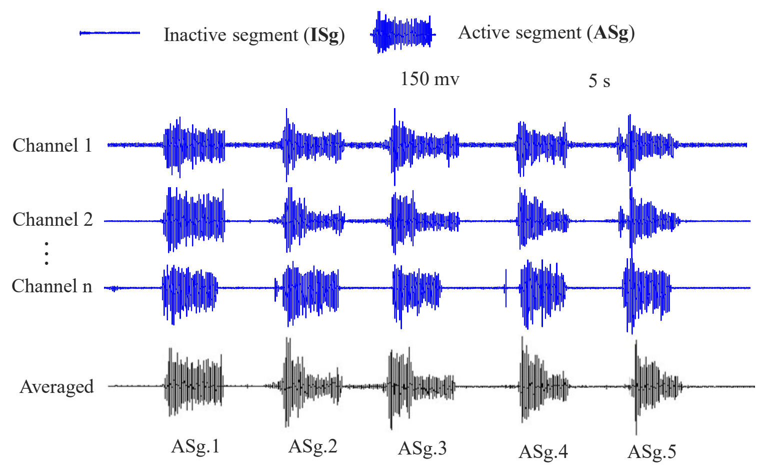
❖ Preprocessing of the Raw EMG Data:

- Applied 5^{th} Order Butterworth filter with frequency band of 20 – 500 Hz (Fs:1024 Hz).
- Applied 50 Hz notch filter to attenuate the power-line interference.

❖ EMG Signal Segmentation



Segmentation of EMG recordings of active limb movements

❖ Feature Extraction & Pattern Classifier

- Proposed an invariant time domain descriptor (***invTDD**, **that extracts spatial & temporal muscle characteristics)***
- Validation: The ***invTDD*** was compared with 4 methods (TD-PSD, TD4, NOV, TDAR, RMS) with LDA classifier.

❖ Data Analyses

- Intra- scenario analysis
- Inter- scenario analysis
- PCA analysis

❖ Performance Evaluation & Statistical Test

- Classification error (CE) $= \frac{\text{No.of incorrectly classified samples}}{\text{Total number of testing samples}} * 100\%$
- Matthew Coefficient Correlation (MCC) $= \frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+F\ \ )(TN+FN)}}$
- $\text{F1\_Score} = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall}+\text{Precision}}$
- Analysis of variance (ANOVA) with a confidence level set to $p<0.05$

EXPERIMENTAL RESULTS

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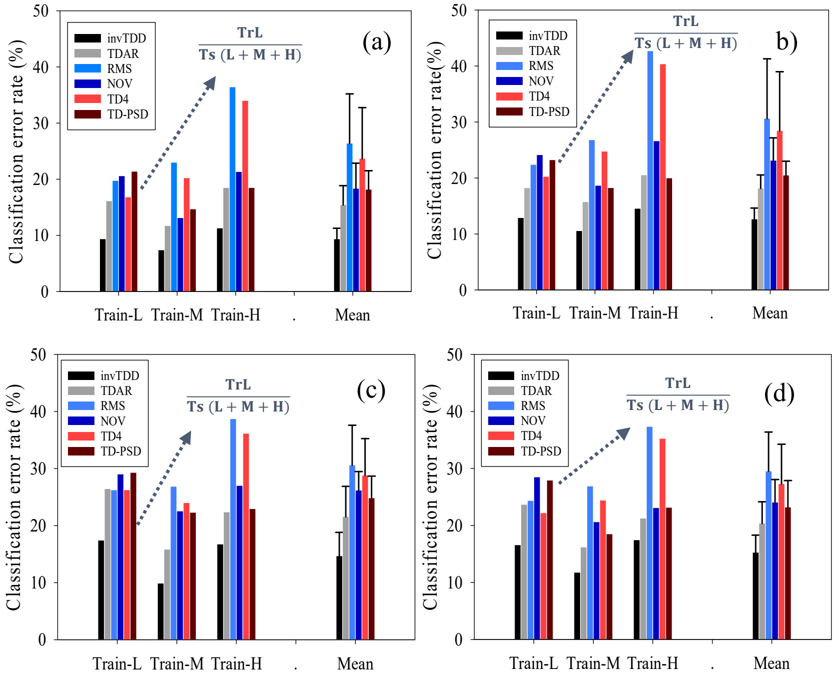
Results: Intra-Scenario Analysis

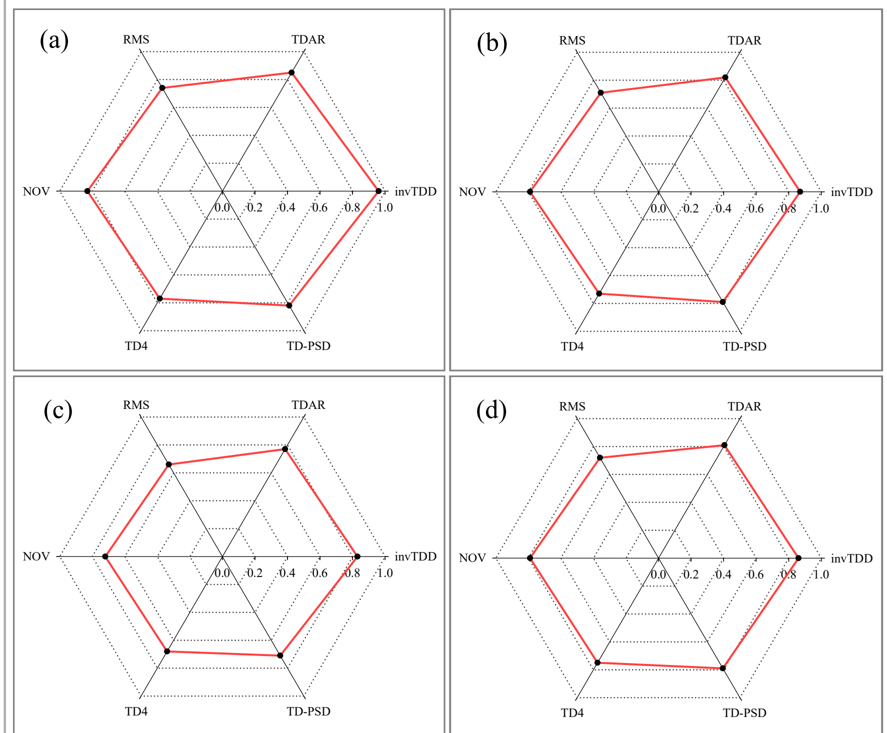
❖ Motor Intent Decoding based on CE



Intra-scenarios generalization results averaged across subjects/motions when the data used for training is pulled from a specific force level while the test data is from all force levels in scenario S1 (a), S2 (b), S3 (c), and S4 (d).

The proposed method recorded significantly lower CE for all the THREE SCHEME (Trail-L, Train-M, and Train-H) across SCENARIOS (S1-S4).

❖ Analysis based on MCC



Intra-scenario generalization results averaged across all subjects and movement classes based on MCC metric for S1(a), S2(b), S3(c) and S4(d).

The proposed method recorded significantly better MCC values across all the SCENARIOS (S1-S4).

EXPERIMENTAL RESULTS

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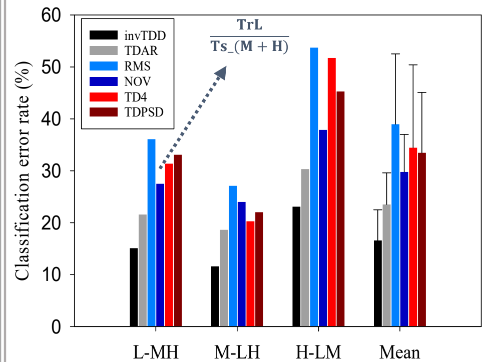
Results: Inter-Scenario Analysis

❖ Motor Intent Decoding (CE)



- The method achieved significantly lower CE on all schemes.
- Also, substantially higher decoding results were obtained for individual motion class.
- High class seperatability was recorded via the PCA plot.

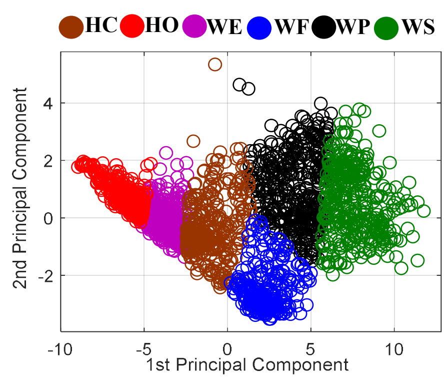
Inter-scenarios results averaged across subjects/motions. The training data were obtained from a particular contraction force level across scenarios and test data from the other two contraction levels across scenario.

❖ Individual Limb Motion Decoding

	HC	HO	WE	WF	WP	WS	NM
HC	90.18	0.68	0.74	0.02	2.39	4.15	1.84
HO	0.27	94.98	0.38	0.02	0.40	0.86	3.10
WE	0.26	0.30	88.39	8.16	1.09	0.33	1.48
WF	0.02	0.00	0.23	97.63	0.60	0.64	0.89
WP	0.23	0.15	0.42	0.00	89.61	7.59	1.99
WS	0.67	8.76	0.23	0.02	10.86	73.65	5.80
NM	0.21	0.33	0.07	0.00	0.54	4.25	94.61

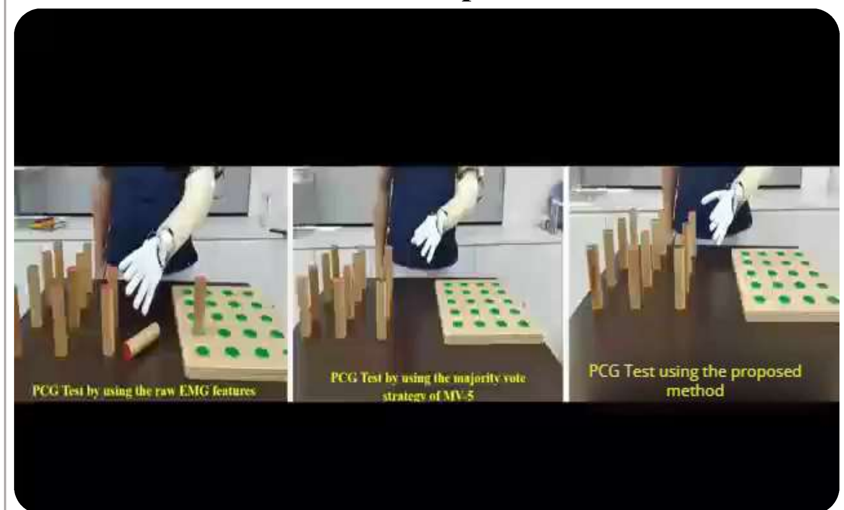
Confusion matrix of CE for individual limb movement across subjects.

❖ PCA - Class Separability



PCA feature space analysis for targeted limb movement across subjects for the *invTDD*

Real-Time Experiment



Conclusion

❖ It was established that the co-existence of MCFV and MoS will significantly affect the performance of EMG-PR control schème.

❖ A solution that effectively mitigated the dual impact of both factors on EMG-PR control schemes was proposed.

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Real-Time Experiment

❖ Ongoing Investigation

- User adaptation (Cross-user model)
- Dual-stage deep learning model for electrode shift resolution

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Some Recent Publications

1) Wei W., Tan F., Zhang H., Mao H., Fu M., Samuel O.W.*, Li G. (2023). Surface electromyogram, kinematic, and kinetic dataset of lower limb walking for movement intent recognition, ***Nature Scientific Data***; 10, 358; https://www.nature.com/articles/s41597-023-02263-3

2) Li H., Han F., Wang L., Huang L., Samuel O.W., et al (2023). A Hybrid Strategy-Based Ultra-Narrow Stretchable Microelectrodes with Cell-Level Resolution. ***Advanced Functional Material***, April 16, 2023; https://onlinelibrary.wiley.com/doi/abs/10.1002/adfm.202300859

3) Zangene, A. R., Samuel, O.W.*, Abbasi, A., McEwan, A. A., Asogbon, M. G., Li, G., & Nazarpour, K. (2023). An efficient attention-driven deep neural network approach for continuous estimation of knee joint kinematics via sEMG signals during running. ***Biomedical Signal Processing and Control***, 86, 105103.

4) Samuel O.W., Asogbon, M.G., Khushaba, R.N., Kulwa, F., Li, G. (2022). Multiresolution Dual-Polynomial Decomposition Approach for Optimized Characterization of Motor Intent in Myoelectric Control Systems. ***IEEE Transactions on Biomedical Engineering***, 70, (5): 1516-1527.

5) Asogbon M.G., Samuel O.W.*, Ensugbe E., et al. (2023). Ascertaining the optimal myoelectric signal recording duration for pattern recognition based prostheses control. ***Frontiers in Neuroscience***, 17.

6) Khushaba, R. N., Al-Timemy, A. H., Samuel, O. W., & Scheme, E. J. (2022). Myoelectric Control With Fixed Convolution-Based Time-Domain Feature Extraction: Exploring the Spatio–Temporal Interaction. ***IEEE Transactions on Human-Machine Systems***. Feb. 24, 2022.

7) Wang, Y., Fang, P., Tang, X.,..., Samuel. O.W.., & Li, G. (2022). Effective Evaluation of Finger Sensation Evoking by Non-invasive Stimulation for Sensory Function Recovery in Transradial Amputees. ***IEEE Transactions on Neural Systems and Rehabilitation Engineering***, 30, 519-528.

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SCHOLARLY ACHIEVMENTS

PUBLICATIONS STATISTICS

- Track Record of Publications: **100+**
- Peer-reviewed Journal Articles: **55+**
- Articles in IEEE Conf. Proceedings: **45+**
- Book Chapters: **3**
- **Citation** on Google Scholar**: 3200+**
- **h-index: 30 and i10-index: 64**

HIGHLY CITATION RECORD

My articles got list among:

- "Top 2 Most Influential Papers",
- "Top 10 Most Cited Papers," and
- "Top Cited Papers"

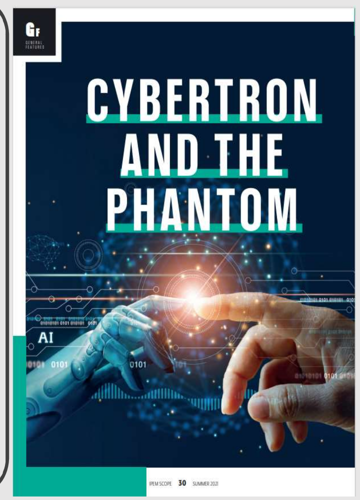
by **Web of Science**, **ESI-Index**, and **IOP Science**.

ARTICLES IN TOP RANKED JOURNALS

- *IEEE TNSRE*: **ranked #1 in Rehabilitation Therapy**
- *Future Generation Computer Systems:* **ranked #2 in Computing Systems**
- *IEEE Robotics and Automation Letters:* **ranked #2 in Robotics**
- *Expert Systems with Applications:* **ranked #8 in Artificial Intelligence**
- *JNER:* **ranked #3 in Rehabilitation Therapy**
- *Journal of Neural Engineering:* **ranked #7 in Biomedical Technology**

RELATED AWARDS AND HONORS

- 2022 STEM for Britain Award, Nominee
- 2021 IPEM-SCOPE, UK, Article Featured
- 2019 IEEE-ICCC Best Presentation
- 2015 IEEE-ICBHI Best Paper
- 2015 IEEE-GHI' Best Presentation



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Thank You

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