

Some Machine Learning Approaches to Enhance
Electromyography-based Hand Gesture Recognition



The thesis submitted in partial fulfilment

for the Award of Degree

DOCTOR OF PHILOSOPHY

by

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Abbreviations

1D-CNN	One-Dimensional Convolutional Neural Network
3D	Three Dimensional
AD	Alzheimer’s Disease
AI	Artificial Intelligence
ANN	Artificial Neural Network
ASL	American Sign Language
AUC-ROC	Area Under the Curve - Receiver Operating Characteristic
AUC	Area Under the Curve
BGRU	Bidirectional Gated Recurrent Unit
BiLSTM	Bidirectional Long Short-Term Memory
BLSTM	Bidirectional Long Short-Term Memory
CSV	Comma-Separated Values
CNN	Convolutional Neural Network
DAE	Denoising AutoEncoder
DARWIN	Dataset for Alzheimer’s Research on Writing kINematics
DCNN	Deep Convolutional Neural Network
DTW	Dynamic Time Warping
EMG	ElectroMyoGraphy
FFT	Fast Fourier Transform
FPR	False Positive Rate
GRU	Gated Recurrent Unit
HCI	Human-Computer Interaction

HCR	H and w ritten C haracter R ecognition
HGR	H and G rasp R ecognition
HMM	H idden M arkov M odel
IMU	I nertial M easurement U nit
IoT	I nternet of T hings
KNN	K - N earest N eighbors
KRE	K raskov E ntropy
LDA	L inear D iscriminant A nalysis
LSTM	L ong S hort- T erm M emory
MCC	M atthews C orrelation C oefficient
MDAE	M ultimodal D eep A uto E ncoder
MDC	M odel of D ynamic C ontraction
ML	M achine L earning
MSE	M ean S quared E rror
MSC	M odel of S tatic C ontraction
MU	M otor U nit
MUAP	M otor U nit A ction P otential
MSSA	M odified S alp S warm A lgorithm
PCA	P rincipal C omponent A nalysis
PSO	P article S warm O ptimization
ReLU	R ectified L inear U nit
RF	R andom F orest
RNN	R ecurrent N eural N etwork
ROC-AUC	R eceiver O perating C haracteristic - A rea U nder the C urve
ROC	R eceiver O perating C haracteristic
SHAP	S hapley A dditive e x P lanations
SLRS	S ign L anguage R ecognition S ystem
SSA	S alp S warm A lgorithm
SSAE	S tacked S pase A uto E ncoder

SSDAE	S tacked S parse D enoising A uto E ncoder
sEMG	surface E lectro M yo G raphy
SVD	S ingular V alue D ecomposition
SVM	S upport V ector M achine
TQWT	T unable- Q W avelet T ransform
TPR	T rue P ositive R ate
t-SNE	t - D istributed S tochastic N eighbor E mbedding
TP	T rue P ositive
UWB	U ltra- W ide B and
XAI	E xplainable A rtificial I ntelligence
XGB	X G B oost

Symbols

D	Dataset consisting of sEMG time series recordings
N	Number of sEMG time series recordings
$TS_i(u)$	Time series recording i with data points u_1, u_2, \dots, u_N
$f_{i,m}$	Feature extracted for a window size where m is the total number of features
Ins_i	i^{th} instance in the dataset
l_k	Class label of hand grasp movement corresponding to the instance Ins_i
$v(S)$	Real-valued profit/payoff for coalition S
$\delta(S, j)$	Marginal contribution of player j to coalition S
$\varphi_j(X, v)$	Shapley value for player j in the coalition game
$G(X_d(t_n), t_n)$	Deterministic part of the Langevin equation
$H(X_d(t_n), t_n)$	Stochastic part of the Langevin equation
$\tau(t_n)$	White Gaussian noise in the Langevin equation
X	Raw sEMG data matrix
T	Number of time samples
$\Phi(X)$	Feature vector generated from raw data
M	Number of features
$\Phi_{S_i}(X)$	Set of relevant features selected by algorithm i
$\Phi_S(X)$	Combined feature vector from multiple methods
h	Classifier function
θ	Parameters of the classifier
\hat{Y}	Predicted gesture label

Symbols

Y	True gesture label
$L(\theta, S)$	Classification loss
ℓ	Loss function (e.g., cross-entropy loss)
A	Classification accuracy
A_{\min}	Specified accuracy threshold
$T_s(u)$	Time series corresponding to each sEMG sensor
m	Data points in time series
$W_s(p, s)$	Window segment of length p
z	Total number of samples
l_i	Annotation (label)

PREFACE

In recent years, the field of Human-Computer Interaction (HCI) has seen a marked increase in efforts to create more user-friendly and interactive interfaces through a variety of inputs. These inputs range from traditional methods like keyboards and mouse to advanced technologies such as voice commands, eye tracking, Brain-Computer Interfaces (BCI), augmented and virtual reality, haptic feedback systems, and hand gestures.

Hand Gesture Recognition (HGR) is a key component of Human-Computer Interaction (HCI), aimed at creating technologies that interpret human commands through gestures. This involves computer systems recognizing and understanding human hand movements to enable device interaction. A promising area in HGR is the use of biosignals generated during hand gestures to establish correspondence with related inputs. These systems play a vital role in improving human-machine and human-robot interactions, enhancing human abilities by utilizing the electrical characteristics of the human nervous system. They make use of signals from tissues, muscles, organs, or the central nervous system to develop interfaces for computers.

One such notable input method for HGR models is surface Electromyography (sEMG) signals, a biosignal that can track skeletal muscles and measure electrical activity generated during static and dynamic gestures. This biosignal can also approximate the intensity and specific type of muscle engagement, providing a clear correlation with the intended motion.

sEMGs are non-invasive and hold significant value in areas like medical rehabilitation, prosthetics, sports science, and beyond. However, sEMG processing faces challenges like signal interference, individual variability, motion artifacts, complex data processing needs, muscle fatigue effects, and sensitivity to electrode

placement. Despite these challenges, advancements in machine learning and signal processing are enhancing the effectiveness and applicability of sEMG-based hand gesture recognition systems.

This thesis presents the design and development of innovative sEMG-based hand gesture recognition techniques, focusing on static and complex dynamic hand gestures. This research encompasses the recognition of Sign Language gestures, hand grasp gestures (static gestures), and handwritten characters (dynamic gestures) using data-centric methods, primarily within a machine learning framework. Additionally, explainable AI methods are predominantly used throughout this thesis to enhance the interpretability of the models developed.

The first contribution is the development of an efficient sEMG-based static hand gesture recognition pipeline for the Sign Language. This includes a novel ensemble feature selection method combining four filter-based techniques—ANOVA, Chi-square, Mutual Info, and ReliefF. A new feature combiner exploits feature-feature and feature-class correlation thresholds, resulting in reduced and representative feature subsets for classifying sign language gestures, aiming to improve recognition accuracy.

As a second contribution, we have introduced an sEMG-based hand grasp recognition (HGR) pipeline that can effectively distinguish between six different static hand grasps using a minimal number of sEMG sensors. To achieve this, we employed a game theory-based feature selection approach to determine the representative feature subset by treating the feature selection as a cooperative game with a transferable utility function. The proposed pipeline was validated using standard performance metrics, and it demonstrated competitive recognition accuracy on a publicly available dataset using single-channel sEMG. This high accuracy with minimal sensors supports the development of cost-effective devices.

The third contribution focuses on sEMG-based dynamic hand gesture recognition. We leveraged deep representation learning to build an efficient and robust

Handwritten Character Recognition (HCR) pipeline. A Stacked Sparse Denoising Autoencoder(SSDAE) network is designed to obtain an effective deep feature representation. The resultant learned feature representation is further introduced into traditional machine learning classifiers, achieving potentially superior results in HCR tasks. Our proposed approach can potentially contribute to real-time Human-Computer Interaction (HCI) systems, promoting the digitization of handwritten notes and enhancing clinical applications that analyze handwriting tasks. For our experiments, we created a new dataset, denoted as $S - HCR$, which includes EMG signals collected corresponding to lowercase English alphabets from participants while writing on paper with a pen.

For our fourth contribution, we developed an efficient multi-modal handwritten character recognition (HCR) pipeline by integrating electromyography (EMG) and inertial measurement units (IMU), building upon our second contribution, which focused solely on sEMG. The system employs a feature fusion approach, incorporating a modified deep autoencoder to achieve an effective combined data representation for both sEMG and IMU signals. For our experiments, we collected a new dataset comprising sEMG and IMU data corresponding to 26 isolated handwritten English alphabets on a whiteboard, referred to as $MM - HCR$. The feature fusion technique enhances the system's performance in terms of recognition accuracy. With its higher recognition accuracy, the proposed method shows potential for applications in digitizing handwritten notes from whiteboards in a smart classroom and in clinical handwriting analysis for conditions such as Alzheimer's.

The fifth contribution addresses high-dimensional feature vectors in the $MM - HCR$ dataset by employing a cost-effective meta-heuristic-based feature selection approach. The Enhanced Salp Swarm Algorithm, a metaheuristic optimization technique, selects relevant information from EMG and IMU features, yielding a robust representation of handwriting dynamics. This method results in a smaller feature subset vector and improved accuracy, showcasing the potential of the integrated feature selection and fusion methodology.

Another key contribution is the extensive use of explainable AI methods to enhance the interpretability of sEMG-based hand gesture recognition models. Techniques like SHAP (Shapley Additive exPlanations) are predominantly implemented where applicable to provide insights into the decision-making process of the machine learning models, ensuring transparency and trustworthiness in practical applications. However, the focus was more functional than foundational and the thesis does not attempt to build formal causal or theoretical models based on explainability.

The thesis concludes with major findings in sEMG-based static and dynamic hand gesture recognition and emphasizes the use of explainable AI methods to improve interpretability. These findings hold significant promise in biomedical signal processing, electromyography, and HCI, with practical applications in Sign Language interpretation, smart classrooms, and clinical analysis.

Keywords: Biomedical signal processing, Deep learning, Human-computer interaction, Sign language, Feature selection, Explainable AI.