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Design and Development of an EMG-Based Interactive Musical Instrument Using the Decision Tree Method

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Abstract – *Hand motor limitations often hinder individuals from expressing their musical creativity, particularly those affected by neurological disorders, musculoskeletal injuries, or playing-related musculoskeletal disorders. Such impairments restrict access to traditional instruments and highlight the need for alternative modes of musical interaction. This study addresses the problem by designing an interactive musical instrument based on surface electromyography (EMG), enabling the conversion of forearm muscle activity into digital notes via a Musical Instrument Digital Interface (MIDI) controller in real time. The system integrates a Muscle Sensor v3, Arduino Uno, and Python-based software with a graphical user interface. The processing pipeline includes EMG signal acquisition, feature extraction using three time-domain features—Mean Absolute Value (MAV), Root Mean Square (RMS), and Waveform Length (WL)—and gesture classification with a Decision Tree algorithm implemented in scikit-learn. Classified gestures are then mapped to MIDI note values and transmitted to a Digital Audio Workstation (DAW) for sound production. Experimental evaluation was conducted on eight hand gesture classes. For each class, 20 repetitions were used for training, and 10 for testing, resulting in 80 independent test trials. The system achieved an overall accuracy of 82.5%, with 66 correct predictions out of 80. Simple gestures such as Hand Open and Index Bend reached 100% accuracy, while gestures with overlapping muscle activation patterns, notably Form Number 1 and Form Number 2, achieved only 60%. These results indicate that Decision Trees, while computationally efficient and interpretable, face limitations when handling non-linearly separable data. Nonetheless, the study demonstrates the feasibility of using Decision Trees as a lightweight baseline for real-time EMG-based musical interfaces. Future work may involve multi-subject, multi-channel EMG datasets and advanced classifiers such as Support Vector Machines (SVM) or Artificial Neural Networks (ANN). This research contributes to inclusive and adaptive digital musical technologies for individuals with motor impairments.*

Keywords – *EMG; Musical Instrument; MIDI Controller; Decision Tree; Support Vector Machines.*

I. Introduction

Musical performance relies heavily on fine motor control, an ability that can be compromised by conditions such as stroke, nerve injury, muscular dystrophy, arthritis, or Playing-Related Musculoskeletal Disorders (PRMDs). PRMDs represent a significant concern, with prevalence rates reported at 34–87% among professional musicians and 34–62% among students [1], with some systematic reviews reaching as high as 80–90% [2]. Such impairments restrict creative performance and directly impact musicians' ability to engage with their instruments.

Electromyography (EMG) has long been applied in diagnosing and rehabilitating music-related injuries [3] while also enabling alternative musical interfaces that bypass physical limitations and open new possibilities for interaction [4, 5]. EMG records electrical activity of muscles through surface electrodes, capturing signals that directly reflect motor intent. Compared to EEG, EMG provides more robust and volitional control for real-time interaction [6], making it particularly attractive for Digital Musical Instruments (DMIs) aimed at musicians with impaired motor function [7].

The field of EMG-based gesture recognition has advanced through the use of machine learning, including Random Forests [8], Support Vector Machines (SVM) [9], and various Artificial Neural Network (ANN) architectures—including RNNs and CNNs—that have consistently demonstrated high classification performance, often exceeding 90%. For example, ANN models have reported 94.0% accuracy in finger gesture classification [10], real-time ANN systems achieving

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98.7% [11], and Random Forests demonstrating 98.7% accuracy for seven hand gestures [12]. However, their high computational demands limit practicality for real-time, low-power, or wearable systems [13]. Meanwhile, Decision Tree has also been applied in biomedical expert systems such as disease diagnosis, proving its value as a lightweight and interpretable model [14].

This research addresses that gap by evaluating the Decision Tree algorithm as a lightweight and interpretable baseline for EMG gesture classification. The emphasis is not on maximizing accuracy but on investigating the trade-off between computational efficiency and classification performance. The objectives of this study are twofold: (1) to design and implement an interactive musical instrument that translates forearm EMG signals into real-time MIDI notes, and (2) to evaluate the feasibility of the Decision Tree method in enabling expressive digital music creation for inclusive and adaptive musical technologies.

II. Research Methods

This section presents the methodology used to develop and evaluate the EMG-based interactive musical instrument. The approach includes the acquisition of EMG signals from the forearm, feature extraction to represent muscle activity patterns, and the design and implementation of the Decision Tree classifier for mapping gestures to MIDI notes. Each step is described in detail in the following subsections.

i. System Design

The system was designed as an end-to-end workflow to capture EMG signals from forearm muscle movements using an EMG module (Muscle Sensor v3), process them, and convert them into digital musical notes in real time. Figure 1 illustrates the detailed system architecture, which is divided into several key stages. The process begins with the physical placement of surface electrodes (non-invasive) on the forearm's flexor muscles to capture raw EMG signals. This signal is then conditioned through an "Amplification & Filtering" stage, handled by a Muscle Sensor v3.

The Muscle Sensor v3 is specifically designed for microcontroller-based applications and integrates amplification, rectification, and smoothing stages, thereby outputting a conditioned signal suitable for direct sampling by the Arduino's ADC without additional preprocessing. Its gain is adjustable, with a theoretical range up to 20,700× depending on resistor configuration, ensuring adequate sensitivity for forearm muscle activity. Importantly, the module does not provide raw EMG output but instead delivers an amplified and filtered signal that has undergone full-wave rectification and smoothing, making it more robust for downstream digital processing [15]. Subsequently, the analog signal undergoes "Digitalization" using the Analog-to-Digital Converter (ADC) on an Arduino Uno, which also manages "Serial Data Transmission" to a laptop.

The final stages, labeled "Processing on Laptop", are executed by a Python-based application. This involves "Feature Extraction" from the incoming data stream, followed by movement classification using a pre-trained Decision Tree model, which maps EMG features to specific hand gestures in real time. The classified gesture is then converted to MIDI commands and sent to a Digital Audio Workstation (DAW) for sound output. This modular architecture represents a standard pattern in DMI development, and the chosen electrode location is a common and effective practice for gesture classification [16].

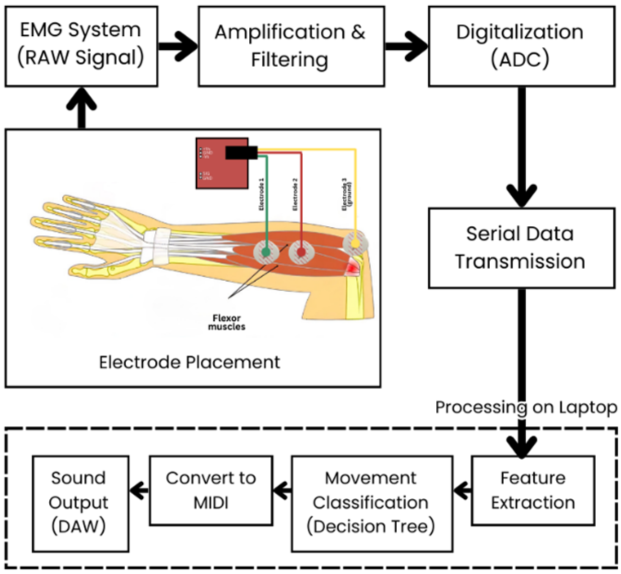

Figure 1: Detailed architecture of the real-time EMG-to-MIDI system.

Two differential electrodes (Electrodes 1 and 2) are positioned over the target muscle group, namely the flexor muscles, which are responsible for finger and wrist flexion. The reference electrode (Electrode 3/Ground) is placed on a bony prominence near the elbow to minimize common-mode noise. This configuration is designed to maximize the detection of EMG signals from the relevant muscle activity.

ii. Flowchart System

The overall workflow of the system is illustrated in Figure 2. The process begins with the acquisition of EMG signals from the sensor, which are first subjected to basic filtering on the Arduino to reduce noise before transmission to the computer. On the computer side, feature extraction is performed to represent muscle activity, followed by classification using the trained Decision Tree model to recognize the intended gesture. Once a stable gesture is detected, the system generates a command to play the corresponding MIDI note. This entire sequence is executed in real time to ensure responsive interaction between muscle activity and musical output.

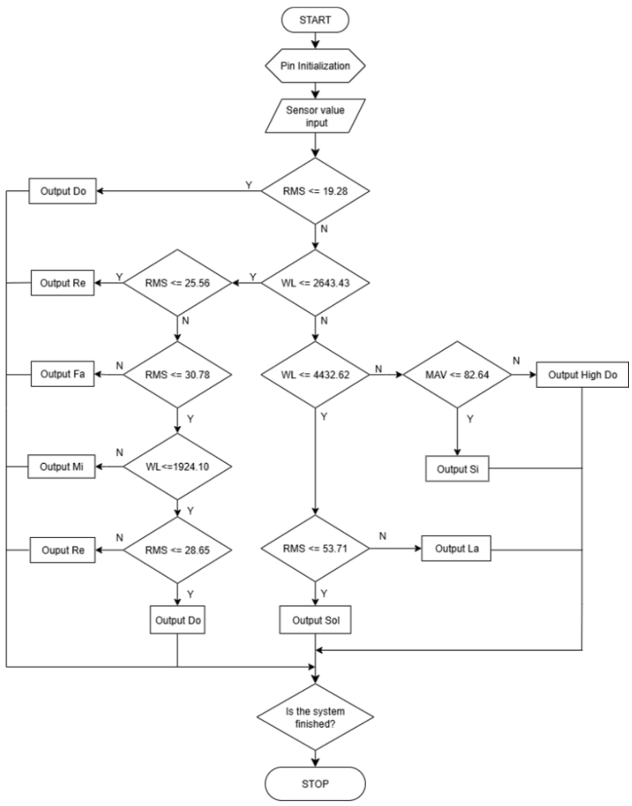

Figure 2: Flowchart representation of the Decision Tree model logic.

Each internal node (e.g., RMS $\leq$ 19.28) represents a condition applied to an EMG feature. Based on the test outcome (Yes/No), the path proceeds until reaching a leaf node (e.g., Output Do), which corresponds to the final classification result.

iii. Hardware Implementation

The core hardware components include the Muscle Sensor v3, an Arduino Uno, and three surface electrodes. Based on previous studies on EMG signal acquisition for finger gestures, the electrodes were placed on the forearm to target the Flexor Digitorum Superficialis muscle, which is primarily responsible for finger flexion and capable of producing distinct signals for various finger movements [17]. Figure 3 illustrates the electrode placement, while the detailed schematic of the hardware configuration is shown in Figure 4.

In this system, the Muscle Sensor v3 is powered by a regulated dual supply (+5 V, –5 V, GND). The negative voltage (–5 V) is generated using an ICL7660-based voltage inverter, converting the Arduino's +5 V supply into a corresponding negative rail [18]. This configuration provides the necessary symmetrical power supply required for the sensor and ensures compatibility with components such as operational amplifiers that demand dual polarity [19]. The sensor's output is connected to one of the Arduino's analog input pins for signal acquisition. To improve connection stability and minimize measurement noise, the components were integrated on a custom-designed PCB [20].

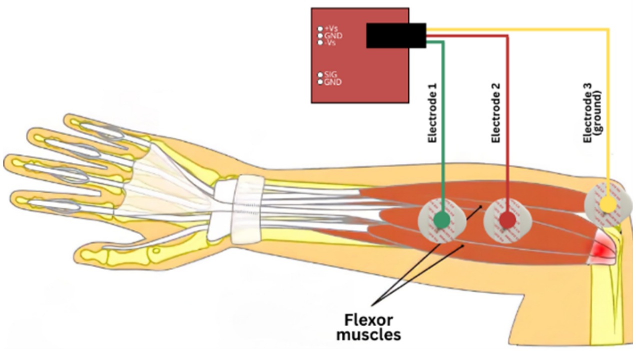

Figure 3: Electrode placement configuration on the forearm flexor muscles for EMG acquisition.

iv. Hardware Implementation (continued)

Two differential electrodes (Electrodes 1 and 2) are positioned over the target muscle group, namely the flexor muscles, which are responsible for finger and wrist flexion. The reference electrode (Electrode 3/Ground) is placed on a bony prominence near the elbow to minimize common-mode noise. This configuration is designed to maximize the detection of EMG signals from the relevant muscle activity. The diagram 4 shows electrode placement, signal conditioning, digitization, feature extraction, classification, and MIDI conversion.

v. Signal Acquisition and Feature Extraction

Data were collected from a single participant (the author), who performed eight distinct hand gestures, each repeated 20 times, resulting in a dataset of 160 trials. The participant was a healthy adult female, aged 22, with no known neuromuscular disorders. While the use of a single subject allows for controlled and consistent data collection, it represents a limitation of this study, as the findings cannot be directly generalized to a broader population.

To prepare the raw EMG data for classification, three time-domain features were extracted from each signal window, which are widely recognized for their

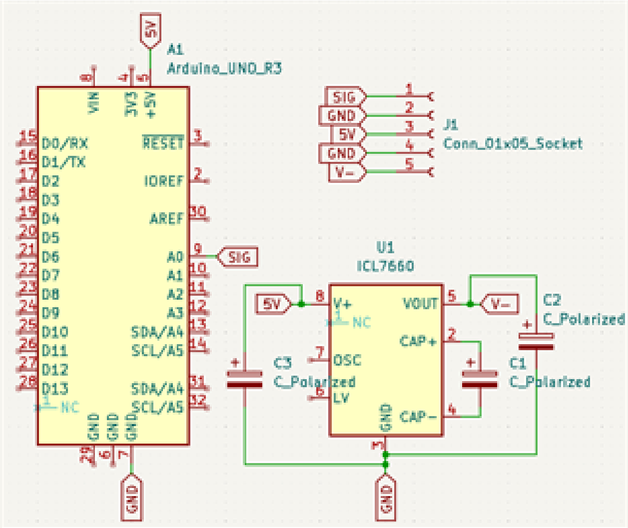

Figure 4: Schematics of the EMG-based interactive musical instrument system.

effectiveness and computational simplicity in EMG analysis [21].

1. **Mean Absolute Value (MAV):** An estimate of the signal's amplitude, indicating the overall level of muscle activation [22].

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i|$$

2. **Root Mean Square (RMS):** Relates to the signal's power and indicates muscle contraction force [22].

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}$$

3. **Waveform Length (WL):** Measures the cumulative length of the waveform, reflecting its complexity [21].

$$WL = \sum_{i=1}^{N-1}|x_{i+1} - x_i|$$

Here, x_i represents the signal sample at time i, and N is the total number of samples in the window.

vi. Gesture Classification and MIDI Conversion

A Decision Tree classifier was trained using the extracted features (MAV, RMS, WL) and corresponding gesture labels, implemented with Python's `scikit-learn` library [23]. The algorithm generates a flowchart-like structure where internal nodes represent feature-based tests (e.g., "Is RMS $\leq$ 25.56?"), and leaf nodes represent the final classification outcome (the gesture).

Once a gesture is classified, the system maps it to a specific MIDI note number, as shown in Table 1. These MIDI commands are transmitted in real time to a DAW (e.g., Virtual MIDI Piano Keyboard) via the `rtmidi` library to produce the corresponding musical note [24]. In addition, a custom GUI developed in C# with WPF provides real-time visualization of the EMG signal, the predicted note, and the associated gesture image.

Table 1: Mapping of Hand Gestures to MIDI Note Numbers

No.	Gesture	Image	Musical Note	MIDI Value
1.	Hand Open		Do	60
2.	Index Bend		Re	62
3.	Ring Bend		Mi	64
4.	Middle & Ring Bend		Fa	65
5.	Form Number 2		Sol	67
6.	Form Number 1		La	69
7.	Wrist Flexion Up		Si	71
8.	Hand Clench		High Do	73

III. Results and Discussion

The system's performance was evaluated through two main tests: feature analysis and classification accuracy.

i. Feature Extraction Analysis

The average values of the extracted features (MAV, RMS, and WL) for each of the eight gestures are presented in Table 2. The results show a clear trend where more intensive muscle contractions yield higher feature values. The "Hand Clench" gesture produced the highest values across all three features, indicating the strongest muscle activation. Conversely, the "Hand Open" gesture, representing a relaxed or minimally active state, had the lowest values. This progressive increase in feature values from gesture 1 to 8 confirms that the selected features effectively capture varying levels of muscle intensity, which is crucial for the classifier to distinguish between different movements.

Table 2: Average Feature Values for Each Gesture

No.	Gesture	MAV	RMS	WL
1	Hand Open	12.41	12.71	1001.78
2	Index Bend	23.06	23.59	1714.32
3	Ring Bend	27.89	28.57	1995.92
4	Middle & Ring Bend	32.73	33.46	2207.74
5	Form Number 2	46.97	48.31	3329.79
6	Form Number 1	55.14	57.21	3988.03
7	Wrist Flexion Up	64.64	67.71	5155.51
8	Hand Clench	104.23	107.21	7117.25

ii. Classification Accuracy

To assess the precision of the Decision Tree model, each of the eight gestures was performed 10 times, for a total of 80 trials. The system's predictions were recorded and compared against the actual gestures performed. The results are summarized in Table 3. The system achieved an overall accuracy of 82.5%, correctly identifying 66 out of 80 gestures.

Table 3: Confusion Matrix for Eight-Gesture Classification

True Gesture	Do	Re	Mi	Fa	Sol	La	Si	High Do
Do (Hand Open)	10	0	0	0	0	0	0	0
Re (Index Bend)	0	10	0	0	0	0	0	0
Mi (Ring Bend)	0	1	8	1	0	0	0	0
Fa (Middle & Ring)	0	0	0	10	0	0	0	0
Sol (Form No. 2)	0	0	0	4	6	0	0	0
La (Form No. 1)	0	0	0	0	4	6	0	0
Si (Wrist Flexion Up)	0	0	0	0	0	1	9	0
High Do (Clench)	0	0	0	0	0	0	3	7

iii. Discussion

The results show that the Decision Tree classifier achieved an overall accuracy of 82.5%. As indicated in Table 3, gestures with distinct activation patterns, such as "Hand Open," "Index Bend," and "Middle & Ring Bend," were consistently classified with 100% accuracy. However, the gestures "Form Number 1" and "Form Number 2" exhibited the lowest accuracy at 60%, frequently being misclassified as one another.

This misclassification can be explained by the similarity of their feature values. As shown in Table 2, the MAV, RMS, and WL values of "Form Number 1" and "Form Number 2" are relatively close, reflecting highly overlapping EMG patterns. This overlap reduces the ability of a Decision Tree to distinguish between the two classes, as the algorithm partitions the feature space using axis-parallel splits [25]. When the optimal decision boundary is curved or diagonal, the Decision Tree's hyper-rectangular regions result in coarse approximations and errors near the class boundary.

When compared with related studies, the achieved accuracy is modest. For instance, Di Maggio et al. [12] reported 98.7% accuracy for seven hand gestures using a Random Forest classifier, underscoring the advantages of ensemble methods in modeling complex distributions. Similarly, ANN-based systems have achieved accuracies exceeding 95% [10,11]. These findings highlight the deliberate trade-off in this study, prioritizing computational efficiency and interpretability over maximum accuracy. Such trade-offs are valuable in contexts where low-latency and lightweight implementation are critical, such as embedded or wearable devices.

While the overall accuracy of 82.5% is modest compared to state-of-the-art approaches, this outcome reflects the deliberate design choice of employing a single-channel EMG setup and a Decision Tree classifier. The intention of this work is not to achieve the maximum possible accuracy, but rather to demonstrate a lightweight and interpretable baseline system suitable for real-time, low-latency applications. The Decision Tree offers transparent classification rules, making it easier to trace errors and optimize system design in the early development stage.

The most notable source of error was the frequent misclassification between "Form Number 1" and "Form Number 2." As discussed, these gestures produce overlapping EMG patterns that are difficult to separate using time-domain features alone. This limitation indicates the potential benefits of incorporating frequency-domain descriptors, dimensionality reduction techniques such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA), or

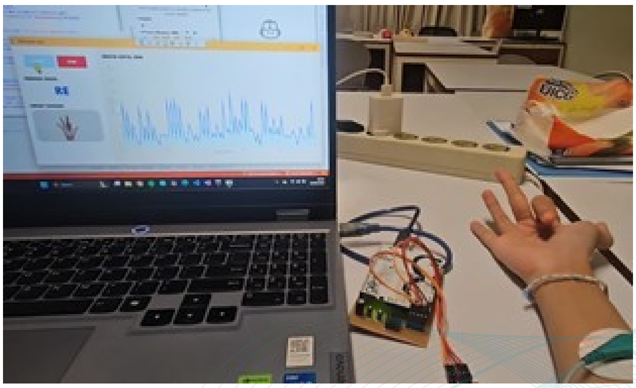

Figure 5: Real-time system demonstration showing the EMG hardware setup connected to Arduino and the GUI interface displaying signal visualization, predicted gesture, and corresponding musical note.

additional sensor channels in future studies. Such approaches could improve discriminability without compromising computational efficiency.

Furthermore, the evaluation was conducted on a single subject with limited repetitions. This scope was intentionally restricted to maintain system simplicity and to validate the feasibility of the pipeline. While this design limits generalizability, it establishes a proof-of-concept that can be extended in subsequent work with richer datasets and more robust validation protocols.

As this study involved human data collection, ethical approval was not required for a single-subject design; however, informed consent was obtained in accordance with the Declaration of Helsinki [26]. To further demonstrate the feasibility of the proposed system, Figure 5 shows the real-time implementation of the EMG-based musical instrument, where the hardware setup and GUI interface visualize the extracted EMG signals, predicted gestures, and corresponding musical notes.

iv. Training and Testing Process

A dataset of 20 repetitions per gesture was collected and used to train the Decision Tree classifier. To evaluate the model, an additional set of 10 repetitions per gesture—collected separately from the training dataset—was used for testing, resulting in 80 independent test trials. This ensured that evaluation was performed on data not seen during training. The Decision Tree was implemented using the `scikit-learn` library in Python.

v. Ethical Considerations

This study involved the acquisition of surface EMG signals from a human participant. Informed consent was obtained prior to data collection, and all procedures were conducted in accordance with the ethical principles outlined in the Declaration of Helsinki [26] and standard guidelines for non-invasive human-subject research.

IV. Conclusion

This study presented the design and implementation of an EMG-based interactive musical instrument that converts forearm muscle activity into real-time MIDI notes using a Decision Tree classifier. With an overall accuracy of 82.5%, the system demonstrated feasibility as an alternative musical interface and established a baseline where computational efficiency and interpretability are prioritized over peak accuracy. Although modest compared to state-of-the-art methods, the accuracy reflects a deliberate choice of a single-channel setup and a lightweight model for real-time use. The main limitation was frequent misclassification between "Form Number 1" and "Form Number 2," caused by overlapping EMG patterns and the restricted use of time-domain features.

The study's constraints—single subject, single muscle, and three-electrode configuration—limit generalizability but serve as proof-of-concept. Future work should include multi-subject validation, multi-channel acquisition, and more advanced classifiers such as Support Vector Machines (SVMs) or Artificial Neural Networks (ANNs), alongside ensemble methods like Random Forests for baseline comparison. Additional directions include applying signal denoising, exploring cross-subject generalization, and embedding the system into wearable platforms for practical performance.

As noted by Pedrosa and Costa [24], EMG-based MIDI controllers represent a growing research direction, and building on this baseline can advance inclusive and adaptive digital musical technologies for both artistic and assistive use.

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