MEDIUM DENSITY DIGITAL ELECTROMYOGRAPHY SENSING SYSTEM

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ABSTRACT

Surface electromyographic (EMG) signals are widely used for diagnostic and control purposes. Traditional EMG recordings typically use sparse electrode setups, limiting their use in dynamic environments like prosthetics or virtual reality. We propose a medium-density EMG armband design that leverages digital technology to capture EMG data from 21 channels. This system, designed to be more practical for everyday use and research, was tested against traditional single-channel methods for classifying six hand gestures using machine learning. Our results indicate the medium-density EMG system offers superior gesture classification accuracy, making it a valuable tool for real-world applications. We aim to further enhance this EMG recording setup and introduce it an open-source platform to the MEC community at the conference.

INTRODUCTION

Electromyography has emerged as a transformative technology in the area of human-machine interfacing, including prosthetics control, offering unique opportunities to bridge the interface between human neural activity and machine operations [1]. Its applications extend far beyond traditional diagnostics, leading into the development of advanced immersive virtual (VR) [2] and extended reality (XR) environments [3], rehabilitation programs [4], and myoelectric prosthetics [5,6]. The essence of EMG lies in its ability to decode the electrical signals generated by motor units during contraction, providing a direct pathway to understanding and harnessing human intent in real-time. This capability is pivotal in creating more intuitive and responsive systems that can cater to a wide spectrum of needs, from assisting individuals with mobility impairments to enhancing user experiences in digital realms.

In the domain of prosthetic development, EMG technology has the potential to be a game-changer and enable the development of limbs that can respond to the user's muscle signals with precision and fluidity. This not only restores a degree of lost functionality for amputees but also empowers them with a sense of autonomy and improved quality of life [6]. Similarly, in rehabilitation, EMG-based systems offer valuable insights into muscle performance and recovery progress. The integration of EMG into VR and XR applications [2, 3] opens new frontiers for interactive technologies, allowing users to control virtual environments through natural body movements.

However, the widespread adoption of EMG technology faces challenges, primarily due to the limitations of existing recording systems [7]. Traditional setups often require a trade-off between signal detail and system portability. High-density arrays [8] offer rich data at the expense of mobility and ease of use, while sparse configurations sacrifice detail for simplicity. Recognizing this gap, the proposed medium-density EMG recording system, implemented as an easily wearable armband, aims to overcome these obstacles. By utilising the principles of digital body area networks (BAN), this innovative approach seeks to provide a balanced solution that offers detailed signal acquisition without compromising on user comfort and mobility. This development not only stands to practically use the way multi-channel EMG is applied across various fields but also emphasises the potential for solid integration of human physiological signals into the rehabilitation and control systems.

We are excited to announce the introduction of our Medium Density System at the upcoming MEC Conference. Our platform will be presented alongside detailed designs and firmware, with the intention of enabling the community to reproduce it for further research. By openly sharing our work, we aim to foster collaboration and drive innovation within the research community. We look forward to engaging with fellow researchers and enthusiasts at the conference as we collectively advance the field.

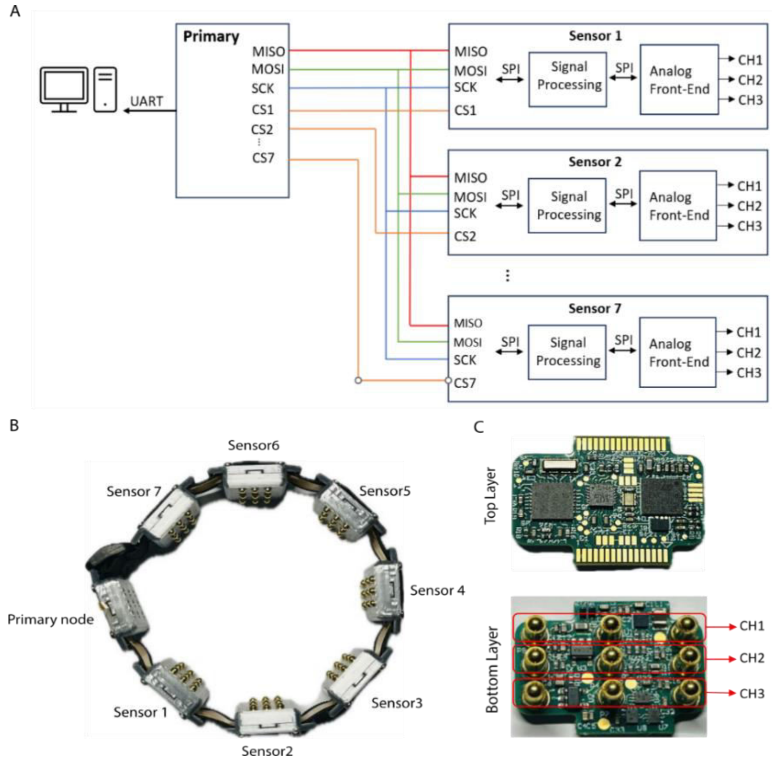

Figure 1: A) Overall block diagram of the system. B) The proposed armband. C) Two sides of sensor's PCB and number of channels on each PCB.

METHODS

Hardware

Figure 1A shows the overall diagram of the system. Each EMG sensor consists of two subsystems for analog front-end (AFE) amplification and EMG signal processing. The front-end circuit is built around an ADS1293 chip (Texas Instrument co., USA), with a built-in fixed gain amplifier and three channels, 24 bits analog to digital converter (ADC). Each channel is connected to two active electrodes for differential recording, along with a reference electrode, namely, E1, E2, and E0, respectively. The reference electrode is connected to the system ground. The EMG signals have been sampled at 1067 Hz. The EMG processing unit comprises an ARM CortexM4 based 32-bit flash microcontroller (STM32L433RCI3, ST Microelectronics). A 16MHz serial peripheral interface (SPI) connects the AFE subsystem to the signal processing subsystem. The EMG processing unit features a 2nd order infinite impulse response (IIR) Butterworth band-pass filter [25-350 Hz] which cancels undesired spectral components. Power-line interference is eliminated by a 2nd order IIR Butterworth notch filter, with cut-off frequency of 50 Hz.

For the sensor contacts, commercially available, gold-coated stainless steel has been used, which were housed in a 3D-printed case. The dimensions of the case met clinical standards and fitted comfortably around subjects' forearm as an armband. The design of the case was crafted using Fusion360, 3D designs and modelling software. To print the case, Bambu Studio software was employed to slice the model into printable layers. The case was then printed on a Bambu Lab P1S printer, with generic PLA (Polylactic Acid) as the printing material. Figure1B and 1C, show the final prototype armband and an 8-layer Printed Circuit Board (PCB) designed for the Primary and secondary nodes.

The network of EMG sensors is structured of two different types of nodes, namely, primary, and secondary. The former serves as a communication initiator and network synchronizer, and data handler and each sensor node acts as a secondary nodes. The SPI bus with a speed of 32 MHz enables data exchange between the primary and all secondary nodes. Each sensor is controlled with chip-select pin where the primary node request in sequence from each sensor. The primary node transfers data from all sensors through Universal Synchronous/asynchronous Receiver/Transmitter (USART) to a computer using USB to TTL Serial Cable (DSD TECH).

Experiment Design

The local ethics committee at Newcastle University (reference number: 20-DYS-050) approved this study. The experiment involved 10 participants, ranging in age from 19 to 43, including 2 females and 8 males. They signed an informed consent. They were tasked with performing six different movements: power grip, lateral pinch, tripod grip, pointer (extension), hand opening, and rest, with each movement repeated in 10 trials. During each trial, participants followed a structured sequence involving 3 seconds of the specified movement followed by 5 seconds of relaxation. Data collection and labelling were conducted automatically using the Axopy platform. The analytical models were developed in Python, utilizing the scikit-learn library for data processing and analysis. Programs ran on a DELL Latitude 5431 laptop, with 12^{th} Gen Intel(R) Core™ i7-1270P, 2200MHz CPU, 32GB of memory.

Feature Extraction

Raw EMG data is too complex to be decoded with such a modest amount of data. Two features were adopted in the experiment, namely waveform length and log variance. They are commonly employed in the EMG experiment, meanwhile they are cost-efficient in terms of computation.

Machine Learning Modelling

Linear discriminant analysis (LDA) is one of the most adopted supervised machine learning algorithm, which exhibits a versatile mastery on both data dimensionality reduction and classification. The programming of the LDA model was implemented in Python, with scikit-learn library. 'Svd', or Singular Value Decomposition, was chosen as the solver for its efficiency with large feature sets. SVD reduces data dimensions by decomposing a matrix into three matrices, capturing the data's essential characteristics in a simplified form [9]. This method is ideal for processing extensive datasets, allowing for effective analysis and classification without significant information loss. The default number of components was set to 5 (n_class - 1), aiming to manage the substantial number of input features - 42 in total, calculated from 2 EMG features across 7 sensors and 3 channels. This approach to dimensionality reduction was intended to enhance the model's robustness while simultaneously lowering computational demands.

The data collection was partitioned into an 80% training set and a 20% testing set, shuffled and reapplied five times to facilitate a 5-fold cross-validation process. During this process, 80% of the data along with its labels were employed to train the LDA model, and the remaining 20% was used to evaluate the model's accuracy by comparing the predicted outcomes against the actual labels. This training and testing process was executed in parallel across five different conditions to ensure a comprehensive comparison. These conditions included the use of all three channels per sensor, three repetitions for each of the first, second, and third channels independently, and three repetitions using a randomly selected channel, applied consistently across all users.

RESULTS

Figures 2A and 2B show the experiment setup and the sample of raw EMG data have been recorded through all 21 input channels, respectively. Figure 2C presents the cumulative findings from a study involving 10 participants, where we explored the efficacy of five unique configurations for channel selection. These configurations include the use of three independent channels, as well as the first, second, and third input channels treated as separate entities, in addition to a scenario involving randomly chosen channels. The objective was to assess and compare their impact on classification accuracy. The data depicted in the graph reveals that the approach utilizing three independent input channels surpassed the performance of other configurations. This outcome suggests that medium-density electrodes, without expanding the spatial recording area, can significantly improve the precision of control systems in interpreting signals.

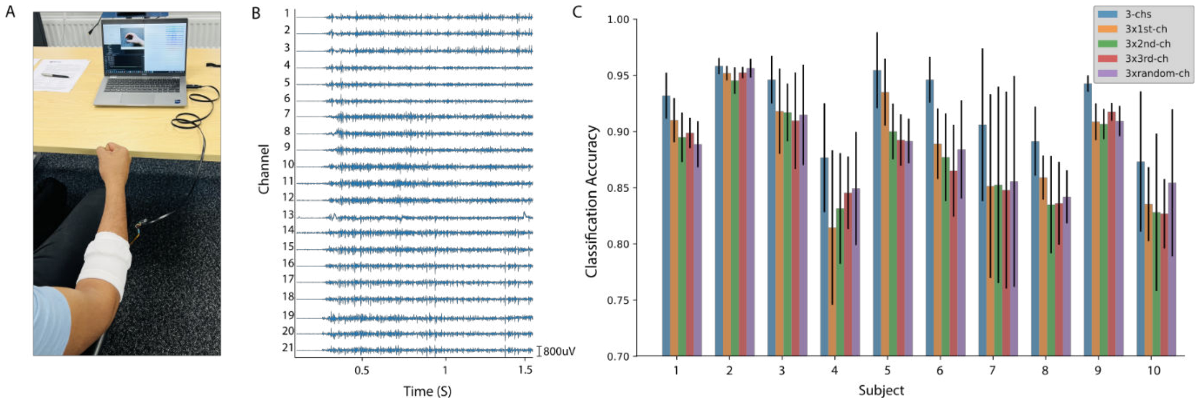

Figure 2: A) Experiment setup. B) Recorded raw EMG data over 21 input channels. C) Results on classification accuracy across subjects have been analyzed. Five distinct configurations to identify the optimal channel selection strategy have been examined.

ACKNOWLEDGEMENTS

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