EMG Controlled Drone Simulation

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***Abstract*—Today, electromyography (EMG) and inertial measurement unit (IMU) readings collected from wearable sensors see a wide variety of applications in robotic systems. These include applications for rehabilitative assistive robots and control systems for robotic manipulators. However, there is less focus on EMG-based control for unmanned aerial vehicles (UAVs). Additionally, limited research has been conducted on control schemes that utilize EMG and IMU measurements together in decision making. This paper examines the fusion of these two data types using several methods of classification. A novel drone control scheme is implemented around these classifiers and tested using Flightmare simulator in a ROS environment. Sensor readings are obtained from a Thalmic Labs Myo Armband. Using EMG and IMU features concurrently aided the accuracy of a support vector machine (SVM) classifier. A cascaded neural network using separate classifiers for the two feature types first provided an increased accuracy. However, the SVM deployment to real-time gesture classification did not provide a usable control scheme.**

***Index Terms*—EMG, IMU, Myo, SVM, NN, LSTM, Data Fusion, UAV, Classification, Drone, Simulation**

I. Problem Statement

The objective of this project is to enable the control of an unmanned aerial vehicle (UAV) through human gestures. These gestures are recorded through a combination of human electromyography (EMG) signals and accelerometer data provided through a wearable sensor package. Machine learning is employed on these data types to classify a finite number of human gestures that serve as commands to the UAV. Proper classification of these two signal types will allow for a simple and intuitive method of input. Currently, extensive research has been completed on the applications of EMG and inertial measurement unit (IMU) signals to various types of robotic control. However, there is limited research on methods that combine these two signal types in formulating commands, especially for UAVs. This project seeks to use machine learning methods to combine these signals together to form more robust gesture classifications and thus a higher classification accuracy compared to existing gesture-based control implementations. This combination is referred to as data fusion.

This paper begins with a presentation on the state-of-the-art in data classification methods and various forms of gesture-based control for robotic systems. Following this, the theory behind the novel data fusion of IMU and EMG signals is explored. Next, the testing methodology used to validate the classifier design is presented in detail. Finally, primary results are presented and discussed.

II. Literature Survey

A literature survey was conducted for the purpose of learning how physiological signals have been applied to different control systems in recent years. Sources were selected for review based on the signals collected (EMG and/or IMU), the robot or vehicle intended to be controlled, and if a data fusion method was introduced. Signal preprocessing techniques, extracted features, machine learning methods and their respective accuracies were noted.

EMG signals were recorded or borrowed from publicly available sources for hand and arm gesture classification. Different filtering techniques were applied to these signals for de-noising purposes, including a band-pass filter [2] [6] [7] [9] [16] [17] [19], notch filter [4] [6] [7], Kalman filter [12], Discrete Wavelet Transform (DWT) [9] [14], Wavelet Packet Transform (WPT) [18]. The Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), DWT, Continuous Wavelet Transform (CWT), and WPT techniques were also used to prepare the signals for feature extraction [9] [13] [18] [23]. Some sources reported applying additional preprocessing techniques such as smoothing filters, rectification, and linear interpolation [13] [16] [19]. Features that were extracted from these preprocessed EMG signals varied. Some sources chose to manually extract human-interpretable features with a mathematical basis, such as mean [3] [13] [23], standard deviation or variance [2] [8] [10] [12] [13], integral or area under the curve [2] [8], root mean squared (RMS) [3] [6] [7] [10] [14] [17], mean absolute value (MAV) [14] [17], slope sign change (SSC) [14] [17], wavelength [3] [10] [17], maximum voluntary contraction (MVC) [6], Willison amplitude [10], myopulse percentage rate (MYOP) [15], average amplitude change (AAC) [15], zero crossing [17], minimum value and maximum value [10], and skewness [17]. Others used libraries to obtain a large pool of features, then applied a machine learning method to reduce the feature space to the most critical/relevant selections. There were also a handful of sources that chose to feed their preprocessed data directly into their machine learning model under the assumption that it would learn distinguishable features of each gesture on its own. Sources that collected IMU data tended to manipulate the data by calculating Euler (roll-pitch-yaw) angles [11] [12] or calculating a few measures like mean and standard deviation of the signal [13] or angle of deflection of the wrist [15] [**?**].

It was discovered through this literature survey that machine learning models like Artificial Neural Networks (ANN), Support Vector Machines (SVM), Long Short Term Memory (LSTM), k Nearest Neighbors (KNN), Convolutional Neural Networks (CNN), Hidden Markov Models (HMM), and Gausiian Mixture Models (GMM) achieved high accuracies on their respective testing datasets. Additonally, data fusion methods such as fusion between sensor readings, cascaded SVMs or even fusion of different signal types consistently improved results.

There is currently limited research on the subject of control schemed based on concurrent EMG and IMU measurements. Most robot control systems explored in the literature use EMG or IMU data exclusively. This is especially true for UAV applications, of which there are few. Therefore, this project seeks to implement a novel control scheme for UAVs using the fusion of EMG and IMU data. It is proposed that the combination of these data types will allow for more accurate gesture classifications and thus a more robust control system than those seen in the literature.

III. Method

Please read sections III-A–III-C below for more information on how data was collected, an explanation of the proposed approach, and an explanation of the result validation process.

A. Dataset

EMG and IMU data are collected using a Myo Armband. This wearable device features eight gold-cup electrodes that allow for the non-intrusive collection of EMG signals from a wearer's forearm. This allows for eight data channels. Additionally, the Myo Armband contains an internal IMU that can record orientation and acceleration data. A sampling rate of 200 Hz is used for all measurements. This is an adequate frequency for EMG measurements, since EMG signals typically fall within a range of 8-25 Hz. The device is connected to a lab PC via a Bluetooth interface. From there, measurements can be observed and saved using LabRecorder software.

A total of fifteen arm/hand gestures are classified to provide a list of commands to a drone. These gestures include making a fist, bending the wrist left or right, and moving the arm inward or outward. To meet this end, training data is collected from each member of the research group. Each of the fifteen gestures is repeated five times and labelled to enable supervised learning. Each repetition lasts about three seconds. An additional set of gestures was collected by one member, leading to a total of 300 samples altogether.

B. Methodology

Based on examples set by the literature survey, preprocessing of the collected EMG data is necessary for it to be useful for classification. To meet this end, the collected signals are sent through a bandpass filter with a passband of 20-95 Hz and then a notch filter centered at 60 Hz. Rectification takes place between the two filter stages.

Several metrics are extracted from the collected and filtered data. For EMG measurements, the maximum, average, and standard deviation for each channel is calculated to start. Additional EMG metrics collected include RMS, waveform length, MAV, and maximum deviations. Additionally, the maximum power of each channel is determined using the *periodogram* method of the *scipy* Python library. For IMU data, the maximum deviations in the X, Y, and Z directions are determined along with the standard deviation in each orientation. Additionally, the range in gyroscope readings for all three directions is calculated. Lastly, the maximum acceleration in each direction is collected.

Based on the literature, several classification methods are viable for use in recognizing a finite set of gestures. These include SVM, LTSM, Neural Networks, and K-means clustering. The first method to be utilized is an SVM. The Python package *sklearn* is used to implement this supervised algorithm. To assist with classification across 15 groups, a linear kernel is employed, and a principal component analysis with an explain variance threshold of 0.9 is included in the classification pipeline.

The LSTM is implemented as follows; first the data is separated into EMG and IMU train test splits. Then it is preprocessed as previously discussed. Two separate LSTMs are created for each set, with an LSTM layer, and two dense layers each before a final dense layer for classification extraction. A third dense layer model is created to join the two separate LSTMs before their classification steps and is also trained. The rectified linear activation function is used inside the networks. Adam is the optimizer used in training.

Two different neural networks are created to examine the concept of data fusion. The first uses EMG and IMU features together as inputs to a single network whose parameters are shown below by Figure 1. The fifteen output nodes are corresponding to the fifteen different gesture classes. This is compared to a more complex model that learns EMG and IMU features separately with two separate branches to produce a total of 64 output nodes. These nodes then serve as the input layer of a third neural network, referred to as the fusion classifier. The fusion classifier has fifteen output nodes, one for each gesture in a similar manner to the original neural network. This fulfills the task of data fusion in a manner similar to the LSTM presented above. The architecture of this cascaded network is shown below by Figure 2. Both networks use intermediate dropout layers are trained using an 80/20 test spit. Confusion matrices are used to gauge accuracy.

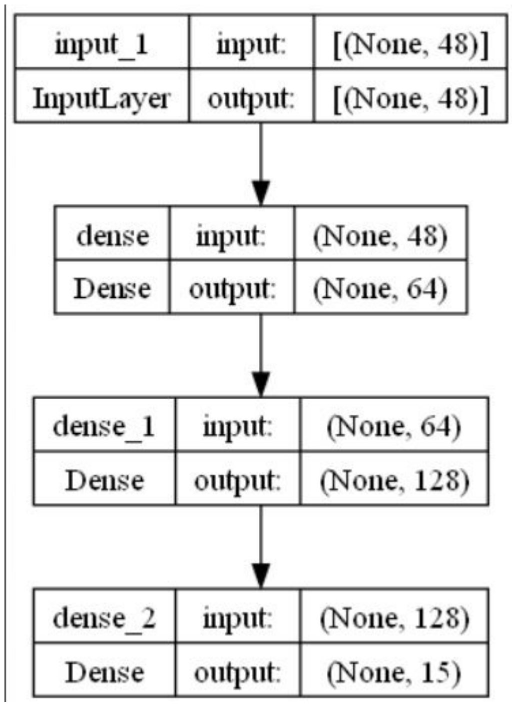

Fig. 1. Simple neural network classifier architecture

C. Validation

The proposed data fusion method is tested using a simulated environment integrated with Robot Operating System (ROS). A model for a UAV will be controlled in a virtual 3D space by the system discussed in this paper. Success is measured by classification accuracy, reliability over time in a single session (i.e. consistency of operation), and overall ease of use, which can be quantified through tallies such as the number of collisions observed within the environment.

Different forms of validation are performed for the different proposed machine learning algorithms. For the SVM, the Leave One Group Out cross-validation method is employed. This process splits the training and test data such that each training set has samples from all but one of the classes to be evaluated. This helps prevent bias in the evaluation of a model during validation. Model accuracy is accessed using a confusion matrix, which visually shows the frequency of predicted values against their corresponding true values. The accuracy of the SVM will be gauged using EMG features exclusively, then IMU features exclusively, and finally both types of features together.

Note that the models presented in this paper are designed to work with the features defined thus far. Therefore, they are subject-specific.

The package *rosmyo* is obtained and modified to allow the Myo armband to interface with ROS. This package contains a script, *myo_rawNode.py*, that opens communication to a Myo Armband through a USB Bluetooth dongle and publishes raw

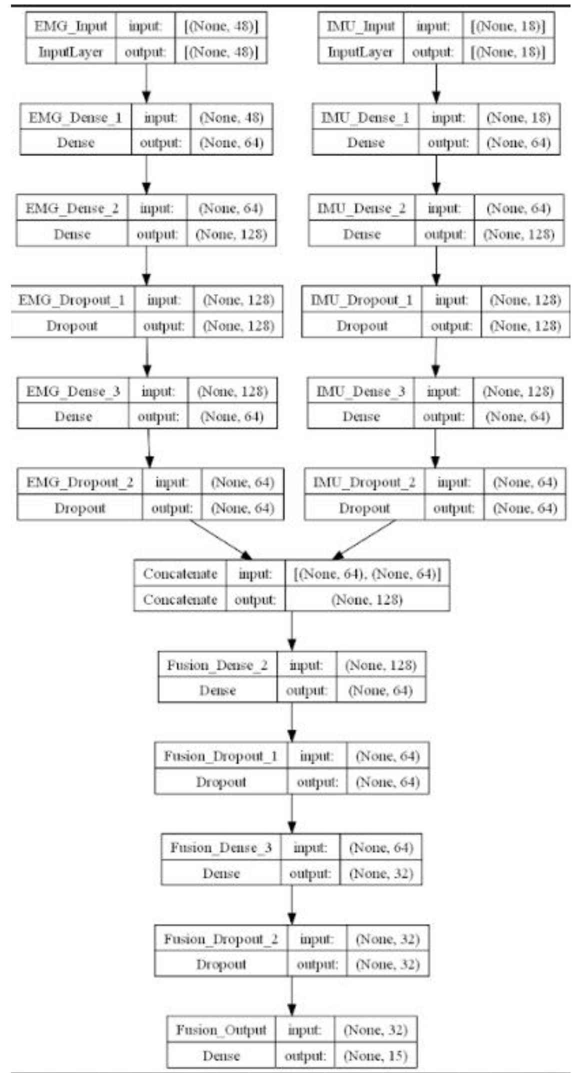

Fig. 2. Fusion neural network classifier architecture

EMG and IMU readings to ROS at a rate of 200 Hz. The ROS topics these readings are published to are */myo_emg* and */myo_imu*, respectively. Classification is performed by the program *myoOutput.py*. This program subscribes to these topics. On each reception, EMG and IMU readings are stored to separate *pandas* dataframes. A variable limits the number of samples that are accumulated in these dataframes. When either data type reaches this maximum, its respective dataframe is no longer recorded to. When both data types have reached the maximum limit of collections, the two dataframes are merged into one, and feature extraction takes place. Afterwards, classification can be performed using a vector containing the feature values with the same order as that used in training the classifier.

The Flightmare simulator can be used with custom launch files that specify specific behavior for objects within it. In this case, a C++ program is called that subscribes to the */COMMAND* topic and moves a simulated drone according to

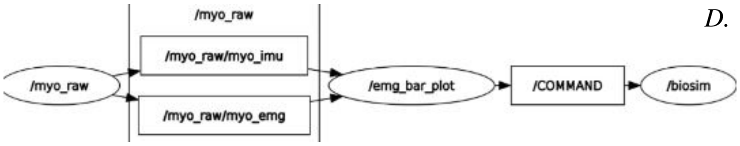

Fig. 3. ROS network for the real-time classifier

a series of pre-defined movement sequences. The drone will move according to one command until another is received, which replaces it. For example, if the user makes a move that is classified as "forward," the drone will move forward until the next classification is made from the user's next gesture. A plot of all relevant ROS topics and nodes is shown by Figure 3.

It is expected that the method of data fusion examined in this paper will allow for higher classification accuracy than with classification using EMG or IMU signals alone. The high classification accuracy of the system will allow for a UAV control scheme that is simple, consistent, and intuitive.

IV. Results

A. SVM Classification Accuracy

The SVM is established and evaluated according to the details outlined in Validation. When using EMG features alone for classification, a 49% accuracy was achieved, with best results seen for the rotate and twist motions. when using IMU features alone for classification, a 58% accuracy was achieved, with best results observed for the lateral arm movements (e.g. "up" or "left"). The highest accuracy of 75% was achieved when using both EMG and IMU features together. The confusion matrix for this case is shown below by Figure 4. The SVM performs well with most gestures but often fails to identify members of the "left," "resting," "rotate left," and "up" classes.

B. LSTM Classification Accuracy

The LSTM model was overall unsuccessful in the classification task here. This is due to the nature of feature extraction we chose. The features extracted were based on statistical extractions from each EMG file. This is not conducive to a temporal learning model. In a majority of cases, the model failed to converge, shown by the training and test loss curves in Figure 5, and if it did, its results were near random-chance guessing.

C. NN Classification Accuracy

The simple NN described by Figure 1 is trained and tested for classification accuracy. This network reached a test accuracy of 90%, as shown by the confusion matrix in Figure 6. The fusion NN shows an increased test accuracy of 95%, as indicated by Figure 7.

D. Real-Time Classification Accuracy

Based on the results of the individual classification programs, the SVM classifier was selected to test the real-time classification process. Despite reaching a 75% classification accuracy in isolation, poor performance was observed in real-time testing. The system overall worked as intended; the user makes gestures upon receiving prompts from the terminal, and classifications are made each time. The simulated drone is able to be commanded by the classification results and move accordingly. However, classification accuracy in this setup was generally very low. The classifier could often distinguish larger arm movements from wrist rotations, but the directions associated with both types of movement were more often incorrect than correct. For example, an arm movement upwards would always be classified as a downward movement, and a wrist rotation downward would usually be classified as to the left or to the right. As a result, the drone in simulation was nearly impossible to properly control. To quantify this issue, each of the 15 gestures was repeated 5 times with the real-time classifier running. Out of these 75 trials, 21 trials were correct, leading to a test accuracy of 28%. A detailed breakdown of these trials is shown below by Table 1.

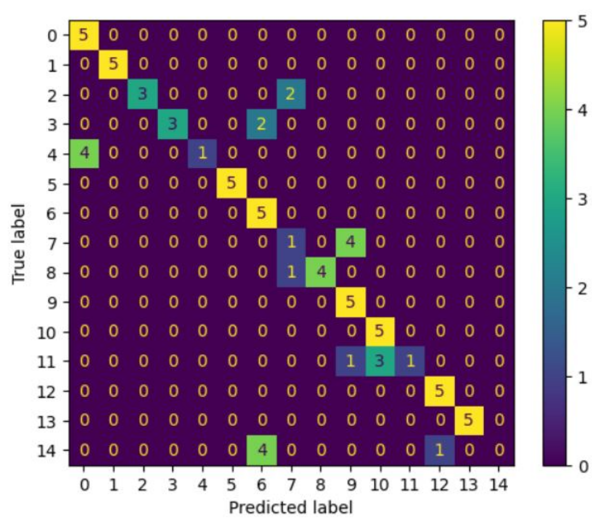

Fig. 4. Confusion matrix for the SVM classifier

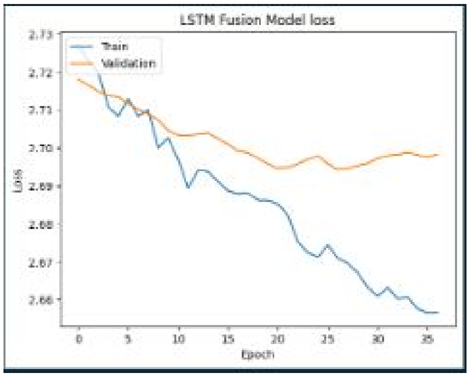

Fig. 5. Loss over time for the LSTM

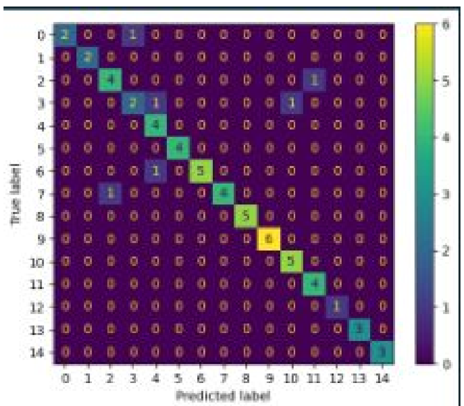

Fig. 6. Confusion matrix for the simple NN

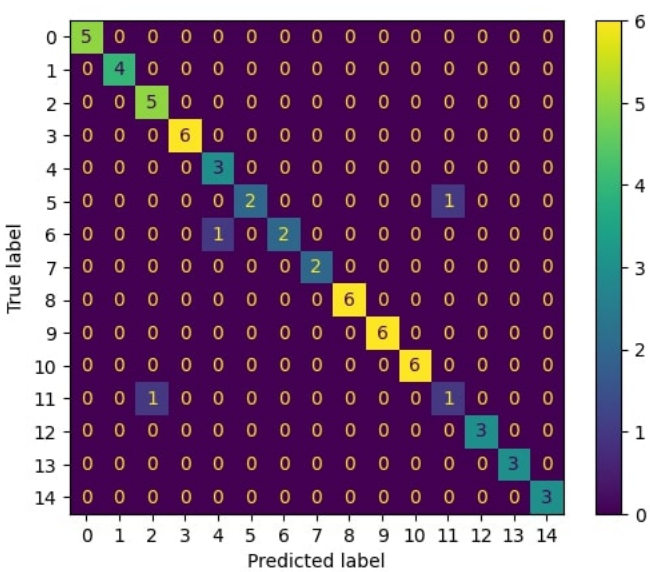

Fig. 7. Confusion matrix for the fusion NN

Fig. 8. Simulated drone in Flightmare.

Gesture	Number of Correct Classifications (/5)	Most Common Misclassification
back	2	rot. right
down	5	N/A
fist	0	rot.up/down
forward	3	rot. right
left	0	stop
right	0	twist right
resting	1	right
rot. down	0	rot. left
rot. up	5	N/A
rot. right	0	rot. left
rot. left	0	rot.up/down
twist left	0	rot.right
twist right	5	N/A
stop	0	rot. left/right

V. Discussion

A. *Model Architecture and Accuracy*

Of the three models proposed, SVM, and NN were deemed sufficient to continue to real-time testing. A real-time implementation was created for both of these models, but only the one for SVM was tested in real-time. The LSTM model was not conducive to the non temporal nature of the statistical feature extraction, and was therefore inconsistent in its functionality. The SVM showed greater accuracy when using more features from both senor types, as expected. However, it still failed to reliably classify all of the gestures. The fusion NN outperformed its simpler counterpart marginally and is competitive with the state-of-the-art. This is an expected result. To obtain better results that would more substantially support the hypothesis, it would be essential to get an extensive training set for data. Additionally, a more exhaustive approach to feature extraction would be used, testing not only statistical methods, but also attempts at extracting from raw data. By learning on raw data, the models would also likely be able to generalize patterns over a continuous input feed for a single gesture.

B. Real-Time Classification

The performance of the real-time classifier discussed in Results fails to prove the hypothesis of this project. There may be a several reasons. The first may be inconsistencies in numeric values between *myo-rawNode* and the LSL-based program used to collect the training data from a Windows environment. It is certain that raw EMG values were used in both cases, but some differences in IMU readings may be present, leading to erroneous classifications. Further investigation is needed. Additionally, the number of iterations collected for each live classification may not reflect the average number used in training, leading to further differences in the extracted features. If this experiment were to be repeated, the training samples should be more carefully regulated to a specific time span as to keep the number of entries in each sample consistent. The second may be differences in how the Myo was worn and used between the sessions used to procure training data and the sessions used to test the real-time classifier. Inconsistencies in sensor placement and gesture execution could also lead to unexpected classifications. The effects of these should also be investigated. Finally, latency in ROS may prevent data from being received at a rate of 200 Hz, preventing important features from being captured or leading to distorted filtering results for the live EMG signals. However, some of the incorrect results can be directly attributed to the model itself. It was seen from the confusion matrix of the SVM that gestures such as "up" were never correctly classified in its initial testing, so naturally such gestures would rarely, if ever, be classified correctly during the run of this program. This may in turn be due to a lack of model optimization or an adequate number training samples.

VI. Conclusion

This project sought to develop a novel control scheme for UAVs using a combination of EMG and IMU data obtained from a wearable sensor pack. It was expected that using these two types of data concurrently with machine learning methods such as LSTM neural networks and support vector machines would allow for classification accuracy higher than that found in the current state-of-the-art. This high accuracy would help realize a 15-class control scheme based on gestures of the arm and wrist. An SVM benefited from the usage of features extracted from both types of data, but did not reach competitive accuracy. Furthermore, this algorithm was shown to be largely inadequate when deployed to the task of making real-time classifications, though there may be other factors, as discussed. A novel fusion neural network increased classification accuracy slightly and was competitive with the state-of-the-art. Overall, this project examined classification methods using data from multiple types of sensors simultaneously in response to limited research on this topic. Greater contributions may be possible with greater amounts of training data, model optimization, and control in experimental procedures.

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