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VALIDATION OF A PIEZOELECTRIC SENSOR ARRAY FOR A WRIST-WORN MUSCLE-COMPUTER INTERFACE

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ABSTRACT

We investigated the viability of a wrist-worn device that uses piezoelectric contact sensors to detect muscle vibrations and deformations, which are then used to classify gestures made by the wearer. Signals were recorded from an array of six piezoelectric sensors while the wearer made simple finger flexion tapping gestures. Using a support vector machine model, a multi-class classification algorithm was developed. The mean gesture recognition accuracy was found to be 96%.

INTRODUCTION

Human biosignals, typically used for medical diagnosis, can instead be used for computer interaction. A popular example is the brain-computer interface, which employs electroencephalography for computer input. Brain computer interfaces offer computer interaction without physical movement, a benefit to certain disabled people. Processing the electroencephalogram for brain computer interfaces is a complex machine learning challenge, and the hardware is often invasive, expensive and cumbersome. Alternative biosignals include electromyography[1] (EMG), mechanomyography[2] (MMG) and electrical impedance[3], which can be much easier to measure, control and interpret depending on the anatomical location. Computer interaction using biosignals can offer other advantages such as increased mobility, reduced physical demand, intuitive use and improved throughput. An example of computer control using EMG or MMG is myoelectric prosthetics.

EMG research, particularly for diagnostics, is much more common than MMG, despite MMG having a higher signal-to-noise ratio.[4] MMG sensors detect muscle vibrations and motion. The most prevalent MMG sensor is the Hewlett-Packard piezoelectric contact sensor[5], which is bulky and obtrusive. Accelerometers and condenser microphones are also used, and some MMG based computer interfaces that use condenser microphones have been investigated.[2], [6] In contrast simple off-the-shelf piezoelectric sensors are cheap, small, and sensitive. Piezoelectric sensors have been used to detect skin conducted sound[7], bone conducted sound[8], and muscle deformation[9] for use in a computer interface. The former used an array of cantilever piezo-electric sensors specifically tuned to a variety of frequencies, while the other two operated as contact sensors.

A piezo-electric sensor array of contact pressure sensors can record many signals simultaneously. A promising location for an array of sensors is across the wrist. Specifically, the palm side (volar) of the wrist deflects very noticeably during finger flexion gestures, such as typing. We hypothesize that the mechanomyogram of the wrist recorded by a piezoelectric contact sensor array contains enough information to accurately determine which finger is flexing. We test this hypothesis by using a custom built wearable device to record the wrist MMG signal for constructing a machine learning model able to classify gestures using the recorded signal.

DEVICE DESIGN

Piezo-electric Sensor

The choice of sensor for this study was critical to designing a functional device. Piezo-electric sensors have a variety of form factors and materials. Quartz crystal sensors are the most common, while newer polyvinylidene fluoride sensors are thin and light. The sensor chosen for this study, shown in figure 1, was a 10mm diameter quartz crystal piezo-electric disc, for several reasons. These sensors were found to be much more sensitive—than other sensors considered—to the small pressure changes that occur at the wrist during finger movements. Thin polyvinylidene fluoride tabs were nearly as sensitive as the quartz discs, and are more flexible.

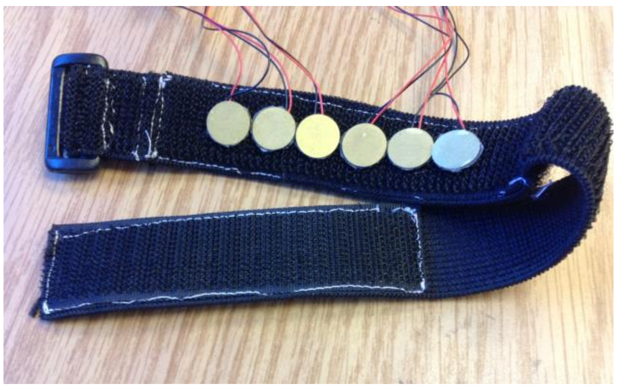

Figure 1: Photograph of the piezo sensor array wrist apparatus. Shown are the 6 piezo disc sensors, the soft Velcro strap, and the hook side Velcro for tightening.

However, a serious drawback of the tabs is that they record a distinct signal at approximately 60 hertz when in contact with the skin. This is due to the body acting as an antenna to background electromagnetic fields created by the power lines within any building. This effect could be eliminated for the discs if the ground side of the disc was the portion of the sensor in contact with the skin. This couldn't be achieved with the tabs as they are sealed in a conductive plastic sheath. Polyvinylidene fluoride piezo-electric cable was also considered, but was found to be entirely lacking in sensitivity.

Signal conditioning

Despite the fine sensitivity of the piezo discs, and their high signal to noise ratio, further signal conditioning was required to improve their voltage signal prior to analog to digital conversion. A charge amplifier circuit was employed to boost the signal and apply some filtering to it, with the circuit diagram shown in figure 2. The circuit was a simple charge amp requiring only two resistors and a capacitor. Although a more complicated circuit may yield better results, charge amps are known for their low-noise and this design was an easy implementation. Through informal tests using an oscilloscope, an appropriate gain for the signal was determined. Applying this value within the charge amplifier gain design, while ensuring a low-pass cut-off frequency of 1Hz or less, the exact value of the circuit components were determined.

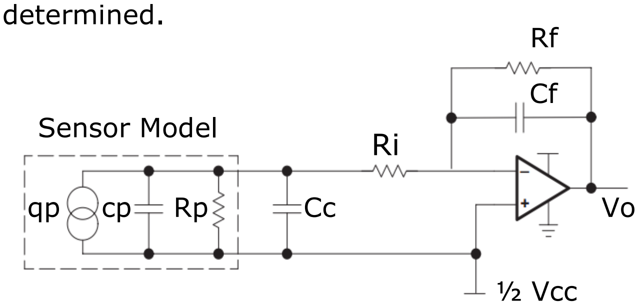

Figure 2: Circuit model of the piezo-sensor and the signal conditioning circuit.

Piezo-electric sensors are modelled as a charge generating capacitors, so they are unable to be used for direct current measurements due to slow discharge. Thus a static pressure yields no signal. As such, a level shift at half the analog to digital range of the piezo-electric signal was added to allow for bipolar signal recording. Essentially, when pressure is applied to the sensor, electric charge is added and when pressure is released, charge is removed, meaning the sensing had to allow for voltage swings in both positive and negative directions.

Sensor apparatus

The electronics hardware chosen permitted six simultaneous sensor measurements. Using the 10mm diameter piezo discs allowed for a 6cm array of piezo discs, which appropriately fits across the volar side of the wrist. This location was chosen for the dense packing of tendons used to mostly control finger flexion, and it is well suited to a watch-like device form factor. Contact pressure of the piezo disc acts as a signal amplifier, as greater pressure allows for the detection of smaller pressure changes. As such, a wrist strap that allowed variable pressure through tightness was designed to house the sensors while ensuring their continuous contact with the wrist. As simple loop of elastic soft-side Velcro was used for the wrist strap. Hook side Velcro was glued to the backs of the piezo discs for their affixation to the strap. Figure 1 depicts the entire wearable. The final experimental setup was a variable tightness wrist strap holding six piezo discs, each wired to individual charge amplifier circuits. The signal was recorded using a micro-controller to perform the analog to digital conversion and then sent to a PC over wired serial communication.

GESTURE CLASSIFICATION EXPERIMENT

Data Collection

The voltage signal of each of the six piezo disc sensors were recorded at approximate 4 kHz during tapping motions conducted by the test subject. Single finger taps were chosen as the recording gesture as they involve rapid finger flexion which would yield a distinct signal, as well as being similar to that of typing. To correlate the signals obtained with each finger tapping motion and to determine precise timing of the gesture contact, a touch tablet was used.

Data was recorded after fastening the piezo discs to the subject's wrist. The piezo disc array produced six continuous signal channels, and the time of contact and release was record for each finger tap using the tablet. Over 60 trials were conducted for each finger tap, with a variable sequence in which each finger was made to move. The voltage signal was band pass filter between 1 and 150Hz, as the information of the mechanomyogram is found in that range.[10]

Feature Analysis

Feature extraction from the voltage signals was completed for use in classification of the gestures. To perform feature extraction, the signal around each tap gesture was windowed, creating a brief time frame in which to calculate pertinent features. The window length affects both the processing speed of the feature extraction and analysis, as well as the ability to classify in real-time. Humans perceive real-time as an event occurring less than 300 milliseconds after the action is initiated. This was the time chosen for the signal windowing, which therefore windowed each channel 150ms forward and backward centered around each time a tap was registered. Figure 3 depicts an example of the windowed voltage signals, showing five unique trials of the same gesture, for two of the six sensors. While this means the actual classification time is 150ms, no great decrease in classification accuracy was expected by reducing the time for feature extraction.

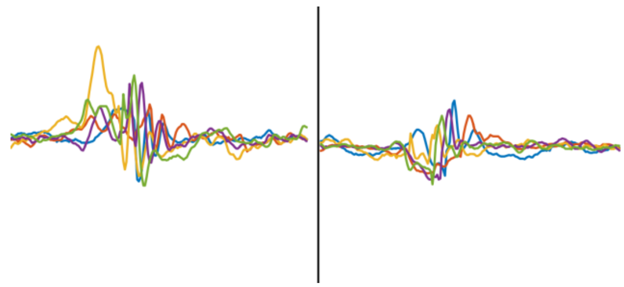

Figure 3: The 300ms signal window from two separate sensors during five unique trials of an index finger tap gesture.

Over 20 features in both the time and frequency domain were considered for use in classification. Using the reciprocal of these values as well, for all 6 sensors, yielded a feature set of over 200 features. Features included the signal maximum, minimum, root mean square, mean absolute deviation, mean and logarithm of mean absolute value, peak to peak value and time, zero crossings, waveform length, slope sign changes, Wilson's amplitude, 7th order autoregression coefficients, peak, mean and median frequency, 2nd, 3rd and 4th order spectral moments, skewness and kurtosis of the frequency spectrum, average power and 99% occupied bandwidth frequency. Subsets of these features have been used in machine learning models for EMG, MMG and other related signal analysis.[7],[8]

We hypothesize that classification is dependent on some ratio of features, e.g. high ratio of the root mean square between two sensors might indicate a gesture with a specific finger, and as such the reciprocal value of all features was included. To apply the ratio of feature values in the machine learning, a polynomial kernel support vector machine, of various orders, was employed for classification.

RESULTS AND DISCUSSION

The support vector machine was trained and validated using k-fold cross validation, using ten groups. Only time domain features were used for the training as it was found that frequency domain features did not add to the accuracy, and are more computationally complex to determine. Polynomial kernels of order one to five were used in the support vector machine classification. An average cross validation classification accuracy of 96% was found for the third order polynomial kernel. Increasing the polynomial order did not seem to have an effect on the classification accuracy. Resubstitution error was zero in nearly all cases, except for the 1st order polynomial kernel.

Classification errors occurred more frequently when trying to determine whether a gesture involved the second or third digit. Gestures with the fourth or fifth digit yielded no classification error, while the first digit was nearly as accurate. These results are summarized in table 1, the classification confusion matrix. It is important to note that a misclassification only occurred with one other gesture, e.g. the thumb was only ever misclassified as a ring finger gesture.

Table 1: Confusion matrix of ten-fold cross-validation for 3rd order polynomial kernel support machine gesture classification model.

Actual Gesture	**Model Classification Occurrence (%)**				
	Thumb	***Index***	***Middle***	***Ring***	***Pinky***
Thumb	97	0	0	3	0
Index	0	91	9	0	0
Middle	0	6	94	0	0
Ring	0	0	0	100	0
Pinky	0	0	0	0	100

CONCLUSION

This study developed a novel piezo electric sensor array worn at the wrist for finger movement identification. Signals from the sensors are suitable for use in a machine learning classification algorithm. Accuracy of up 96% is achievable using only a limited number of features and just six sensors. Accuracy could be improved, and additional gestures, including simultaneous finger flexions, could be classified by increasing the number of signal features and sensors or using alternative machine learning methods. The gesture recognition method of this device can be used in myoelectric active prosthetics, for mobile computer interaction or hands-free virtual reality immersion.

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