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The effects of Electromagnetic Interference from Machines towards Classification of EMG Signals within an Industrial Environment

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Abstract **- The electromyographic signal (EMG) is a low level bioelectric signal which originates from the contraction of muscles. The viability of EMG as a control signal is dependent on various factors, one being easily corruptible by interference from electromagnetic radiating devices. Moreover, in an industrial environment, the power line is prone to noise and spikes from operating machines. This research aims to investigate the extent of the interference of electrical noise towards the EMG signal, and characterize the noise which couples to the human body. The EMG data of selected gestures from the forearm of 20 subjects were acquired while operating selected manufacturing machines. Subsequently, time domain feature extraction and classification was performed unto the signals. The results indicate that noise intrusion from manufacturing machines into the EMG signal is minimal, and only affects gestures with very low amplitude. As a conclusion, it has been demonstrated that with modern EMG acquisition and good isolation, the EMG signal can be used in an electrically noisy industrial environment.**

Keywords – electromyography, electromagnetic interference, lower forearm, industrial machines, noise, classification

I. INTRODUCTION

The electromyogram (EMG) is an electrical biosignal which manifests in conjunction with muscle contraction. The EMG is a signal with low amplitude, and is thus, susceptible to degradation due to interference. From the human body, EMG interference sources originate from muscle crosstalk, motion artifacts and ECG contamination. The EMG signal is further prone to electrical interference from power line interference (PLI) [1], [2] and electromagnetic interference (EMI) from machines and equipment [3], [4]. PLI and EMI can couple onto the EMG signal through the human body. While PLI is widely acknowledged and studied, the effect of electromagnetic radiation towards EMG classification is examined on a lesser degree. Nonetheless, there are recent researches on the issue. Various means of filtering was proposed [3], [5][6] to mitigate EMI degradation.

The EMG has many applications; It is used for motor-neuron diagnosis [7], [8], muscle fatigue [9] and gesture prediction [10]. In many applications, the main goal of EMG analysis is to perform classification [4], [11]. The aim of classification is to categorize the EMG signals according to their feature set. Therefore, the acquired signal must be of highest quality as it is the first process in the chain. As reported in [12], the elimination of EMI in the form of Gaussian noise shows considerable improvement in classification accuracy of up to 10%.

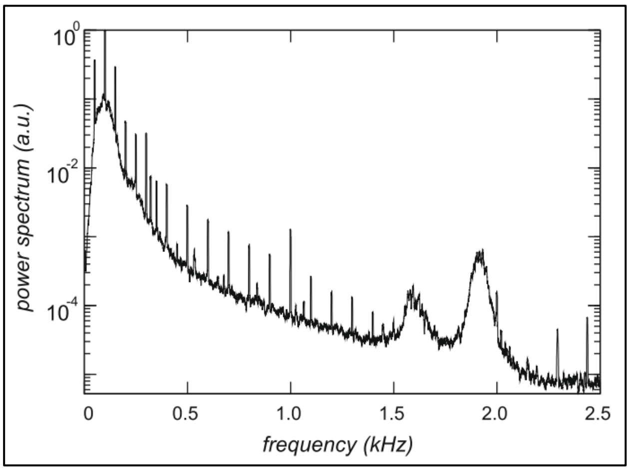

Figure 1. Normalized power spectrum for an EMG recorded in a noisy clinical environment. The spikes represent the interfering noises. The most significant contribution is the 50 Hz PLI. However, other sources are present too. [3]

Although existing filtering methods are effective in reducing the effect of EMI noise within their effective bandwidth, the interfering EMI noise in an actual working environment is unpredictable and may cover a wide range over frequency domain. As shown in Figure 1, the spikes represent the fundamental frequency of the noises created by the electronic equipment in a clinical environment. Therefore, the application of any noise suppressing must account for the EMI noise profile of the intended environment.

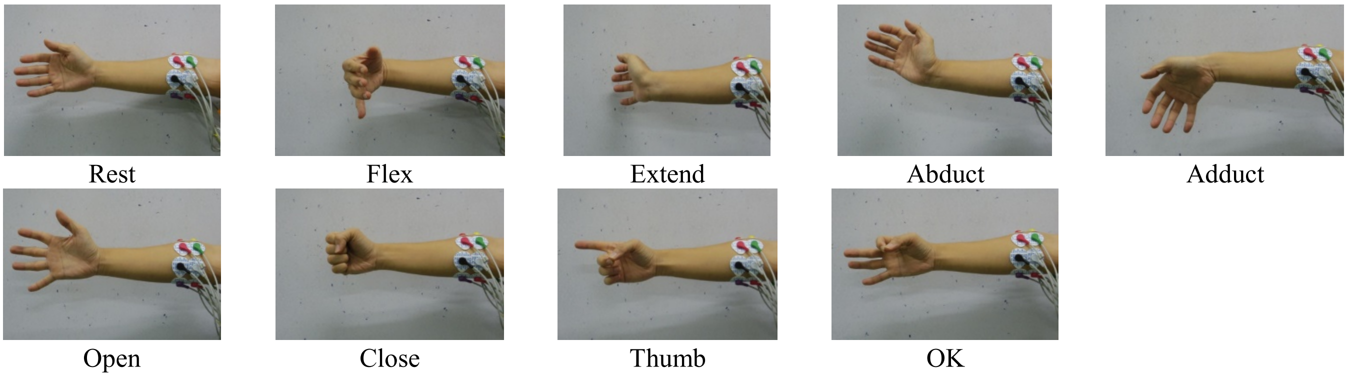

Figure 2. Gestures performed for classification. There are six wrist gestures: FLX, EXT, ABD, ADD, OPN and CLS; and three finger gestures: FIN, TMB, and OKE. The gestures were recorded in sequence with the arm down in natural position.

In existing literature, good EMG acquisition is normally performed in controlled environments with medical grade equipment [13] [14]. Therefore, there is little data to show the extent of EMI in practical working environments. Much like the equipment in a clinical environment, industrial machines emit considerable EMI noise which can couple onto the human body. We build upon the issues mentioned heretofore to determine if the EMG signal as a control is affected by the EMI noise in an industrial setting.

This study aims to assess the impact of EMI towards the classification the EMG signals. The objective of this study is to perform classification on EMG signals from subjects who performed gestures with the lower forearm in proximity of selected manufacturing machines.

II. METHODS

Six pairs of EMG electrodes were attached to the lower forearm of a group of subjects. The subjects performed nine gestures in successions and the EMG was recorded into six individual channels. The procedure was repeated with the ubjects in proximity and in contact with some manufacturing machines. After that, basic filtering followed by dimensional reduction and classification was performed to classify the signals.

A. *Subject demographics*

For the experiment, 20 subjects were selected. The sample consisted of 10 male and 10 female subjects. The subjects agreed to participate at will and have signed the consent form. Generally, most subjects are young within the age of 24-42 with mean age of 30. The subjects BMI range from 15 to 32 with a mean of 23, with 55% having a normal BMI class. No subjects reported any accident and pain associated with the wrist and finger. However, two subjects one male and female, reported having mild essential tremor.

B. *Equipment used*

We developed an EMG amplifier for this experiment. The EMG amplifier is based on INA121P instrumentation amplifier and has a working CMRR of 78.64 dB and adjustable gain of 250. Basic filtering incorporated into the design consists of a band pass filter with the range of 18.97 Hz to 709 Hz. More details about our design can be found in [15] and [16].

Ag-Cl wet electrodes were used in this experiment. Each channel consists of two electrodes. A reference electrode is attached to the elbow. A shielded cable was used to connect the EMG amplifier to the electrodes.

The data was acquired with the National Instruments NI-cDAQ 9178 data acquisition unit with the NI9205 module, sampled at 5 kHz and Labview as the user interface. Post processing was done with the Matlab 2010 software.

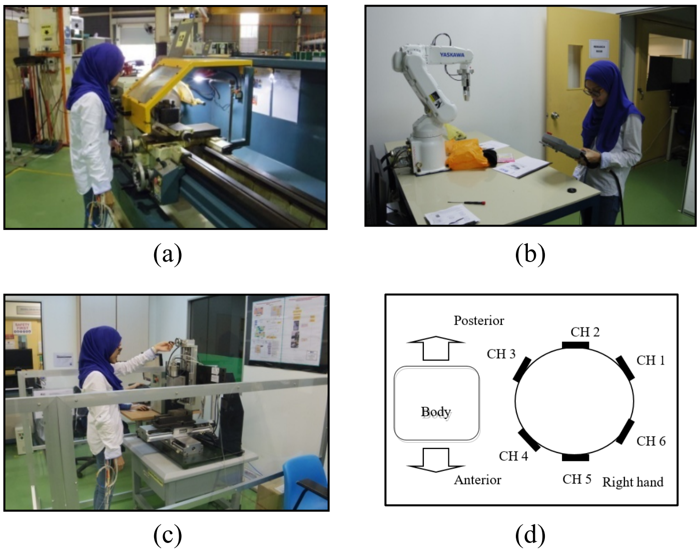

Figure 3. The machines in study (a) lathe machine, (b) robot arm, (c) CNC machine, (d) the placement of electrodes on the lower forearm.

Three machines were selected for this study are commonly used in an industrial environment, shown in Figure 3. They consist of (a) lathe machine, (b) robot arm and (c) CNC machine.

C. *Experimental Procedures*

Prior attaching electrodes, the subject skin was cleaned with alcohol but not shaved. Figure 3 (d) shows the setup of the electrode channels. Then, six pairs of electrodes were placed evenly around the lower forearm of the left hand. The subjects were asked to perform nine gestures, which in sequence are flex (FLX), extend (EXT), abduct (ABD), adduct (ADD), open (OPN), close (CLS), finger (FIN), OK (OKE) and thumb (TMB). The gesture sequence was performed with the right hand in down neutral position. The left hand was used to operate the machines.

Each subject performed the gestures in Figure 1 at distances of 2 m, 1 m, and 0 m (contact) from the machines. Two readings were taken at each step, one when the machine is on and another when it is off.

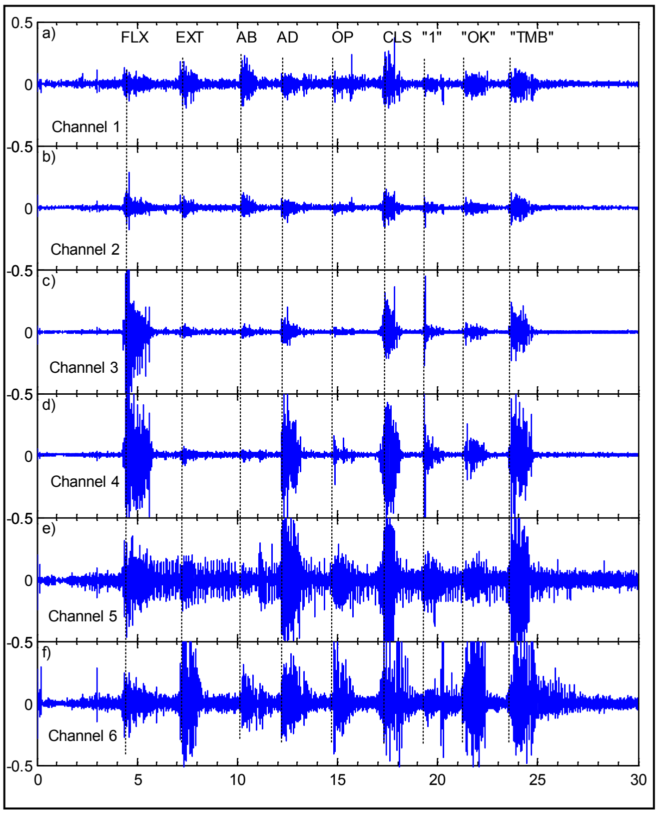

Figure 4. Sample raw EMG signal from a subject. The subject is 24 years of age, female and has an BMI of 24.32. Some ECG interference is picked up in Channel 5 and Channel 6.

D. *Dimensional reduction and feature extraction*

The time domain EMG data is a one dimensional stochastic time varying signal. To process the data, several steps were involved. First the data was linear rectified and applied with a 10 Hz linear envelope. Then, the peak amplitude time domain feature was selected to represent the data.

Principle component analysis (PCA) is a useful tool to reduce the dimensionality of the EMG signal. After application of PCA, the final classification was performed with linear discriminant analysis (LDA). PCA and LDA are established and reliable methods used widely in biosignal analysis [17], [18].

III. RESULTS

A sample of the acquired EMG data is shown in Figure 4. The gestures were performed in succession and it is evident that every gesture produces distinctively different gestures. However it is difficult to distinguish the gestures by EMG waveforms solely from visually observing the raw data. Figure 5 shows the EMG signal distribution as a gradient display. The plot was obtained following rectification and linear envelope. The strength (amplitude) of the signal is shown by the colour. Red signifies high amplitude while weak signals are coloured dark blue. The plot suggests that most gestures registers different EMG data field.

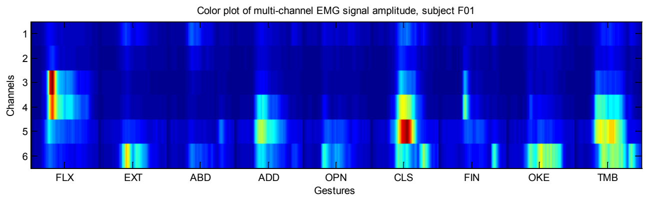

Figure 5. Linear enveloped EMG output of the nine gestures. The sample shown here show here is from subject F01. The EMG peaks represent the peak contraction during the gestures. The two sets EMG patterns show some similarity in terms of the output levels.

We repeated the gesture sequence on the three machines. Table 1. Only the robot arm causes an increase in baseline noise. This happens when the subject is holding the teach pendent and activating the robot by pushing the switch. In this case, the robot arm produced an increase in baseline noise from 0.004 V to 0.009 V. Since the EMG amplifier, computer and the data acquisition device were powered by an isolated power supply line, it is clear that the noise from the robot has coupled to the body of the subject through the teach pendent.

Table 1. Results of baseline noise of manufacturing machines in study. No change was observed in the lathe machine and CNC machine. Only the robot arm produced EMI which caused interference to the EMG.

Type of machine	Average baseline noise when machine is on, at distance 2 m	1 m	Baseline noise when machine is operated in contact (0 m)
Robot arm	0.004 V	0.004 V	0.009 V
Lathe machine	0.004 V	0.004 V	0.004 V
CNC machine	0.004 V	0.004 V	0.004 V

A sample of the linear envelope gesture sequence during robot operation is shown in Figure 6. The baseline noise only increase when the robot is activated by pressing the teach pendent switch. The resulting floor noise is increased from 0.004 V to 0.009 V. Most gestures are still distinct, as there is enough amplitude headroom above the noise level. Only the finger gestures with lower amplitude are buried by the noise.

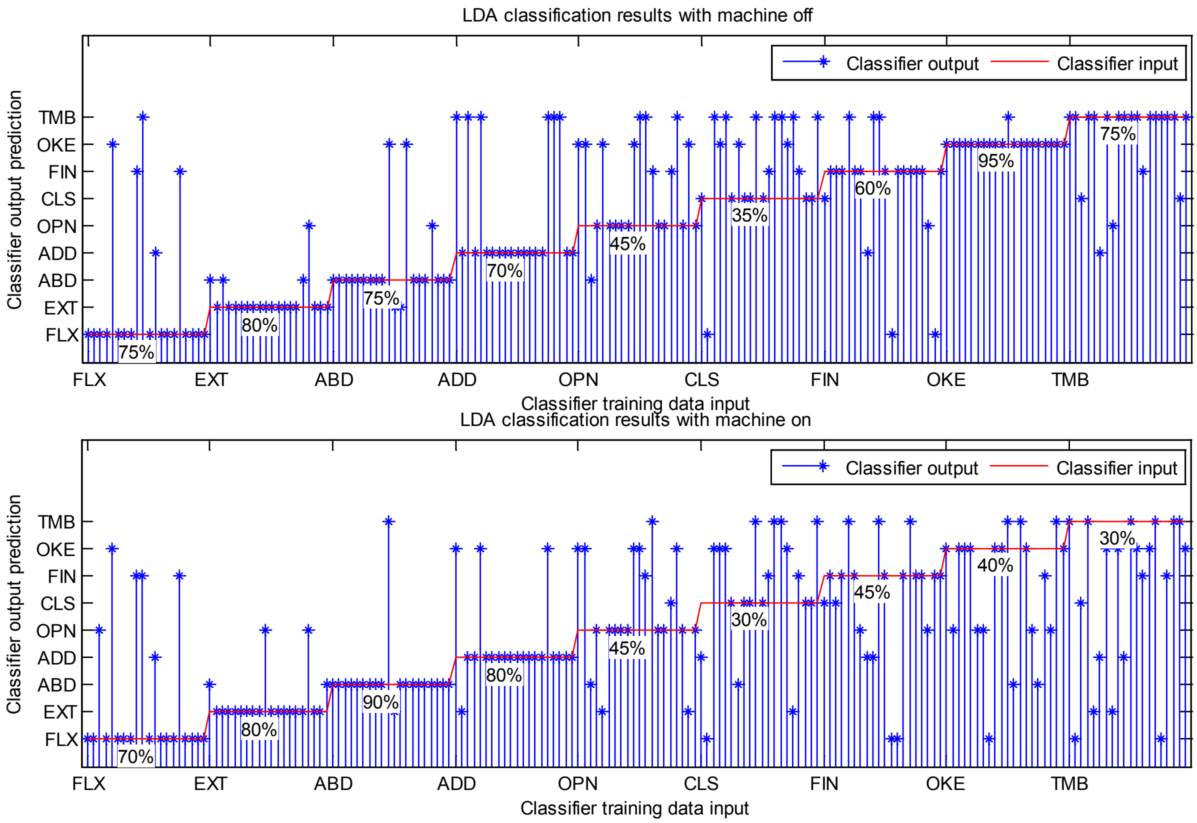

Figure 6. Classification results with teach pendant off as training data (top) and teach pendant on as test data (bottom). Generally the classification accuracy of the wrist gestures are consistent while the finger gestures are deteriorated. This is due to the lower dynamic range of the finger gestures.

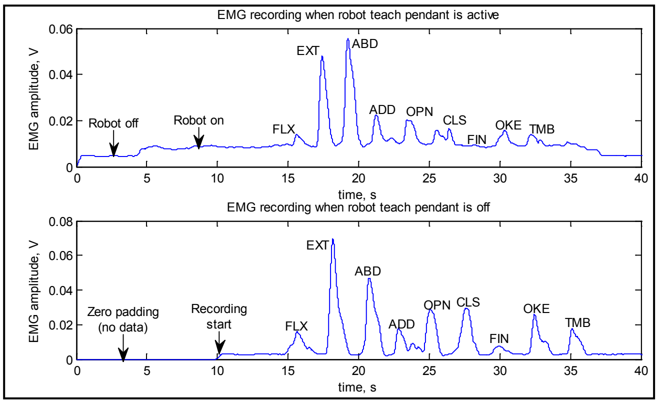

Figure 7. Sample linear enveloped EMG signals showing the effects of activating the robot teach pendant. Of all machines in study, only the robot affects the EMG signal by introducing a baseline noise of approximately 0.01 V. As a result, the dynamic range of the lower level finger gestures (FIN, OKE, TMB) are diminished.

Classification was performed with the clean signal as training data, and the contaminated signal as test data. The results are almost identical, with the exception of a significant drop in classification accuracy of the FIN, OKE and TMB gestures.

The contaminant signal was analysed with Fast Fourrier Transform (FFT), as shown in . Figure 7. With the arm at rest, the noise is mainly from the 50 Hz power line noise and its 150 Hz harmonics. However with the robot activated, there was an increase in not only the power line noise, but also an introduction of a 200 Hz and 300 Hz signal.

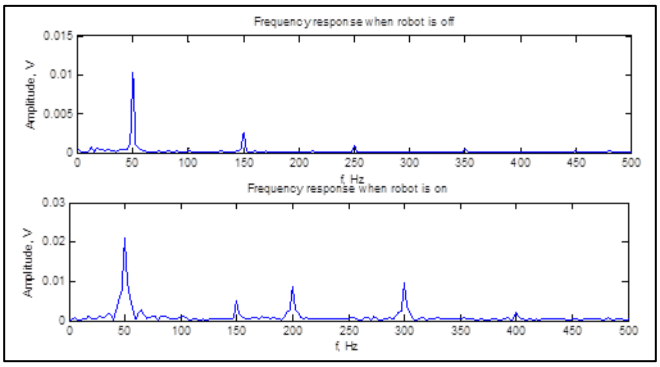

Figure 8. Frequency domain plot of baseline signal during rest. When the robot teach pendant is off, only the 50 Hz common-mode signal and its 150 Hz harmonics is present. Switching on the teach pendant introduces a 200 Hz and 300 Hz signal into the signal.

Our interest now lies in the classification results of the data from the robot arm. Classification is performed not only across the gestures, but also encompasses the 20 subjects. In other words, for instance the FLX having a score of 75 % during 'robot off' state means that 75 % of the subjects produced the same EMG profile for the gesture. The OPN, CLS and FIN gestures has lower classification accuracies, due of the higher variance of signals among the subjects.

Table 2. Tabulated classification accuracy comparison when the robot is on and off. The finger gestures are affected more than the wrist gestures.

	Classification accuracy, %	
	Robot off	Robot on
FLX	75	70
EXT	80	80
ABD	75	90
ADD	70	80
OPN	45	45
CLS	35	30
FIN	60	45
OKE	95	40
TMB	75	30
Mean accuracy	68	57

Figure 8 shows the detailed LDA classification of the all subjects when the robot arm is in on and off state. Each gesture consists of 20 stems, which represents the 20 subjects. Misclassification occurs more during the OPN and CLS gestures. The red line shows the expected class. The stem marker intersection with the red line shows a correct classification result.

When the robot is off, classification accuracy is generally very high, with results over 70 % with the exception of the gestures OPN, CLS and FIN. When the robot is on, the baseline noise increases and interferes with the EMG signals. As a result, the classifier could not differentiate between the lower level signals of the finger gestures due to the lack of dynamic range.

IV. CONCLUSION

In this paper we have shown that most manufacturing machines do not produce significant noise that can interfere with the EMG signals. Therefore the EMG signal can be used as a control signal within a working environment. In our experiment, we discovered only the robot arm is a cause for concern. We have also demonstrated that the EMG signals are generally robust to EMI.

In order to use EMG as a practical control signal in an industrial environment, we recommend that the gestures used produce signals of high strength. Next, a study on the the noise profile of the working environment is crucial so that the appropriate filters can be designed. In any case, the PLI is the bigger noise contributor, and together with other noises, can be eliminated with notch filters.

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