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# MODELLING OF PHYSIOLOGICALY ACCURATE ELECTROMYOGRAPHY SIGNAL

**Aim:** To simulate electromyography (EMG) signal from the physiological description of motor unit activity based on MATLAB and comparison with Gaussian signal

**Objective:** Physiological accurate EMG modelling and simulation using single motor unit activity.

**Apparatus Required:** MATLAB Software.

**Theory:**

Any muscle found in the human body can be categorized as one of three types: skeletal muscle, smooth muscle, or cardiac muscle. Skeletal muscles are attached to bones and are primarily responsible for limb control. Skeletal muscles are voluntarily controlled using motor nervous system. Skeletal muscles are innervated by somatic motor neurons. The axon, the elongated body of the motor neuron, starts in the spinal cord and splits into many branches that terminate in the motor end plate of the neuromuscular junction, the region of the sarcolemma (the plasma membrane surrounding the muscle fiber) that receives the input from the nervous system. Each one of these terminating branches stimulates exactly one muscle fiber. Together, a motor neuron and all of the muscle fibers innervated by that neuron make up a single motor unit.

The process through which muscles are stimulated for contraction is known as excitation-contraction coupling. An action potential (AP), or electrical impulse with biochemical origins, begins in the spinal cord and propagates down the axon of the somatic motor neuron. When the action potential reaches the neuromuscular junction, the neurotransmitter acetylcholine crosses the post-synaptic cleft (the region between the motor neuron branch and the motor end plate) where it binds to receptors in the motor end plate. This process opens sodium ion channels, which create an action potential in the sarcolemma.

It is this exchange of sodium and potassium ions that generates the electric field responsible for the myoelectric signal or electromyogram. This action potential propagates through the transverse tubules, resulting in the opening of voltage gated calcium channels in the sarcoplasmic reticulum (the main vessel for calcium ion storage in muscle tissue), which releases calcium into the sarcoplasm of the muscle fiber (analogous to the cytoplasm of a regular cell), causing a contraction.

**Methodology:**

The EMG signal measured by a conventional surface electrode is actually a combination of many distinct action potentials produced by the muscle tissue, called motor unit action potentials (MUAPs). In general, MUAPs have a distinct spike-like shape, which can be affected by several factors. The stochastic combination of individual MUAPs from multiple muscle fibers is what gives the surface EMG its characteristic noise-like appearance. Figure 1 shows the shape of the MUAP and a schematic representation of the EMG signal generated by the summation of individual MUAPs.

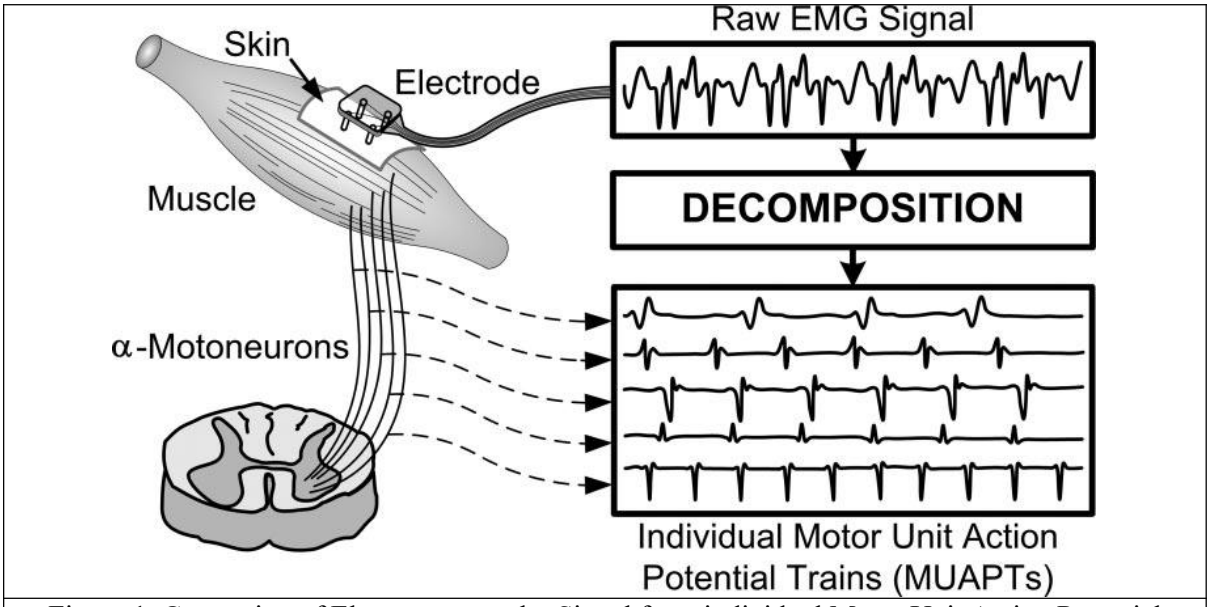


Figure 1. Generation of Electromyography Signal from individual Motor Unit Action Potential trains

The physiological signal was generated in a similar fashion to the generation of the EMG in muscle tissue, using the summation of (uniformly) randomly spaced simulated motor unit action potential spikes to generate a signal which was then bandpass-filtered (10-400 Hz). The custom MATLAB function took as a parameter the distance from the recording site to the muscle fiber, which was randomly generated from a uniform distribution over the interval of 0.5 to 2 in the calling function. Units used in these functions were arbitrary. A muscle fiber was simulated by specifying a length (500 units in this case) down which the action potential would travel. The positive portion of the MUAP was created by looping from 1 to the length of the simulated muscle fiber. Assuming that the signal strength at the recording site was directly proportional to the distance from the electrode to the action potential, the following equation was used to simulate the signal:

$$MUAP = \frac{1}{\sqrt{distance^2 + \left(\frac{fiber\ length}{2} - 1\right)^2}}$$

The signal was then zero-padded on both sides (1000 zeros on each side). Next, the negative-going portion of the MUAP was simulated by inverting the already generated signal, and shifting it to the right by 150 units to create second component of MUAP. The complete MUAP was created by adding these two components together. The MUAPs are superimposed to generate physiologically accurate.

Additionally, Gaussian EMG signal is generated to compare the signal characteristics such as spectrum shape and amplitude distribution between the signal originating from a Gaussian process and a more complex system having multiple asynchronous motor units.

**MATLAB code:**

```
%% Construct and Plot EMG with Physiologically Accurate Algorithm
fs = 1000;
emg_phys = zeros(1, 100000); % Initialize EMG vector
for i = 1:1000
   % Sum 100 random MUAPTs
   emg_phys = emg_phys + makeTrain(makeMUAP(0.5 + (2-0.5).*rand()));
end
% Lowpass filter EMG
[b, a] = butter(4, [10/(fs/2) 400/(fs/2)]); % Use sampling rate of 1kHz
emg_phys = filter(b, a, emg_phys);
emg_phys = emg_phys(4000:85000);
% Normalize
max = 3 * std(emg_phys);
emg_phys = emg_phys / max;
% Plot EMG and power spectrum
% Time domain plot
t=0:.0005:40.5; % Time vector
subplot(3, 1, 1); plot(t, emg_phys);
xlabel('Time (s)'); xlim([0 40]);
ylabel('Amplitude'); ylim([-2 2]);
title('Physiologic EMG Signal Simulation');
% Power spectral density plot
subplot(3,1,2); periodogram(emg_phys);
title('Physiologic EMG Power Density Spectrum');
% Distribution plot
subplot(3,1,3); hist(emg_phys, 100); xlim([-2 2]);
xlabel('Value');
ylabel('Samples');
title('Physiologic EMG Distribution');

skew2 = skewness(emg_phys);
fprintf('Skewness in Physiological EMG: %.4f\n',skew2);

kurt2 = kurtosis(emg_phys);
fprintf('Kurtosis in Physiological EMG: %.4f\n',kurt2);

median2 = median(emg_phys);
fprintf('Median in Physiological EMG: %.4f\n',median2);

mean2 = mean(emg_phys);
fprintf('Mean in Physiological EMG: %.4f\n',mean2)

%% Construct and Plot EMG from Gaussian distribution
fs = 1000;
emg_gauss = randn(1, 81001); % Length chosen to match physiologic
% Lowpass filter EMG
[b, a] = butter(4, [10/(fs/2) 400/(fs/2)]); % Use sampling rate of 1kHz
emg_gauss = filter(b, a, emg_gauss);
% Normalize
max = 3 * std(emg_gauss);
emg_gauss = emg_gauss / max;
% Plot EMG and power spectrum
% Time domain plot
t=0:.0005:40.5; % Time vector
```

```
figure(2);
subplot(3, 1, 1), plot(t, emg_gauss);
xlabel('Time (s)'); xlim([0 40]);
ylabel('Amplitude'); ylim([-2 2]);
title('Gaussian EMG Signal Simulation');
% Power spectral density plot
subplot(3,1,2), periodogram(emg_gauss)
title('Gaussian EMG Power Density Spectrum');
% Distribution plot
subplot(3,1,3),hist(emg_gauss, 100);
xlabel('Value'); xlim([-2 2]);
ylabel('Samples');
title('Gaussian EMG Distribution');

skew1 = skewness(emg_gauss);
fprintf('Skewness in Gaussian: %.4f\n',skew1);

kurt1 = kurtosis(emg_gauss);
fprintf('Kurtosis in Gaussian: %.4f\n',kurt1);

median1 = median(emg_gauss);
fprintf('Median in Gaussian: %.4f\n',median1);

mean1 = mean(emg_gauss);
fprintf('Mean in Gaussian: %.4f\n',mean1)

function[MUAP]=makeMUAP(distance)
% Note: distance parameter specifies the distance of the fiber of interest
% below the skin (and recording site)
%% Construct vector to represent single muscle fiber
fiberLength=500;
MUAP1=zeros(1, fiberLength);
%% Construct MUAP
% Simulate action potetial propagating down muscle fiber
for i=1:fiberLength
   % Calculate signal strength at recording site by calculating distance
   % Assumes that signal strength is proportional to distance
   MUAP1(i)=1/sqrt(distance^2+(fiberLength/2-i)^2);
end
MUAP1=[zeros(1,1000) MUAP1 zeros(1,1000)]; % Pad with zeros
% Add inverted peak with specified offset
% Accounts for the effect of bipolar differential recording electrodes
MUAP2=-[zeros(1,150) MUAP1];
MUAP1=[MUAP1 zeros(1,150)];
MUAP=MUAP1+MUAP2;
end

function[MUAPT]=makeTrain(MUAP)
%% Initializes MUAPT with a random number of leading zeros
MUAPT=[zeros(1, randi([2000 7000])) MUAP];
for i=1:10
   % Add MUAPs to train at random intervals
   MUAPT=[MUAPT zeros(1, randi([2000 7000])) MUAP];
end
MUAPT=[MUAPT zeros(1, 100000-length(MUAPT))];
end
```

**Results:**

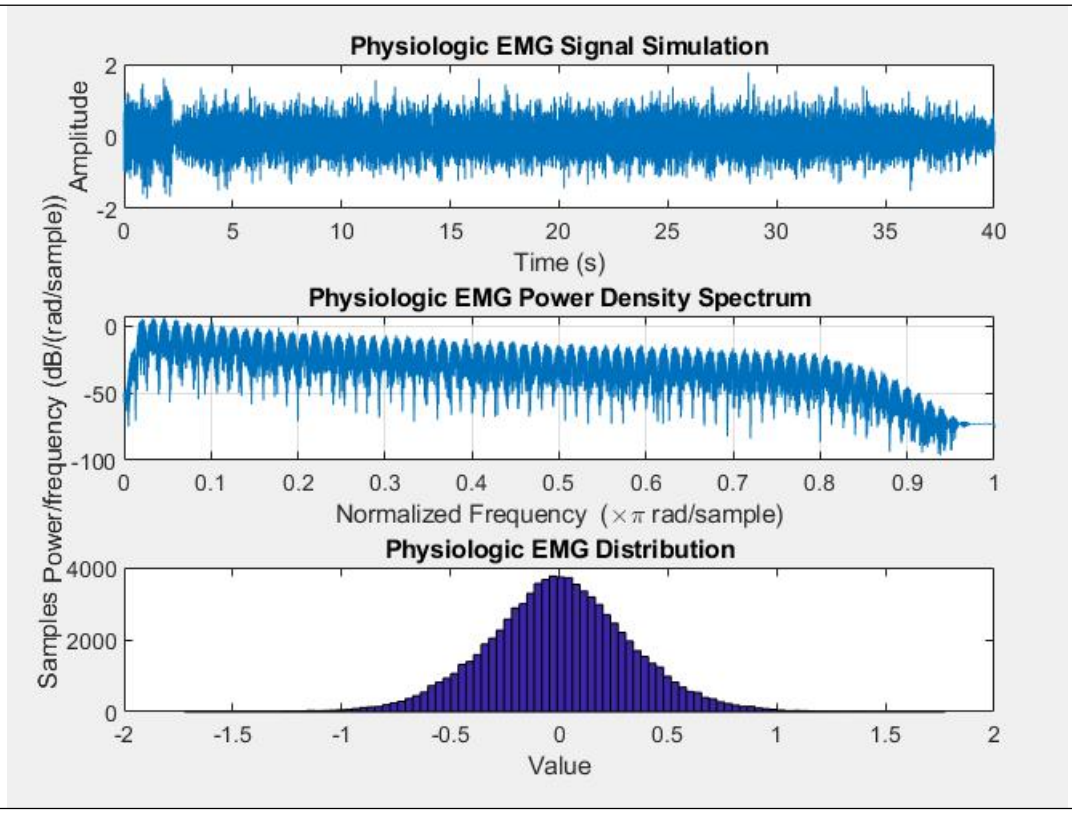


Figure 2. Physiologically accurate EMG signal

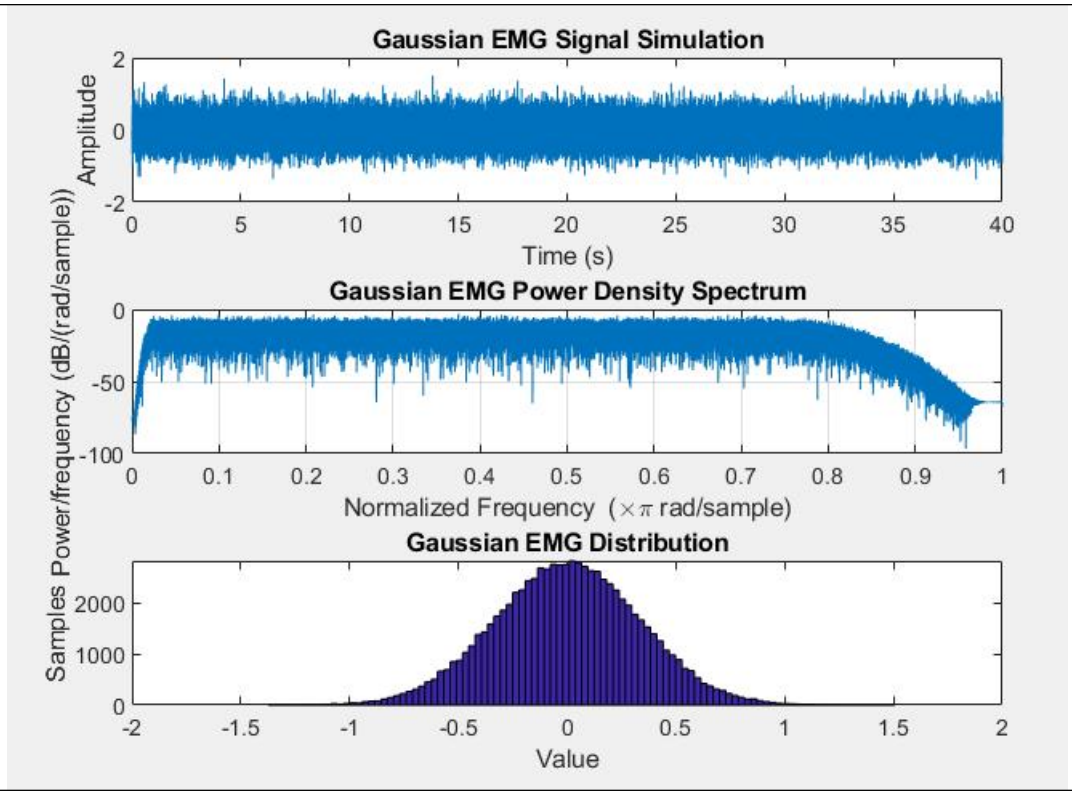


Figure 3. Gaussian approximation of EMG signal

**Characteristics of Synthetic Signals**

```
Skewness in Physiological EMG: 0.0263
Kurtosis in Physiological EMG: 3.5518
Median in Physiological EMG: -0.0011
Mean in Physiological EMG: 0.0001
Skewness in Gaussian: 0.0154
Kurtosis in Gaussian: 3.0314
Median in Gaussian: -0.0007
Mean in Gaussian: 0.0000
```

| Signal Characteristics | Physiologic EMG | Gaussian EMG |
|---|---|---|
| Amplitude Distribution, Skewness | 0.0263 | 0.0154 |
| Amplitude Distribution, Kurtosis | 3.5518 | 3.0314 |
| Mean Frequency | -0.0011 | -0.0007 |
| Median Frequency | 0.0001 | 0.0000 |

**Outcomes:** The similarities and dissimilarities between the physiologic EMG and signal generated from Gaussian process assumption can be analysed using the present modelling approach.

**Conclusion:** This model is effective to simulate a physiologically accurate EMG signal.