MUSCLE ACTIVITY DETECTION FROM MYOELECTRIC SIGNALS BASED ON THE AR-GARCH MODEL

Ghulam Rasool, Nidhal Bouaynaya and Kamran Iqbal

Systems Engineering Department, University of Arkansas at Little Rock, AR, USA.

ABSTRACT

Myoelectric (EMG) signals contain temporal muscle activation information, that is essential in understanding and diagnosing neuromuscular disorders. Given the biological stochasticity and measurement noise, statistical signal processing methods are adopted in the literature to detect the muscle activity onset and offset periods. However, these methods carry an implicit assumption of stationarity. In this paper, we show that the EMG signal is non-stationary and the nature of its non-stationarity is reminiscent of the heteroscedasticity, i.e., the conditional variance of the signal is time-varying. We therefore model the EMG signal using an Autoregressive-Generalized Autoregressive Conditional Heteroscedastic (AR-GARCH) process, which captures the heteroscedasticity of the signal. The Akaike information criterion test confirms that the AR-GARCH model better fits the EMG signal than the stationary AR model. We subsequently propose a muscle activity detector that relies on the estimated conditional variance of the AR-GARCH model. The application of the proposed detector to real EMG signal shows that the proposed AR-GARCH-based detector achieves a higher accuracy than the widely used double threshold detector.

Index Terms— Myoelectric signal; Heteroscedasticity; Muscle activity detection; AR-GARCH model.

1. INTRODUCTION

The electromyography (EMG) signal is the signal recorded from the surface of the muscles and is a representation of the electric potential field generated by the depolarization of the outer muscle membrane. EMG signal measurements are used in a variety of physiological, biomechanical and neuromuscular applications such as reaction-time delay, stroke and Parkinson's disease. In particular, these applications require an accurate detection of the onset, offset, and the duration of the EMG burst. One of the main challenges in designing such detectors is the stochastic and noisy nature of the EMG signal. Biological stochasticity results from the interference of motor units that are far away from the detection point. The recruitment of the motor units by the central nervous system as well as their firing rates may vary even when identical actions are performed. Additionally, measurement noise resulting from the sensors, skin contact and ambient noise adds to the stochasticity of the signal. It is therefore imperative to use statistical and stochastic signal processing methods in order to analyze and process EMG measurements.

The main methods investigated in the literature to detect muscle activity periods from EMG measurements are based on the hypothesis testing framework, where a likelihood ratio test is performed in order to decide the onset and offset periods of the recorded signal [1]. The likelihood computation assumes independent and identically distributed (i.i.d.) Gaussian samples. However, given that EMG samples are highly correlated, a pre-whitening filter must be applied prior to the likelihood computation [1]. The whitening filter characteristics (e.g., filter order and coefficient values) depend on the correlation structure of the EMG signal, and are usually unknown. As an alternative to the hypothesis testing framework, modeling-based approaches have been used to model, analyze and extract features from the EMG signal. Specifically, the autoregressive (AR) and autoregressive moving-average (ARMA) models were widely adopted to model the EMG signal [2]. ARMA models, however, implicitly assume that the underlying process is stationary.

In this paper, we show that the EMG signal is non-stationary and its type of non-stationarity is reminiscent of heteroscedasticity [3]. A stochastic time-series is called heteroscedastic if its conditional variance varies over time [3]. In particular, the presence of heteroscedasticity can invalidate statistical tests that assume that the residual variances are uncorrelated. Heteroscedastic processes are characterized by a volatile nature, and are often encountered in econometrics and finance, as for instance in stock prices, which exhibit periods of large swings followed by periods of relative calm. The economist Robert F. Engle won the 2003 Nobel Prize in Economic Sciences for his work on modeling heteroscedastic processes using the Autoregressive Conditional Heteroscedasticity (ARCH) model [3]. The ARCH model is suitable for processes where the unconditional variance may be constant but the variance during some periods of time is changing. A generalization of the ARCH model, the Generalized ARCH (GARCH), was proposed in [4] to model heteroscedasticity in stochastic time series more parsimoniously. In this paper, we use the GARCH model to represent myoelectric signals.

This paper is organized as follows: In Section 2, we briefly present the GARCH and AR-GARCH processes. In Section 3, we test the EMG signal for heteroscedasticity and show that it can be modeled by an AR-GARCH process. The proposed AR-GARCH-based muscle activity detector is presented in Section 4. Section 5 presents results on real EMG measurements and compares the AR-GARCH-based detector with the double threshold detector [5]. Finally, concluding remarks and future directions are summarized in Section 6.

2. THE GARCH PROCESS

Let (Z_t) be a sequence of i.i.d. random variables with zero mean and unit variance from some specified probability distribution (usually assumed to be Gaussian or t-distribution). The process Y_t is called a GARCH(p, q) process if

$$Y_t = \sigma_t Z_t, \quad t \in \mathbb{Z} \tag{1}$$

where σ_t is a non-negative process such that

$$\begin{aligned} &\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i Y_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \text{ and} \\ &\alpha_0 > 0; \quad \alpha_i \geq 0,\ i = 1, \ldots q; \quad \beta_j \geq 0,\ j = 1, \ldots, p. \end{aligned} \tag{2}$$

When $p = 0$, the process is an ARCH(q) process.

Let us denote by $E[.]$, the expectation operator and by $V[.]$, the variance of the process defined as $V[X] = E[X^2] - (E[X])^2$. From Eqs. (1) and (2), we have

$$\begin{aligned} E[Y_t] &= E[\sigma_t Z_t] = E[\sigma_t]E[Z_t] = 0. \\ V[Y_t] &= E[Y_t^2] = E[\sigma_t^2 Z_t^2] = E[\sigma_t^2] \\ &= \alpha_0 + \sum_{i=1}^{q} \alpha_i E[Y_t^2] + \sum_{j=1}^{p} \beta_j E[\sigma_t^2] \\ &= \frac{\alpha_0}{1 - \sum_{i=1}^{q} \alpha_i - \sum_{j=1}^{p} \beta_j}. \end{aligned} \tag{3}$$

That is, the GARCH process has zero mean and constant variance. However, a further look at the conditional variance reveals that the latter is time-varying. We denote by ψ_t the set of past observations up to the current time t, i.e., $\psi_t = \{Y_k, k \leq t\}$. Then, we have

$$\begin{aligned} &E[Y_t|\psi_{t-1}] = E[\sigma_t Z_t|Y_{t-1}, Y_{t-2}, \ldots] = \sigma_t E[Z_t] = 0. \\ &V[Y_t|\psi_{t-1}] = E[Y_t^2|Y_{t-1}, Y_{t-2}, \ldots] \\ &= E\left[\alpha_0 + \sum_{i=1}^{q} \alpha_i Y_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 | Y_{t-1}, \ldots\right] \\ &= \alpha_0 + \sum_{i=1}^{q} \alpha_i Y_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 = \sigma_t^2. \end{aligned} \tag{4}$$

Equation (4) demonstrates that the conditional variance is time-varying. Moreover, we notice that the GARCH process is uncorrelated, since

$$E[Y_t Y_s] = E[\sigma_t Z_t \sigma_s Z_s] = E[\sigma_t Z_t \sigma_s]E[Z_s] = 0. \tag{5}$$

Therefore in order to model heteroscedastic processes, which exhibit a correlation structure like the EMG signal, we consider the AR-GARCH model.

2.1. The AR-GARCH Process

The process Y_t is AR(M)-GARCH if it is an AR(M) process with GARCH innovations, i.e.,

$$Y_t = \sum_{m=1}^{M} \phi_m Y_{t-m} + \epsilon_t, \tag{6}$$

where ϵ_t represents the white noise process generated by a GARCH(p, q) model, i.e., we have $\epsilon_t = \sigma_t Z_t$, where σ_t satisfies Eq. (2) and Z_t is a zero mean, unit variance white noise process.

3. THE EMG SIGNAL AS AN AR-GARCH PROCESS

We fitted an AR model to the EMG signal with an appropriate order that results in white residuals. Specifically, we used the Ljung-Box modified Q-statistic [6] to test that the series of residuals exhibits no correlation. We found that an AR model of order 35 (or higher) corresponds to uncorrelated residuals. We performed this test for hundreds of EMG signals recorded from different muscles performing different movements. We found that the AR model order ranges between 35 to 40 in most cases.

3.1. Heteroscedasticity of the EMG signal

In his seminal paper, Engle proposed a test for heteroscedasticity [3]. Under the null hypothesis, all ARCH parameters are zero and under the alternate hypothesis, at least one ARCH parameter is non-zero. Formally, we have from Eq. (2)

$$\begin{aligned} &H_0 : \alpha_1 = \alpha_2 = \ldots = \alpha_p = 0, \\ &H_1 : \alpha_i \neq 0, \quad i = 1, 2, \ldots, p. \end{aligned} \tag{7}$$

Engle showed that the derived statistic, R^2, can be viewed as the coefficient of determination of the regression of ϵ_t^2 on an intercept and p lagged values of ϵ_t^2 [3]. Additionally, it can be shown that R^2 is asymptotically distributed as χ^2 with p degrees of freedom when the null hypothesis is true. The test procedure is therefore to run OLS (Ordinary Least Squares) regression and save the residuals. Regress the squared residuals on a constant and p lags and test R^2 as a χ_p^2. This test can be shown to be asymptotically locally most powerful test [3].

We performed the heteroscedasticity test on various EMG signals and the test resulted in the rejection of the null hypothesis for all the signals. That is, EMG signals are heteroscedastic. As an example, the results of the test on the EMG measurements collected from the tibialis anterior muscle are shown in Table 1 for $p = 10, 20$ and 50, and with a 95% confidence interval.

Table 1. Results of the test for the heteroscedasticity

p	Test statistic	Critical value
10	456.93	18.31
20	526.17	31.41
50	597.48	67.50

3.2. Goodness of fit

Finally, we used the Akaike Information Criterion (AIC) to compare the goodness of fit of the EMG signal to AR(p) and AR(p)-GARCH models for different values of p. Figure 1 shows that the AIC values for the AR(p)-GARCH(1,1) model are lower than the corresponding values for the AR(p) model for $p = 1, \cdots, 50$. This confirms that the AR-GARCH process better models the EMG signal than the corresponding stationary AR model.

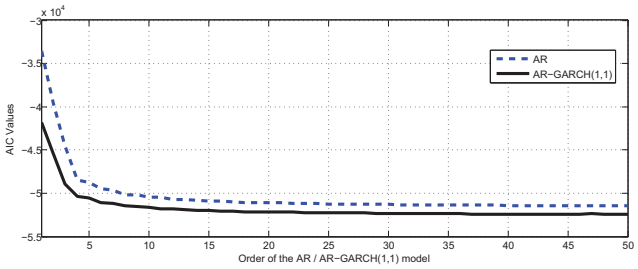


Fig. 1. Goodness of fit of the EMG signal to the AR(p) and AR(p)-GARCH(1,1) models.

4. MUSCLE ACTIVITY ENVELOP DETECTION USING AR-GARCH

Once we have modeled the EMG signal as an AR-GARCH process, we estimate the parameters of the model using the maximum likelihood technique [4, 3]. First, from (2), we obtain the maximum likelihood estimate of the conditional variance σ_t^2. Next, we propose a detection scheme based upon the (estimated) AR-GARCH conditional variance in order to detect the muscle contraction periods from noisy EMG measurements. Our method relies on the assumption that the volatility behavior obtained by σ_t^2 is reflective of the activity period of the EMG signal. Therefore, to search for the segments corresponding to muscle activity, we extract the large volatility parts from the signal. We perform the segmentation using a threshold that depends on the expectation and standard deviation of the conditional variance σ_t^2. In each window segment, the threshold is computed as

$$t_1 = E[\sigma_t^2] + g \times \text{std}(\sigma_t^2), \tag{8}$$

where g is an arbitrary number and its value may depend upon the noise in the EMG signal; in our simulations we used $g = 100$. We can further compare the threshold at each frame with the threshold at the previous frame as follows; for the first frame of samples, we compute the first threshold t_1 using Eq. (8). For the second frame, we calculate the second threshold t_2. We select t_2 as the threshold if $t_2 \leq t_1$, otherwise use t_1 as the threshold. Similarly, in each frame, we choose the minimum value of the current and previous threshold values. This procedure leads to a smoother detector.

4.1. Post-processing

Given the stochastic nature of the signal, the detector output can be affected by erroneous transitions. It is generally accepted that a muscle activation shorter than 30 ms has no effect in controlling the joint motion during gait [5]. Most EMG activity detection algorithms perform a post-processing step in order to ignore detected periods lasting less than 30 ms [5]. We applied post-processing using this criteria to the detector output.

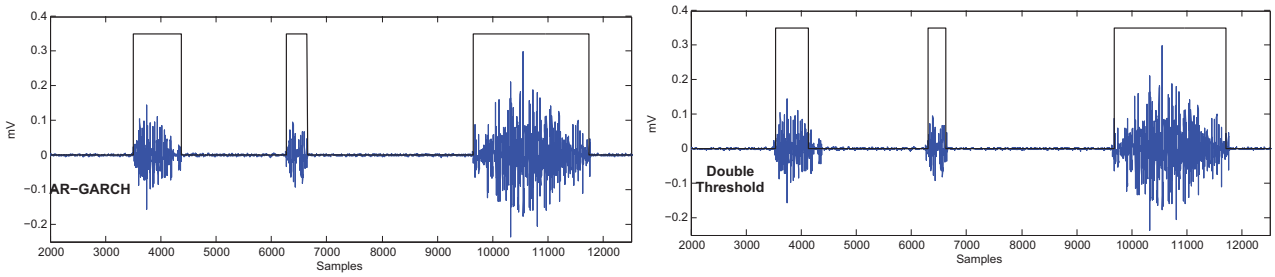
5. EXPERIMENTAL RESULTS

5.1. EMG data recording

We measured the EMG signals of both healthy and young participants from lower extremity muscles while performing various movements. We used the Noraxon TeleMyo DTS Wireless EMG system to record the EMG data on Vicon Nexus 1.7.1. In this work, we present the EMG signals from the tibialis anterior muscle in a Sit-to-Stand movement recorded at 1500 Hz. To show the importance of accounting for the time-varying nature of the conditional variance of the EMG signal, we compare our AR-GARCH-based detector with the standard double threshold detector [5]. The double threshold technique is based on a hypothesis testing framework and can be viewed as a variant of the energy detector.

5.2. Muscle activity detection

Figure 2 shows the EMG activity detection from the tibialis anterior muscle with three activity periods using the AR-GARCH and the double threshold detectors. Figure 3 provides a closer look at the performance of both detectors. We found that the detection accuracy of the AR-GARCH-based method was 98.06%, whereas the double threshold detector had a lower accuracy of 92.41%.



(a) (b)

Fig. 2. Detection of muscle activity periods: (a) The AR-GARCH detector; (b) The double threshold detector.

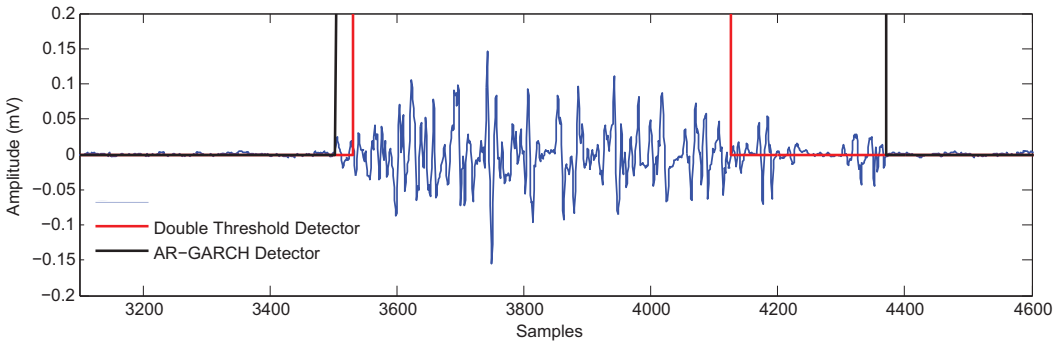


Fig. 3. Detection of muscle activity period: a zoomed view of the first envelop of activity from Fig. 2.

6. CONCLUSION

In this paper, we showed that the EMG signal is non-stationary and this non-stationarity is due to the time-varying nature of its conditional variance. This type of non-stationarity is called heteroscedasticity. Heteroscedastic processes are characterized by volatility segments as in the case of EMG signal. We exploited this feature in order to detect the onset and offset periods of muscle activities in the EMG signal. An accurate detection of these periods is crucial in many clinical and biomedical applications, such as Parkinson's disease and the development of robotic arms. We used the AR-GARCH model, suitable for heteroscedastic processes, to model and estimate the volatility as measured by the conditional variance of the model. The proposed algorithm relies on the fact that large-volatility periods of the signal correspond to muscle activity. We showed that the proposed AR-GARCH-based detector is more accurate than the widely adopted double threshold detector. Future research will extend this work to include further applications of the heteroscedastic model such as EMG feature extraction for multi-function myoelectric control and EMG amplitude estimation.

7. REFERENCES

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