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# Prediction of muscle performance during dynamic repetitive exercise

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## ABSTRACT

A method for predicting human muscle performance was developed. Eight test subjects performed a repetitive dynamic exercise to failure using a Lordex spinal machine. Electromyography (EMG) data was collected from the erector spinae. Evaluation of the EMG data using a 5$^{th}$ order Autoregressive (AR) model and statistical regression analysis revealed that an AR parameter, the mean average magnitude of AR poles, can predict performance to failure as early as the second repetition of the exercise. Potential applications to the space program include evaluating on-orbit countermeasure effectiveness, maximizing post-flight recovery, and future real-time monitoring capability during Extravehicular Activity.

## INTRODUCTION

For the last 30 years, Extravehicular activity (EVA) has been an important aspect of the human development and exploration of space. During this time, the frequency and duration of EVAs has increased along with the complexity of tasks to be performed. For example, during the assembly phase of the International Space Station (ISS), an average of 125 hours per year will be dedicated to EVA construction with an estimated 138 hours per year projected for on-orbit maintenance (1). EVAs are very strenuous due to a number of factors: 1] operational tasks performed in microgravity are exceedingly more complex compared to unit gravity; 2] the EVA space suit restricts astronaut mobility; and 3] many tasks involve repetitive movements and/or the use of specialized tools. Human performance during EVA is further compounded by the effects of microgravity on the musculoskeletal system. In space, antigravity muscles are particularly susceptible to deconditioning and exhibit reduced strength and endurance as well as atrophy. For example, a reduction of up to 18% of back muscle and 25% of leg muscle extension strength was observed after longer duration flights on MIR and Skylab (2). As muscle atrophy progresses with mission duration, operational tasks become more difficult due to decreased muscle strength and associated fatigue. Long-duration missions are associated with extended post-flight recovery times and increased risk of injury; i.e., a 65% higher risk of back injury (2). Shuttle postflight data shows that approximately 65% of all crew members experience Space-Induced Back pain while on-orbit (7). Exercise countermeasures are currently being implemented in an attempt to minimize these adverse effects. However, there is a critical need for the capability to maximize muscle performance and minimize risk to crew members during EVA and intravehicular activities particularly on long-duration missions. Crew performance and safety would be enhanced if it were possible to accurately monitor and predict muscle performance in real-time. The effectiveness of countermeasures could also be assessed and enhanced on an individual basis both on-orbit and postflight.

This study evaluated the feasibility of developing a reliable, empirical model capable of predicting human performance early during dynamic repetitive exercise by applying autoregressive and linear regression analyses to EMG data. Although this analysis emphasizes the Erector spinae back muscle, it has the potential to be applied to other muscle groups.

## METHODS

### *Subjects*

Test subjects (3 males, 5 females) were healthy and physically active with no prior history of chronic lower back pain. Their mean age was 28.4 years (range 20-39), mean height was 172.6 centimeters (range 144.8 to 188.0), mean weight was 71.6 kilograms (range 49.1 to 117.7) and mean percentage of body fat was 14.3% (range 6.6 to 19.1%). Informed consent was obtained from all subjects prior to testing. All test protocols were approved by the local IRB.

### *SEMG Measurements*

Two pairs of silver-silver chloride surface electrodes (Sentry Medical Products) were placed bilaterally on the ES by measuring in line from the iliac crest to the center of the spinal column and then 2 cm lateral to the L3 vertebrae. The paired electrodes were placed 2 cm apart from each other with a reference or ground electrode over the upper thoracic spinous processes.

SEMG data was collected using the Muscle Tester ME 3000 (Mega Electronics LTD, Kuopio, Finland). EMG signals were recorded with a continuous sampling mode at a frequency band of 500 kHz, sampling frequency of 1 kHz, and signal acquisition between DC and 1 kHz. The metered values recorded in memory were transferred, via an optical interface, to a PC for processing.

*Dynamic test*

Test subjects were seated in a fully upright position in a Lordex Spinal Machine (Lordex Inc., Houston, Texas) and restrained across the upper thighs and at the knees and ankles. After 65% percent of the subject's upper torso weight was quantified by the Lordex, the full range of motion was then performed by each subject; i.e., moving from the upright sitting position through to a maximum forward flexion position and then extending back to the initial upright position by the count of six (6 seconds) until unable to perform the full range of motion.

*Autoregressive Modeling*

A versatile model widely used to represent the SEMG signal at discrete time points $[t_n]$ is the autoregressive (AR) model, also called a linear prediction model. The Power Spectral Density (PSD) or power distribution describes the power density along the frequency axis. The PSD associated with the AR model can be monitored while a test subject performs repetitive dynamic exercise. In the AR model, each sample say $x(t_n)$, of the SEMG at time $t_n$ is described as a linear combination of $p$ previous samples plus a random error term, $e_n$, which is independent of past samples (3,4).

$$x_n = - \sum_{k=1}^{p} a_k x_{n-k} + e_n \tag{1}$$

where $x_n$ is the $n^{th}$ sample of the modeled signal at time $t_n$, $(a_1, \ldots, a_p)$ are the AR coefficients, $e_n$ is the random error term at time $t_n$, and $p$ is the model order.

The corresponding generating polynomial in the complex plane:

$$P(z) = 1 + \sum_{k=1}^{p} a_k z^k \tag{2}$$

plays an important role in characterizing the behavior of $x_n$. In particular, $H(z)$, the transfer function can be explicitly expressed as (3):

$$H(z) = \frac{1}{P(z)}. \tag{3}$$

In the complex plane, $H(z)$ has poles ($z_1$, …, $z_p$); i.e., the zeros of $P(z)$ but no zeros. The transfer function $H(z)$, and hence the whole process, is stable over time if and only if all poles lie strictly inside the unit circle; i.e., $|Z_i| < 1$ (6).

For a given sequence of data $\{x_n\}$, the coefficients $\{a_k\}$ can be estimated by solving the Yule-Walker equations (8) if the model order $p$ is known. From the $a_k$, the poles $\{z_k\}$ of H(z) can then be calculated as the solutions to P(z) = 0. In general, the poles occur in pairs of complex conjugates. If $p$ is odd, then there is at least one real pole. Comparisons between SEMG signals obtained under different physiological states can be summarized in terms of the behavior of the AR poles or AR coefficients as the EMG signal progressively changes during repetitive dynamic exercise. Some evidence suggests (5) that the power distribution of the SEMG changes according to a person's physiological and psychological state during repetitive dynamic exercise.

The AR model order was determined by comparing the PSD for a candidate $p$-th order with an empirical PSD obtained directly from the data. In obtaining the empirical PSD, no assumption for any particular model was made for $\{x_n\}$. The empirical PSD was calculated using the Fast Fourier Transform. When the AR model holds, the PSD has the form (3):

$$S(\omega) = \frac{1}{\left|1 + \sum_{k=1}^{p} a_k e^{-j\omega k}\right|^2} \qquad \text{where } j = \sqrt{-1}. \tag{4}$$

The AR PSD for various model orders was compared with the empirical PSD. This comparison was performed separately for each repetition of the dynamic exercise over its corresponding block of samples. A $5^{th}$ order AR model, $p = 5$, was selected since it was the closest fit between the two PSDs. AR models with $p < 5$ did not adequately match the empirical PSD for this EMG data. Those with $p > 5$ were unreliable, modeling random noise fluctuations. Five distinct poles were calculated for separate AR models and fit to the SEMG signal over 1024 samples for each repetition. The five poles are representative of the dynamic muscle performance process and are utilized to calculate derived AR parameters to predict a subject's ability to exercise to failure.

*Statistical Regression Analysis*

For linear regression analysis, STATA statistical software was used (Stata Corporation, 1999). Inputs to STATA were the derived AR parameters described below.

## RESULTS

*Statistical data analysis of derived AR parameters for prediction of $R_{max}$*

After EMG data processing and evaluation using a $5^{th}$ order AR model, analysis was performed to identify simple functions of the AR poles as potential predictors of the maximum number of repetitions ($R_{max}$) that a test subject could perform prior to failure. With a 5th order AR model, there are five poles, one of which is real, the others appearing as two conjugate pairs of complex numbers. Let $Z_{ikn} = X_{ikn} + jY_{ikn}$ be the $n^{th}$ pole at the $k^{th}$ repetition for the $i^{th}$ test subject, where $j \equiv \sqrt{-1}$. The poles are numbered as follows: n = 1: complex pole with smaller real part, positive imaginary part; n = 2: complex pole with smaller real part, negative imaginary part; n = 3: complex pole with larger real part, positive imaginary part; n = 4: complex pole with larger real part, negative imaginary part; and n = 5: real pole. It was hypothesized that either the rate of change or the average position of the poles could reflect fatigue across subjects.

For each repetition throughout the exercise, poles with the largest real parts (n = 3 and n = 4) remained largely stationary, whereas the real pole (n = 5) and the poles with smaller real parts (n = 1 and n = 2) moved within the complex plane.

Six candidate predictors of performance were chosen consisting of the average value and average rate of change over repetitions 2-8 for: 1] real pole, 2] average real part of AR poles, and 3) average magnitude of AR poles. Average rates of change were estimated by least squares regression. To predict the maximum number of repetitions ($R_{max}$) before failure, the calculation of the predictors was limited to repetitions 2-8 since the $9^{th}$ repetition was the earliest any test subject reached failure. Based on simple correlations with $R_{max}$, the mean average magnitude of AR poles across repetitions was the best single predictor ($r = 0.75$).

The mean average magnitude of AR poles over all repetitions is given by

$$M_i = \frac{1}{n} \sum_{k=1}^{R\max_i} A_{ik} \tag{7}$$

where

$$A_{ik} = \frac{1}{5} \sum_{n=1}^{5} \|Z_{ikn}\| = \frac{1}{5} \sum_{n=1}^{5} \sqrt{X_{ikn}^2 + Y_{ikn}^2} \tag{8}$$

and $Z_{ikn} = X_{ikn} + jY_{ikn}$ is the $n^{th}$ pole at the $k^{th}$ repetition for the $i^{th}$ test subject.

There were several reasons for selecting repetitions 2-6 for the prediction of $R_{max}$. The range of $R_{max}$ for all eight test subjects was 8 to 27. Thus, for this data set, the intent was to calculate $M_i$ over fewer than 8 repetitions and to predict $R_{max}$ as early as possible.

The best predictor of $R_{max}$ was the mean average magnitude of AR poles calculated by summing all the average magnitudes of AR poles across repetitions and then dividing the total average magnitude of AR poles by the number of repetitions performed. To construct a predictor for the maximum number of repetitions, a linear regression was fit to the data

$$R_{\max i} = \beta_0 + \beta_1 M_i + \varepsilon_i \tag{9}$$

where $R_{max}$ is the response variable for the $i^{th}$ subject (for repetitions 2 through 6). The model parameters $\beta_0$ and $\beta_1$ are fixed constants and $\varepsilon_i$ is the error amount equal to the increment by which the $i^{th}$ individual $R_{max}$ value fails to lie on the regression line. Estimates $b_0$ and $b_1$ of $\beta_0$ and $\beta_1$ were calculated by least-squares leading to the prediction function $\hat{R}\text{max}$ for a new test subject, given by

$$\hat{R}_{\max} = b_0 + b_1 M, \tag{10}$$

where M is the mean average magnitude over early repetitions 2-6 for the new test subject. The coefficient $b_1$ was significantly different from zero at a level of $P = 0.05$. The predicted versus actual number of repetitions, $R_{max}$, based on the calculated mean average magnitude of AR poles, $M_i$, over repetitions 2 through 6 showed values of $r = 0.75$ and $P = 0.03$ (see Figure 1). Results revealed that the values of $M_i$ were smaller in male test subjects compared to female, with males performing fewer repetitions than females (see Figure 2).

## DISCUSSION

A 5$^{th}$ order AR-based statistical model was developed to predict ES muscle performance to failure based on early performance during repetitive dynamic exercise; i.e., as early as the second repetition. This model utilizes a linear function of the average magnitude of AR poles, obtained from AR models fit separately to the SEMG signal for each repetition in order to predict performance. The best predictor of $R_{max}$ for repetitive dynamic exercise to failure was the mean average magnitude of AR poles with $r = 0.75$ and $P = 0.03$. Although the $P$ value is statistically significant, a slightly higher $r$ value of 0.85 would be indicative of a more powerful predictor. It is anticipated that the inclusion of a larger number of test subjects in future studies would result in an increased *r* value.

An advantage of this model compared to previous approaches is that five parameters (AR poles) per repetition are quantified and available for analysis as potential predictors of muscle performance. In this preliminary study, the mean average magnitude of AR poles was used to predict muscle performance. However, in future studies, combining the mean average magnitude of AR poles with one or more of the other AR parameters may further enhance predictability of muscle performance. In contrast, the mean, median, and mean power frequency EMG-derived parameters consist of single values per repetition and have thus far been used exclusively to document, not predict, performance to failure for repetitive dynamic exercise.

Overall, a trend toward smaller mean average magnitude values was observed in male test subjects compared to female. In addition, males tended to perform fewer repetitions for this particular dynamic repetitive back exercise. This observation may reflect inherent differences in back muscle physiology between the sexes, since differences in distribution of fiber types and sizes have been established. This possible interrelationship will receive further investigation.

Previous investigations applying AR modeling to EMG have largely focused on the use of the AR coefficients to detect changes indicative of muscle fatigue. This is in contrast to the study reported herein which applies AR modeling to EMG: 1] to analyze parameters calculated from the AR poles (i.e., average magnitude) to identify a reliable predictor of muscle performance to failure; and 2] to develop a model capable of predicting the maximum number of repetitions, $R_{max}$, a test subject can perform early on during repetitive dynamic exercise-- not simply to monitor AR coefficient variations as the muscle fatigues.

This new model has the potential to meet several immediate needs for the space program. These include: 1] development of on-orbit capability to monitor reduced muscle performance associated with the progression of atrophy; 2] the monitoring and evaluation of in-flight countermeasure effectiveness; and 3] enhanced postflight astronaut recovery by enabling the development and implementation of individualized rehabilitation programs to reduce injury. With further development, this approach may provide the capability for achieving real-time monitoring of muscle performance for repetitive movement during EVA operations. This real-time monitoring capability may be used to enhance astronaut performance, maximize safety during operational tasks, and optimize work-task sequencing and rest periods, since it is only during the actual execution of EVA tasks that an accurate assessment can be obtained. This is particularly relevant due to the greater utilization of senior astronauts.

In summary, a method for predicting muscle performance was developed for dynamic repetitive exercise to failure for the ES muscle. Future research directions would include the application of this model to: 1] other muscle groups; 2] different types of repetitive exercise in different environments; and 3] the development of a capability for real-time assessment of muscle performance.

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## FiGURE LEGENDS

**Figure 1**- Predicted versus actual maximum number of repetitions ($R_{max}$) based on calculated mean average magnitude of AR poles ($M_i$) over repetitions (2-6) for test subjects (TS1-4, TS7-10) during repetitive dynamic exercise to failure. Prefix "M" designates male test subjects and "F" indicates female. $P = 0.037$, $r = 0.73$ for the regression line in this Figure.

**Figure 2**- Mean average magnitude ($M_i$) of AR poles versus number of repetitions (k) for the dynamic repetition exercise to failure for all test subjects. Male test subjects are numbers 3, 8, and 9 are designated by the prefix "M"; e.g., M-TS3. Female test subjects are 1, 2, 4, 7, and 10 and are designated by the prefix "F"; e.g., F-TS4.