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# Electromyographic Assessment of Muscle Fatigue During Isometric Vibration Training at Varying Frequencies

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*Abstract*— **Resistance exercise is essential to improve or maintain muscle performance. Vibration training has been suggested as an alternative option for muscle conditioning, aiming especially at improving muscle strength and power. Several studies link the effects of vibration training to enhanced neuromuscular stimulation, measured by electromyography (EMG) and typically ascribed to involuntary reflex mechanisms. However, the underlying mechanisms are still unclear, limiting the use of vibration training. This paper proposes additional methods to analyze the mechanisms involved in vibration training. A dedicated measurement setup was realized to relate vibration parameters to muscle fatigue in the biceps brachii. Fatigue is estimated by EMG mean frequency and conduction velocity assessments as well as by maximum voluntary contraction (MVC) force measurements. A modified maximum likelihood algorithm is proposed for the conduction velocity estimation based on high-density EMG recording. Five volunteers performed four isometric contractions of 50 s at 80% MVC with no vibration (control) and with superimposed vibration at 20, 30, and 40 Hz. Fatigue was estimated from the decay of force, EMG mean frequency, and EMG conduction velocity. 30-Hz vibrations represented the most fatiguing stimulus. Our preliminary results also show a better correlation between force and conduction velocity decay than between force and mean frequency decay, indicating the former as a better EMG indicator of fatigue. The proposed methods provide important advancements for the analysis of vibration exercise and guidance towards the definition of optimal training protocols.**

## I. INTRODUCTION

It is widely accepted that muscle disuse leads to atrophy while resistance exercise improves neuromuscular performance in young and old individuals by increasing or retaining muscle size and neural drive to the muscles [1]. Various forms of exercise have been suggested to increase muscle strength and power. To this end, resistance exercise, due to the high neuromuscular demand, is considered the most appropriate training modality [1]. The level of neuromuscular demand can be assessed by electromyography (EMG) [2]: the root mean square of the EMG signal has been shown to increase in parallel with the intensity of muscular activity and force production [2] while the average conduction velocity (CV) of the motor unit action potentials along the muscle fibers has been shown to decrease in parallel with an increase in fatigue [3]. Fatigue has also been shown to be indirectly estimated by a shift in the EMG mean frequency (MF) [3], but the relationship between muscle fatigue and MF is still under discussion [4].

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In the last decade, an alternative form of exercise, characterized by the superimposition of vibration, has been suggested as an effective option to improve muscle strength and power performance [5], [6], [7]. Whole body vibration platforms are the most widely adopted devices for vibration training and have been suggested to be an effective modality to exercise the lower limbs [5], [6]; alternative devices have also been proposed for the upper limbs [7]. Vibration training has been shown to enhance muscle strength and power, mainly due to the neuromuscular demands of such vibrating loads on skeletal muscles [8], [9], [6], [7]. These results seem to be partly due to a neuromuscular phenomenon named tonic vibration reflex (TVR) [9], [10]. This mechanism is ascribed to muscle tuning to vibration damping with preferential recruitment of faster motor units [9], [11]. TVR seems also to be modulated by alterations in spindle sensitivity [9], [12]. The increase in neuromuscular response observed with vibration may therefore derive not only from motor unit recruitment strategies but also from alterations in spindle sensitivity through the gamma feedback [9], [12].

To date, there is limited information on the most appropriate vibration training protocols. In particular, the effects of various vibration parameters on neuromuscular responses and fatigue are still unclear. In this work, we studied the effects of vibration frequency during 50-s sustained isometric contractions of the biceps brachii. A dedicated measurement setup was realized in order to load muscles with the superimposition of a constant and an oscillating (vibrating) force. Fatigue was assessed by the difference in MVC before and after each treatment and by EMG analysis. Force and EMG were recorded by strain-gauges and a high-density electrode grid, respectively.

The progression of the EMG MF and CV over time was estimated during each contraction. Among the CV-estimation methods reported in the literature [13], a modified version of the maximum likelihood (ML) method proposed in [14] was implemented. This method, by performing the CV estimation in the frequency domain, permits integrating an efficient removal of the signal components at the vibration frequency and its harmonics, where severe motion artifacts are present [7]. This removal can be obtained by multiplication of a mask in the frequency domain. Additional modifications of the ML algorithm consist in the introduction of an error-weighting strategy for the improvement of the CV-estimate accuracy and in the replacement of the original Gauss-Newton minimization algorithm by the Nelder-Mead Simplex method [15] for the reduction of the estimate sensitivity to parameter initialization. The analysis results are expected to provide

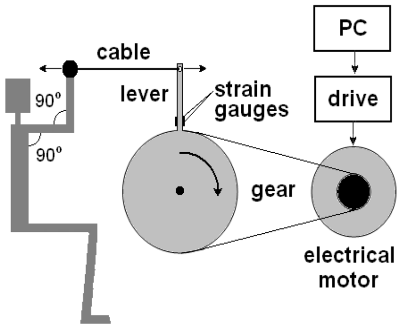


Fig. 1. Scheme of the measurement setup.

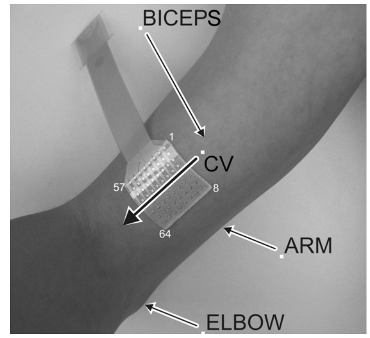


Fig. 2. High-density electrode grid positioned on the arm.

insight in the relationship between EMG parameters and muscle fatigue as well as in the frequency that produces the most fatiguing stimulus when vibration is superimposed to a high levels of contractile activity.

## II. METHODOLOGY

### A. Measurement setup

A dedicated electromechanical actuator, whose scheme is shown in Fig. 1, was realized in order to apply an oscillating (vibrating) mechanical load to the biceps brachii. The core of the actuator is an electrical motor (MSK060C Indradyn®, Bosch-Rexroth, the Netherlands) generating a force that can be modulated to produce the required vibrating load at varying frequencies up to over 40 Hz. The input voltage to the motor drive is generated by a wave generator (PCI 5402, National Instruments, Austin, TX) connected to a PC and controlled by dedicated software implemented in LabView® (National Instruments, Austin, TX).

The actuator can be calibrated by means of two strain-gauges positioned on the lever fixed to the motor shaft that is used to transform torque into linear force. The strain-gauges, positioned on the opposite sides of the lever, are connected to a Wheatstone bridge in a half-bridge configuration [16]. After blocking the lever end, the relationship between the output voltage of the wave generator (determined by the control software) and the voltage at the bridge output was determined at each frequency. This procedure permitted to estimate the electromechanical transfer function of the actuator. The employment of a calibrated dynamometer permitted then the determination of the relationship between the output voltage of the bridge and the force at the lever end. As a result of the complete calibration procedure, the force generated by the actuator can be accurately controlled for varying frequencies, up to 40 Hz.

As shown in Fig. 1, the output lever of the electromechanical actuator loaded the biceps brachii by a short metallic cable connected to a handle held by the test subject. A support system was realized to keep the elbow at a forward fixed elevation of 90° and an angle of 90° while performing isometric contractions of the biceps brachii. The biceps surface EMG was measured during each experimental trial by a high-density grid (8x8) of contact Ag-AgCl electrodes positioned between the tendon at the elbow side and the muscle belly, as shown in Fig. 2. This position, distant from the fiber innervation zone, facilitated the CV estimation by detecting a single propagation direction [2]. The electrode diameter and the interelectrode distance was 1 mm and 4 mm, respectively. The EMG signals were acquired by a 64-channel Refa® amplifier (TMS International, Enschede, the Netherlands) implementing active grounding and cable shielding for reduction of the electromagnetic interference. The adopted sampling frequency was 1 kHz. The EMG signals, initially referred to the average value recorded by all electrodes, were subsequently bipolarized along the fiber direction, leading to 8 parallel columns of 7 bipolar signals.

### B. Measurement protocol

Five young healthy males (mean age $= 25.5 \pm 4$ years) volunteered to partake in the experiment. The maximal voluntary contraction (MVC) for each subject was measured by the calibrated strain-gauge system embedded in the actuator. Subjects were required to produce a maximal effort for 3 s. The average force estimate of three isometric MVC of 3 s was used for establishing the treatment protocols. The treatment protocols consisted of maintaining a constant tension equal to 80% of the MVC. The experimental conditions were characterized by four sustained (50 s) isometric contractions of the right biceps brachii with no vibration (control), and vibration at 20, 30, and 40 Hz. Each condition was followed by resting periods of 15 min. A randomized cross-over design was used. The vibration amplitude was fixed for all frequencies and equal to 30 mN. Before and after each trial, the MVC was measured to assess the extent of fatigue.

### C. EMG data analysis

The progression of MF and CV is estimated by time-frequency analysis of the recorded bipolar signals. A sliding window of 5 s with 4-s overlap is adopted to calculate the signal Fast Fourier Transform (FFT). For the analysis in the frequency domain, only frequencies between 20 and 450 Hz are considered [2], and all components relative to the vibration frequencies and their harmonics are set to zero as shown in [7]. To this end, each EMG amplitude spectrum is multiplied by a mask $|T(k)|$, where $k$ indicates the discrete frequency. The MF is estimated as the first statistical moment of the FFT amplitude spectrum averaged over all channels while the CV is estimated by a modification of the ML method reported in [14]. Eventually, muscle fatiguing rate is estimated as the angular coefficient of the regression line fitting the estimated CV and MF over time.

Given the acquisition matrix in Fig. 2, the EMG signal is detected by $N_r$ rows (7) and $N_c$ columns (8). Assuming the same signal shape $s(n)$ to be present in each (bipolar) channel, the ML method is developed under the hypothesis that the signal $x_{rc}$ measured at the channel $(r,c)$ in the $r^{th}$ row and $c^{th}$ column of the electrode grid can be modeled as

$$x_{rc}(n) = s(n-(r-1)\tau_r) + w_{rc}(n), \tag{1}$$

where $n$ indicates the time sample ($n \in [1,2,...,N]$) and $w_{rc}(n)$ is zero-mean white Gaussian noise with variance $\sigma_{rc}^2$. In each channel $(r,c)$, the reference signal shape $s(n)$ is delayed by $\tau_r$ time samples with respect to the previous row.

The CV calculation requires the estimation of $\tau_r$, which can be obtained by maximization of the probability density function $p(\tau_r|x_{rc}(n),s(n))$. Using Bayesian inference and assuming $p(\tau_r)$ uniform, the maximization of $p(\tau_r|x_{rc}(n),s(n))$ corresponds to the maximization of the probability $p(x_{rc}(n)|\tau_r,s(n))$ of the signal samples $x_{rc}(n)$. Since $x_{rc}(n)$ is available only at discrete values of $\tau_r$, maximization of $p(x_{rc}(n)|\tau_r,s(n))$ in the time domain results in discrete $\tau_r$ estimates, which depend on the sampling rate. By Parseval's equality, $p(x_{rc}(n)|\tau_r,s(n))$ can be maximized in the frequency domain, where $\tau_r$ becomes a phase coefficient and can be estimated without resolution limits [14]. Indicating with $X_{rc}(k)$ and $S(k)$ the FFT of $x_{rc}(n)$ and $s(n)$, respectively, the ML estimation of $\tau_r$ corresponds in the frequency domain to the minimization of the cost function $E^2(\tau_r)$, whose expression is given as

$$E^2(\tau_r) = \frac{2}{N}\sum_{r=1}^{N_r}\sum_{c=1}^{N_c}\sum_{k=1}^{N/2}|T(k)|^2\Big[X_{rc}(k) + -S(k)e^{-j2\pi k(r-1)\tau_r}\Big]^2, \tag{2}$$

where $|T(k)|$ is the frequency mask for the extraction of the EMG signal of interest [7]. The shape function $S(k)$ can be estimated as the average of all the channels $X_{rc}(k)$ after alignment as

$$\widehat{S}(k) = \frac{1}{N_c N_r}\sum_{r=1}^{N_r}\sum_{c=1}^{N_c} X_{rc}(k)\, e^{j2\pi k(r-1)\tau_r}. \tag{3}$$

The resulting estimated cost function $\widehat{E}^2(\tau_r)$ is then

$$\widehat{E}^2(\tau_r) = \frac{2}{N}\sum_{r=1}^{N_r}\sum_{c=1}^{N_c}\sum_{k=1}^{N/2}|T(k)|^2\Big[X_{rc}(k) + -\frac{1}{N_r N_c}\sum_{m=1}^{N_r} X_{mc}(k)e^{j2\pi k(m-r)\tau_r}\Big]^2. \tag{4}$$

The assumption in (1) that signals recorded at different channels are delayed versions of the same reference shape $s(n)$ is unfortunately not always fulfilled [17], and shape variations often contribute to the noise term $w_{rc}(n)$ in (1). To increase the robustness of the CV estimation to EMG shape variations, we improved the ML method by multiplying proper weights, $a_{rc} \in \mathbb{R}^+$, to the cost function. The resulting weighted cost function $\widehat{E}_a^2(\tau_r)$ is defined as

$$\widehat{E}_a^2(\tau_r) = \frac{2}{N}\sum_{r=1}^{N_r}\sum_{c=1}^{N_c}\sum_{k=1}^{N/2}|T(k)|^2\Big[a_{rc}\Big(X_{rc}(k) + -\widehat{S}(k)e^{-j2\pi k(r-1)\tau_r}\Big)\Big]^2. \tag{5}$$

The weights are chosen to be inversely proportional to the standard deviation of the channel noise $\sigma_{rc}$ [18], i.e.,

$$a_{rc} = \frac{A}{\sigma_{rc}} = \frac{A}{\frac{2}{N}\sqrt{\sum_{k=1}^{N/2}|W_{rc}(k)|^2}}, \tag{6}$$

where the factor $A$ normalizes the weight sum to 1. For the expression of $a_{rc}$ in (6), Parseval's equality is used; $|W_{rc}(k)|^2$ is the noise power spectrum in the channel $(r,c)$. In order to estimate the noise power for the generic channel $(r,c)$, the model in (1) is expressed in the frequency domain $k$ as

$$X_{rc}(k) = S(k)e^{-j2\pi k(r-1)\tau_r} + W_{rc}(k). \tag{7}$$

By assuming the reference shape $S(k)$ and the noise $W_{rc}(k)$ to be uncorrelated, the noise can be estimated from

$$\sum_{k=1}^{N/2} X_{rc}(k)\cdot X_{rc}^*(k) = \sum_{k=1}^{N/2} S(k)\cdot S^*(k) + \sum_{k=1}^{N/2}|W_{rc}(k)|^2, \tag{8}$$

where $(\cdot)^*$ is the conjugate operator. The noise power derived by (8) can then be substituted in (6) to determine the weights

$$a_{rc} = \frac{A}{\frac{2}{N}\sqrt{\sum_{k=1}^{N/2}\left(X_{rc}(k)\cdot X_{rc}^*(k) - S(k)\cdot S^*(k)\right)}}. \tag{9}$$

The shape estimate $\widehat{S}(k)$ in (3) is adopted as estimate of the reference signal $S(k)$ in (9).

The Nelder-Mead Simplex search method is used to minimize (5) [15]. According to the average CV values reported in the literature [19], the search method is initialized with $\tau_r = 0.23$ ms, corresponding to CV $= 4.3$ m/s. All the analysis was implemented in Matlab (MathWorks, Natick, MA).

## III. RESULTS

The CV estimation method was validated by simulations where real EMG signals were artificially delayed and white Gaussian noise was added with SNR ranging from 1.5 to 10 dB across the channels. The proposed weighting strategy improved the CV estimate accuracy by over 50%.

Fig. 3 shows the MF and CV progression for a volunteer. As for most measurements, both MF and CV decay up to about 40 s, when a sudden increase occurs. The decay was therefore estimated as the average slope of the data in the first 40 s. The MF and CV slopes, expressed in Hz/s and mm/s$^2$, respectively, were assessed by linear regression.

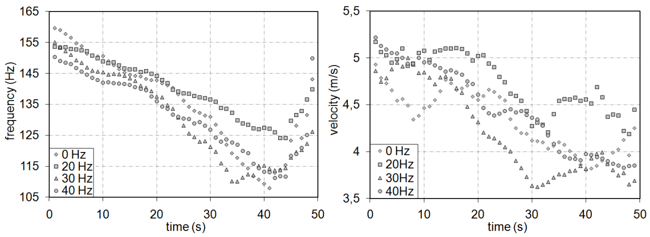

Fig. 3. Example of MF (left) and CV (right) estimates for varying vibration frequencies from 0 (no vibration) to 40 Hz.

TABLE I

FATIGUE INDICATORS.

| Freq. | Force decay | MF slope | CV slope |
|---|---|---|---|
| 0 Hz | $-18.6\pm10.0$ % | $-0.64\pm0.32$ Hz/s | $-28\pm9$ mm/s$^2$ |
| 20 Hz | $-16.4\pm9.1$ % | $-0.72\pm0.46$ Hz/s | $-26\pm14$ mm/s$^2$ |
| 30 Hz | $-23.9\pm8.7$ % | $-0.76\pm0.31$ Hz/s | $-36\pm16$ mm/s$^2$ |
| 40 Hz | $-20.5\pm7.8$ % | $-0.67\pm0.31$ Hz/s | $-32\pm12$ mm/s$^2$ |

The regression correlation coefficient $R$ was larger than 0.8 and 0.9 for all the MF and CV data, respectively. Our results, summarized in Table I, show a consistent decay of maximal force, MF, and CV. In particular, all the indicators show the highest decay for 30-Hz vibrations, suggesting this frequency to provide the most fatiguing stimulus. The correlation coefficient between force decay and CV slope ($R = 0.99$) is higher than that between force decay and MF slope ($R = 0.48$) and that between MF and CV slopes ($R = 0.44$). The average CV slope over all frequencies is only 4.4% of the average MF slope. All the CV estimates were between 2.5 and 7.5 m/s, in line with the values reported in the literature for the biceps brachii [19].

## IV. DISCUSSION AND CONCLUSIONS

As hypothesized, vibration produced a larger degree of fatigue as compared to the control condition. Direct application of vibration to the muscle has been reported to cause larger degrees of fatigue, probably due to the increased neuromuscular demands placed by vibration [8]. Previous work using vibration applied to hand muscles has also suggested an effect of vibration frequency on motor unit synchronization causing fatigue [10].

In our study, it was evident that superimposing vibration to relatively high levels of muscle tension causes a higher degree of fatigue in the biceps brachii. In particular, frequencies higher than 20 Hz seem to be particularly taxing for the biceps brachii, causing a larger degree in the inability to produce force in parallel with a marked decrease in CV. It has been clearly established that the rate of change of spectral variables and CV during a sustained contraction is indicative of muscle fatigue [3]. The results of our study show that possibly different mechanisms of fatigue are evident with vibration, as the relationship between MF slope and the MVC decrease was moderate to low. This suggests that motor unit recruitment patterns may be different during vibration and specific neuromuscular strategies used to damp vibratory stimuli require the synchronization of higher number of motor units, possibly involving fast motor units. The CV and MF increase in the last part of each contraction might also be the result of an alteration in motor unit recruitment strategies.

The results of our preliminary validation confirm the value of the proposed methods for the analysis of the effects of vibration training and suggest that more studies are needed to elucidate the relative mechanisms of fatigue. Our results also suggest vibration exercise to be an effective and beneficial training option in various populations due to the larger neuromuscular demands as compared to conventional resistance exercise.

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