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Electromyography Indices of Handgrip Force with Swinging Motion

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ABSTRACT

Electromyography (EMG) is a powerful tool for studying muscle activity, but there is limited research on EMG signals in the muscles of the human forearm, which poses challenges for prosthetic hand development. This study utilized the maximum voluntary contraction (MVC) normalization method to analyze the flexor carpi radialis muscle during handgrip and swinging motions. The MVC indices revealed a significant proportion of high-amplitude MVC results. We conducted three statistical analyses to validate the indices. One-way ANOVA showed significant differences in mean values among the seven subjects during the percent MVC test. RMS study demonstrated a linear correlation between muscle contraction and movement. Boxplot analysis revealed variations within the interquartile range and median values across the entire MVC range. To achieve these results, we employed an eighth-order Gaussian function for curve fitting and exponential weighted moving average. The median interquartile range showed high discrepancies, while the differences between MVC increments were minimal, providing reliable indices for swinging motion. This suggests that the fat layer thickness may influence the muscle signal's frequency characteristics. In summary, our study highlights the untapped potential of EMG signals in the forearm muscles for prosthetic hand development. By employing MVC normalization and conducting rigorous statistical analyses, we uncovered significant findings that contribute to advancements in this field. Our insights provide hope and inspiration for researchers and practitioners seeking to enhance prosthetic technology.

1. Introduction

Muscle activity plays a pivotal role in our daily lives, influencing our ability to perform various tasks. Understanding and monitoring this activity is crucial, which is why electromyography (EMG) has emerged as a powerful tool. By evaluating and recording the electrical signals produced during muscle contractions, EMG provides valuable insights into neuromuscular activities [1,2]. With a

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frequency range of up to 5000 Hz, it captures the myoelectric signals that directly correlate with our body movements, such as hand gestures (see Figure 1).

Recent studies have primarily focused on healthy individuals, harnessing EMG as an input source for control modalities like prosthetic hands, grip control, finger movements, and arm swings [2,3]. Remarkably, these advancements have yielded impressive levels of accuracy, reaching up to 95% [2]. By utilizing EMG signals, researchers aim to enhance the control and precision of these modalities, revolutionizing the way we interact with technology.

However, it is important to acknowledge the challenges that researchers face in achieving even greater accuracy. Signal noises, data collection methods, and environmental factors pose significant hurdles that must be overcome to ensure the robustness and reliability of EMG pattern recognition [4-6]. To address these challenges, researchers have relied on key references such as "Human lower limb activity recognition techniques, databases, challenges and its applications using sEMG signal" by Vijayvargiya *et al.,* [7], and "The study of principle component of the surface electromyography signal of the Bicep Brachii muscle" by Sabri *et al.,* [8]. In the pursuit of accurate EMG analysis, the development of recommendations for SEMG sensors and sensor placement procedures by Hermens *et al.,* [9] and study of EMG sensor to muscle serves as a valuable resource [10-12]. Additionally, studies by Corbett *et al.,* [13], as well as Yahya *et al.,* [14], have shed light on the extraction of neural strategies from surface EMG and the associations between motor unit action potential features and surface electromyography parameters.

Harnessing the potential of EMG technology not only holds tremendous promise for the field of prosthetics but also opens exciting avenues for applications in rehabilitation, sports performance, and ergonomics. By capitalizing on the wealth of information provided by EMG signals, we can unlock new insights into the human body's capabilities and design innovative solutions that enhance our quality of life [15-18]. In summary, EMG is a game-changing technology that empowers us to delve deeper into the intricacies of muscle activity. By leveraging its capabilities and drawing upon the latest research in the field, researchers and innovators are paving the way for groundbreaking advancements in various fields [19]. Through persistent efforts, we are poised to conquer the challenges and unlock the full potential of EMG, revolutionizing the way we interact with and understand the human body.

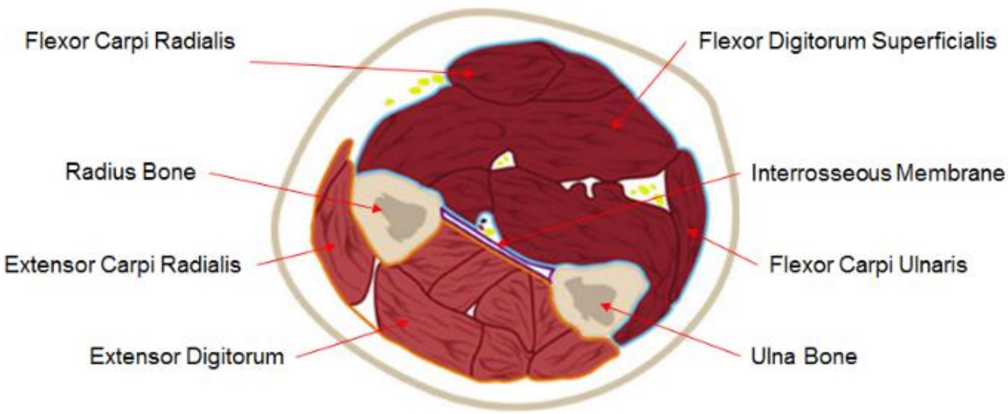


Fig. 1. The forearm with cross section area showing the muscles properties [17]

Myoelectric (EMG) signals are generated in human skeletal muscle during contraction of the muscle fibre, which is always random [20]. These EMG signals provide evidence of the anatomy and functional activity of a muscle [21-24].

Figure 2, shows basic blocks of pattern recognition for EMG signal. The acquisition block which also refers to detection and recording of the EMG signals. Meanwhile, processing the signal is required to align the suitability of the collected EMG data in terms of their amplitude, frequency, or space. Important transformation of raw signal or data into a set of a new column with reliable information known as feature extraction. Usually, the accuracy of the result from the feature extraction is affected greatly due to the noise environment and error. Lastly, signal normalization is important to categorize all EMG data acquired from different samples.

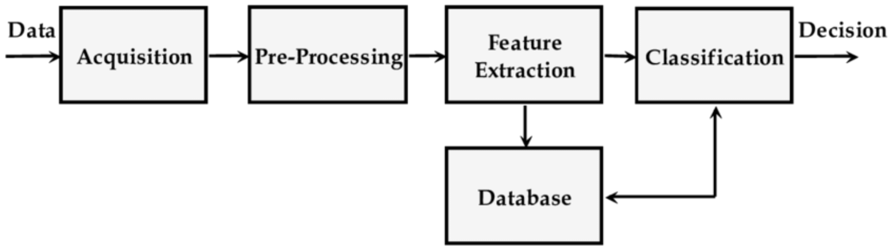


Fig. 2. The block diagram of basic electromyography signal processing

The raw EMG signal, although informative, is highly susceptible to artefacts and data distortions. Its inadequacy as a reliable feature source has hindered advancements in signal processing and analysis. But fear not, as the breakthrough technique of sEMG holds the key to unlocking a new realm of possibilities. Feature extraction of EMG signals has shed light on the variations of signal information, including artefacts, which depend on the signal strength. Studies have demonstrated the effectiveness of extracting features in both the time and frequency domains [25]. However, achieving a set of robust features has remained an elusive goal, challenged researchers and limited progress in the field. Numerous review papers by esteemed researchers have highlighted these challenges and called for innovative solutions [26,27]. The recognition and analysis of EMG patterns are profoundly affected by these inconsistencies, hindering the development of reliable and accurate methodologies. By utilizing specialized external sensors or electrodes, sEMG enables the capture of high-quality signals, untethered by the limitations of the raw EMG. This breakthrough technology offers a path to unparalleled precision and accuracy in muscle activity analysis [28].

2. Methodology

2.1 Materials and Methods

With the ability to capture electrical potentials across a broad muscle area, EMG sensors provide invaluable insights despite challenges such as low-frequency components (20-500Hz), resolution limitations, and susceptibility to artefacts. Harnessing the SENIAM standard operating procedure, we unlock a realm of possibilities [29,30].

Unveiling the Power of Seven Exceptional Volunteers. Our meticulously selected team consists of four remarkable males and three extraordinary females. Their impeccable health records, devoid of musculoskeletal disorders or nerve diseases, guarantee the integrity of our study. With a shared trait of right-handedness, they embody precision and dexterity. Aged between 21 and 25 years, their youthful energy and enthusiasm fuel our research. The day before the experiment, they were conscientiously advised to abstain from rigorous forearm or hand exercises. Together, we forge ahead, ready to uncover groundbreaking insights into muscle activity.

Empowering Progress through Thorough Documentation. We meticulously recorded essential details, including gender, weight, dominant hand, age, and height, ensuring comprehensive future references. Our commitment to excellence extends to the data collection setup, meticulously optimized for subject comfort and efficiency. By minimizing fatigue and streamlining preparation time, we prioritize an environment conducive to groundbreaking discoveries [31,32]. Together, we pave the way for transformative advancements. Devices used for the data collection is multiple-channel surface EMG system known as Vernier Labquest mini (See Figure 3(b)). Before the electrode placement, the subject is advised to calm and rest. The alcohol swab applied to the subject skin, to clean the surface and prevent high impedance. This will prevent any harm to the skin from rashes. Several disposable EMG electrodes are used in the experiment (Nihon Kohden). The size of electrode diameter is 10mm, but the recording surface estimated around 5mm in area covered. The EMG sensor is placed on the right forearm, wrist while electrodes placed on two muscle groups on forearm, which are flexor carpi radialis and flexor pollicis longus as shown in Figure 3(c). Subjects were instructed to sit on a chair with adjustable armrest position, to suit their comfort. Subjects were asked to perform a swing with handgrip force using Vernier hand dynamometer. To get the effective signals, each channel using bipolar configuration and distance between two electrodes is chosen at 15mm [30].

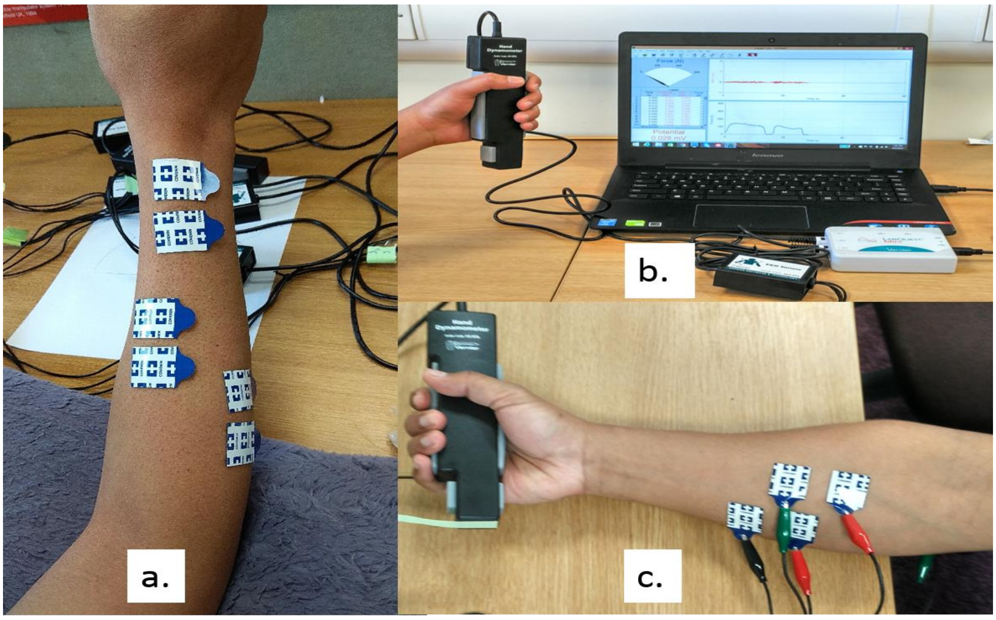


Fig. 3. The Example of electrodes placement for EMG sensors and the muscles; (a) Electrode placement for the extensor muscles, ECRL and EDC, (b) data acquisition system with hand dynamometer for subject force measurement, and (c) Electrode placement and sensor cable connection for flexor muscles FDC and FCR

Feature extraction is one of the challenging parts in surface EMG pattern recognition [14,32]. It is important to reduce noise in EMG signal. Usually, EMG signal contains a great amount of noise and robust features are needed to get the best surface EMG indices for further assessment [33]. The selected features are described as follows

i. Means absolute value (MAV) is used for calculation of mean value of the linear envelope. It can be express as

$$MAV = \frac{1}{N}\sum_{N=1}^{N}|X_n| \tag{1}$$

ii. Root mean square (RMS) is modeled by the amplitude modulated Gaussian random process. It can be computed as

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} X_n^2} \tag{2}$$

where N represents the length of the signal and Xn stands for the EMG signal in specific segment.

iii. Standard deviation feature represents EMG signal confidence interval between statistical data. It can be express as

$$STD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N} X_n^2} \tag{3}$$

where N represents the length of the signal and Xn stands for the EMG signal in specific segment.

iv. Modified mean absolute value 1 (MMAV 1) is a assemble feature based on MAV and it can be expressed in mathematical form as

$$MMAV = \frac{1}{N}\sum_{n=1}^{N} w_n |x_n| \tag{4}$$

$$w_n = \begin{cases} 1, if\ 0.25N \leq n \leq 0.75N \\ 0.5,\ otherwise \end{cases} \tag{5}$$

where N is the length of signal; wn is the weighing window function of sampling signal and xn represents the EMG signal in a specific segmentation.

v. Modified mean absolute value 2 (MMAV 2) is an assemble feature based on MAV with continuous weighing window function and it can be expressed in mathematical form as

$$MMAV = \frac{1}{N}\sum_{n=1}^{N} w_n |x_n| \tag{6}$$

$$\begin{cases} 1,\ if\ 0.25N \leq n \leq 0.75N \\ \frac{4n}{N}, \quad if\ 0.25N > n \\ \frac{4(n-N)}{N},\ if\ 0.75N < n \end{cases} \tag{7}$$

where N is the length of signal; wn is weighing window function of sampling signal and xn represents the EMG signal in a specific segmentation.

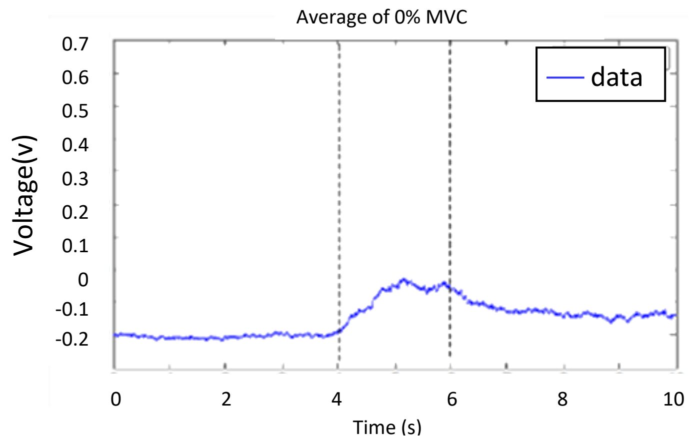
Several experiment and trials were done, for data collection and to analyse the performance of the feature to be used as EMG indices. Each of the experiment is associated with two main objectives of this study. At first, to analyse the EMG signal using statistical analysis methods, and to increase the efficiency of pattern recognition by finding an optimal feature as EMG indices. After all the required EMG signal is collected from the experiment, the signal is then analysed [34]. Statistical analysis proven to be good at indicating muscular activities which makes the process easier to make analysis on muscle activation. There are three methods that will be applied to approach statistical analysis and according to previous studies, these methods have shown good results. The methods are the ANOVA, root mean square (RMS), and boxplot analysis [34,35].

3. Results

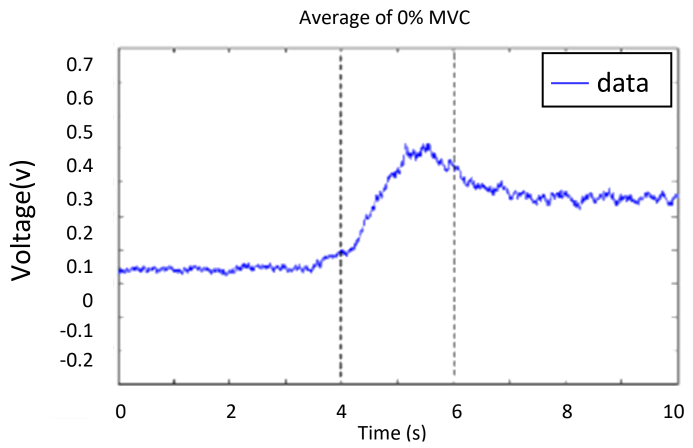
The raw EMG signal has been processed for further analysis. As shown in Figure 4, the times of 0 to 4 seconds, demonstrate that the hand muscle EMG signal amplitude is relatively small, due the relaxed condition of a subject. After four seconds of relaxing phase, subject was asked to perform task as instructed for 0%, 50% and 100% MVC. This can be seen whenever the percentage of MVC increases, the normalized amplitude of the spinal EMG signal is also increased. This means that the contraction of the muscle increases as the handgrip force increases as there is no swinging motion. A swinging motion occurs from 4 to six seconds, and the graphs in Figure 4(c) shows an enormous increase in normalized amplitude, as subject was asked for 100% MVC. There's a holding period from six to ten seconds as shown in graphs (Figure 4), indicates that the normalized amplitude has started to decrease thus showing that it becomes unstable. Most of this transition periods have been discussed by much research as muscle fatigue [34-37]. All data collected is further processed for the indices assessment.

The one-way ANOVA analysis is performed at the average percentage of each MVC handgrip and swinging level. The significant level was observed based on the setting level; $p < 0.05$ to allocate variance with respect to the various data set. The findings indicate statistically significant difference between mean and variance for 100% MVC and 50 % MVC. Additionally, it is noted that not all subjects have the same mean and variance. The null hypothesis, H_ostate is rejected for the methodology and sampling. This disparity was due to unstable condition of the subject body. Based on ANOVA analysis, it shows that linear identification is impossible for different subject as indices being provided by each subject at the same percentage of MVC, are nonlinear.

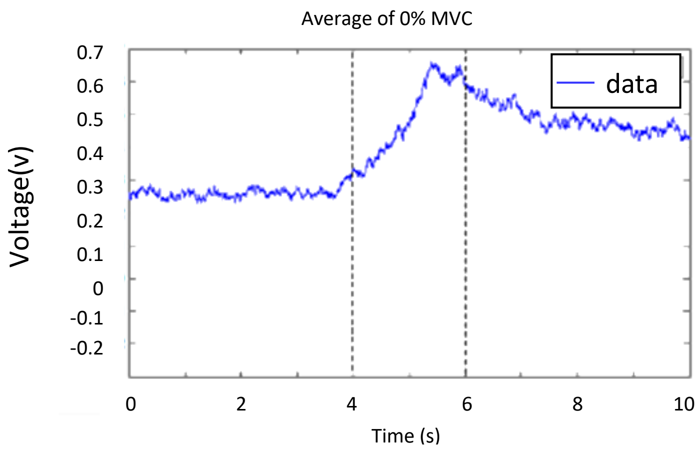
The RMS analysis is performed at the average percentage of MVC handgrip and swinging level. Table 1 tabulates the results with the estimation of the RMS value. The RMS is determined to rectify the useful information about the EMG signal amplitudes. Higher MVC level will result to the higher RMS indices, as shown in Table 1. This reveals that, the percentage RMS value of MVC excited from muscle function increase as the contraction is increased. In swinging phase motion, the percentage of each MVC are analysed using the boxplot. Figure 5 displayed the percentage of MVC for 0%, 50% and 100% and their respective boxplot analysis. In boxplot, the x-axis corresponds to different percentages of MVC while the y-axis corresponds to the normalized EMG signal amplitude. In boxplot, the red line in the box represents the median for each respective box. In addition, the boxes display the maximum and minimum uniform amplitude for any unit MVC. 100% MVC has the highest mean, interquartile range, and average standardized amplitude compared to those in Table 2. The difference of average median of 0% MVC to 100% MVC is 77.34mV, while interquartile range (IQR) difference is 266.54667mV in average, for the same MVCs. This can be concluded that the median is linearly correlated with the percentages of MVC.



(a)



(b)



(c)

Fig. 4. Average of (a) 0% MVC, (b) 50% MVC, and (c) 100% MVC. Graph plotted using MATLAB software

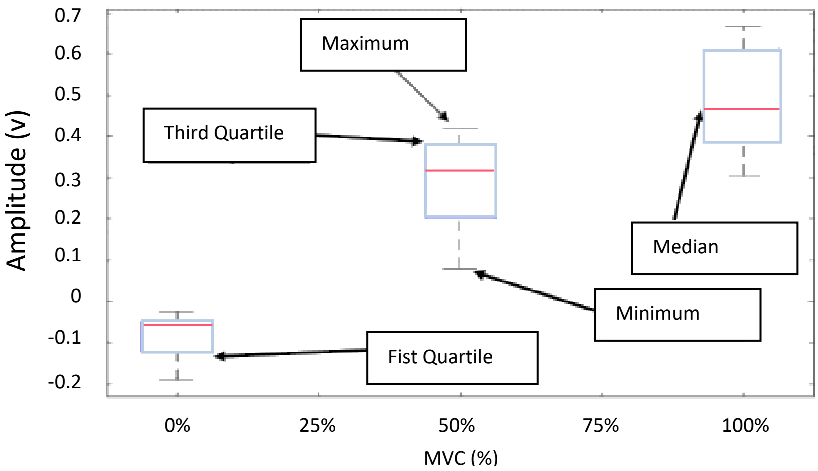


Fig. 5. Boxplot analysis of %MVC

Table 1
RMS and Mean results (%MVC)

	0% MVC	50% MVC	100% MVC
Mean (mV)	-81.35	287.1	491
RMS (mV)	93.1	306.8	505.3

Table 2
AQR difference and average median

MVC (%)	Median difference (mV)	IQR difference (mV)
0-50	661.86	103.65
50-100	136.78	51.03
Total	799.64	154.68
Average	266.54667	77.34

Table 3 shows the 8th order of Gaussian function for the 0%, 50%, and 100% MVC. The difference in average median from 0% to 100% MVC is noted to be at 129.367mV while the difference of IQR average median from 0% to 100% MVC is 37.645mV. However, the average amplitude is 656.4mV.

Table 3
3 (8^{th} order Gaussian function) boxplot analysis

MVC (%)	Median (mV)	IQR (mV)	Max. Amplitude (mV)
0	-61.013	68.313	-30.325
50	340.591	150.95	405.91
100	469.51	221.54	656.43

Standard deviation is used in statistical analysis for quantifying the sum of variance in a dataset. Results analysed shown that difference between median and IQR indicates a lowest variations in standard deviation error. In addition, the IQR gap indicates the lowest deviation in normal condition. Based on the results tabulated in tables, it shows that median and IQR indicates very high concentrations in their average value and difference value. Since the EMG was analysed with 8th Gaussian function, the average IQR difference from 0% to 100% are the lowest, 47.397mV while the signal undergoes the highest exponential weight moving average filter, 72.34mV. This was due to the low quality of data but offers more variable values.

The implementation of exponential weight moving average filter resulted for maximum amplitude, 743.79mV, in between three different boxplot analysed. In addition, for EMG signal that's applied for 8th order of Gaussian function resulted for higher average mean difference from 0% to 100% MVC which is 133.20475mV, while 124.118475mV for mean average of moving average filter. The value for median shows the highest increment from 0% to 100% MVC compared to IQR based on results. Thus, the median value is the perfect indices to exhibits the differences in MVC percentages. These produces identical and consistent data after the boxplot analysis is performed. Based on findings in median, standard deviation, and IQR difference, there is the need for multiple references to calculate perfect MVC value for swinging motion.

4. Conclusions

Unveiling the Secrets of MVC Tests. we delve into the fascinating differences between MVC tests, uncovering their hidden intricacies. The results paint a compelling picture: during swinging motions, a significant increase in normalized amplitude is observed. This surge can be attributed to the heightened percentage of MVC, signifying greater muscle contraction induced by higher loads. Consequently, muscles generate a substantial amount of myoelectric activity. These findings shed light on an important aspect: the average mean of the 7 subjects does not exhibit significant correlation. Hence, the MVC standardization approach emerges as the preferred method for evaluating EMG signals in swinging motions. Moreover, direct recognition based on indices proves unfeasible due to the inherent variabilities in EMG signals across subjects at the same percentage MVC. The analysis of RMS further supports these observations, showcasing heightened muscle activity with increased muscle contraction. Prepare to embark on an engaging journey that unravels the mysteries of MVC tests, offering profound insights into the dynamic world of muscles.

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