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Bispectrum Analysis of Surface EMG Signal to Assess Muscle Fatigue during Isometric Contraction

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Abstract: *The objective of the present study was to investigate the possible relationship between bispectral parameters extracted from surface EMG (sEMG) signals and muscle force and fatigue. Our hypothesis was that changes in motor unit recruitment during muscle contraction and fatigue, affect sEMG distribution and the degree of complexity and irregularity in the muscle. Thus, four features based on higher order spectra and cumulants were extracted from sEMG signal, recorded from biceps brachii muscle of a healthy female volunteer during rest, sustained (fatiguing) 50% MVC, 100% MVC and recovery. Results obtained from weighted center of bispectrum (WCOB) analysis showed that the values of f_{1m} and f_{2m} were higher during rest and recovery states, while they decreased during MVCs. However, when fatigue occurred, these parameters increased slightly, again. Moreover, entropy features, namely NBE and NBSE decreased with contraction compared to rest and recovery states, indicating less complexity of time series during MVCs. However, the changes were not significant during fatigue and during changes in MVC levels from 50% to 100%. On the other hand, test of non-Gaussianity based on negentropy showed the reverse pattern of WCOB, NBE and NBSE. In addition, contour maps of bispectrum enabled us to visually differentiate each trial.*

Keywords: Biceps brachii muscle, entropy, higher order statistics, surface electromyographic signal, muscle fatigue.

1. Introduction

Biomedical signals carry information about the physiological activities of human or animal organisms and their processing aims at extracting significant information to facilitate understanding different pathologies [1]. Surface electromyographic (sEMG) signals, which represent a train of motor unit action potentials (MUAPs) plus noise, can provide useful information about muscular function and underlying mechanisms of sustained fatiguing contractions [2,3,4]. The MAUPs vary in amplitude, duration and frequency of occurance, which are related to the amount of force the muscle may produce and thus the level of contraction [2,3]. However, extracting information about motor unit (MU) recruitment strategies during muscle contraction from the analysis of sEMG data is a challenging task [5]. Different parameters in time, frequency and higher order statistics domains were extracted from sEMG signals to examine the influence of the increase in voluntary contraction [3]. The most frequently used parameters were the mean frequency (MNF), the median frequency (MDF), the number of zero crossings per second (zc/s), the power spectrum and bispectrum shape and the Gaussianity and linearity test of the normalized bispectrum, which led to many discrepancies between findings. These contradictory results may originate from the fact that different researchers have recruited limited and different number of participants. In addition, various recording protocols and recording durations were chosen, which may affect the results, for example, fatigue may occur in large recording times [3]. Kaplanis te al. [3], reported that the time domain parameters (zc/s) and turns per second, increased significantly with force level, while the power spectrum MDF parameter, decreased dramatically in isometric voluntary contraction. Although, test of Gaussianity and linearity using bicoherence analysis did not show significant changes, the sEMG signals revealed a more Gaussian distribution with increase in force level up to 70% of maximum voluntary contraction (MVC). In contrast, the results of [4,6] showed that signals became less Gaussian and more linear with increasing in walking speed/force. However, the study group of Nazarpour [7], measured the non-Gaussianity of sEMG signals using negentropy feature during elbow flexion at four different levels of contraction. Their results demonstrated that the distribution of sEMG signals was non-Gaussian during light contractions (below 30% of MVC) and it tended toward a Gaussian process at higher force levels due to central limit theorem. Kaplanis et al. in [8] achieved even more conflicting results. They reported that the EMG signal was highly non-Gaussian at low and high levels of

force which tended to Gaussian distribution at the mid level of MVC (i.e. 50%).

In this study, we revisit this problem using higher order spectra analysis methods, applied to sEMG signals at various muscle contraction/force stages (rest, fatiguing 50% of MVC, 100% of MVC, recovery) for right biceps brachii muscle. These nonlinear features are exploited to enhance the diagnostic character of sEMG signals and to quantify the degree of non-Gaussianity as well as the irregularity and complexity of signals at each stage.

2. Materials and Methods

2.1 Subjects

One healthy female volunteer (age 20 years, mass 61 Kg, Body Mass Index 23.82 Kg/m^2) with right hand dominant, participated in this study. The subject had not specifically trained her hand and shoulder muscles. The measurments were carried out in the Physiology Laboratory, Department of Biomedical Engineering, Islamic Azad University, Mashhad, Iran.

2.2 Recording Setup

A Surface EMG activity was measured from right biceps brachii muscle using PowerLab/ML865[1] system. In addition, recording was done bipolarly using Ag/AgCl circular self-adhesive disposable pre-gelled surface electrodes[2] of 15mm diameter. According to Surface Electromyography for the Non-Invasive Assessment of Muscles (SENIAM) [9], the electrodes were placed on the line between the medial acromion and the fossa cubit at 1/3 from the fossa cubit, with 20mm spacing. Moreover, the reference electrode was placed on the left wrist (Fig. 1). To keep the interelectrode resistance low, the electrode sites were cleaned with 70% isopropyl alcohol. The leads were fixed by medical tape to reduce motion artifacts.

For sEMG recording, the subject was asked to seat quietly on a comfortable armchair, while instructed to assume a standardized position with her hip and back against the back of the chair, her feet flat on the floor, her right arm fixed on the chair and the left one on her lap. After the adaptation period of one minute, she was asked to perform maximum voluntary contraction (MVC) for three times, using a hand dynamometer/MLT003/D[3] connected to the PowerLab system with two minutes rest intervals between trials. In order to perform 50% of MVC, firstly, the maximum recorded MVC was chosen, then, 50% of MVC was calculated using LabChart 7.3 software[4], which was installed on the computer, lastly, this value fed back to the subject visually on a monitor positioned in front of her. Visual feedback enabled the subject to maintain the requested percentage of MVC as constant as possible till exhaustion. However, after exhaustion, recording was continued for another one minute period to assess the recovery process. The surface EMG signals were recorded online. A computer was connected to the recording system via USB cable for the storage and display of signal. The raw signals were filtered through hardware lowpass and highpass filters with cut-off frequencies at 500Hz and 10Hz, respectively. A notch filter with center frequency at 50Hz was also used to reduce power line noise. The signals were made discrete using 16-bit analogue-to-digital (A/D) converter. Moreover, according to the mentioned frequency band, the sampling frequency was chosen at 2KHz. Furthermore, the sampling frequency and the recording process (start/stop and duration of adaptation and recovery stages and the percentage of MVC) were controlled through LabChart 7.3 software.

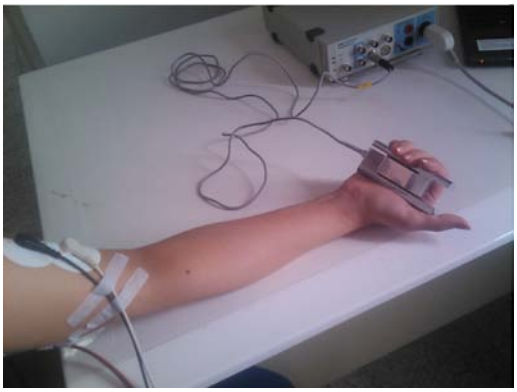

Fig. 1: Bipolar surface electromyographic electrode placement over the biceps brachii muscle.

2.3 Higher Order Specrtal Analysis

Physiological signals are nonlinear and chaotic in nature and uncertainty and imprecision are the inherent characteristics of them. Higher order statistical based nonlinear dynamical techniques, which are based on the chaos theory, have the ability to detect nonlinearity, deviations from Gaussianity and the phase relationships between harmonic components [10].

For a stationary, discrete, zero mean random process x(n), the higher order spectra (HOS) or polyspectra are defined based on moments or cumulants of order greater than two. The bispectrum is a particular form of HOS, which is defined as the two-dimensional Fourier transform of the third order cumulant [11,12]:

$$B(\omega_1,\omega_2)=\sum_{\tau_1=-\infty}^{+\infty}\sum_{\tau_2=-\infty}^{+\infty}c_3^x(\tau_1,\tau_2)e^{-j(\omega_1\tau_1+\omega_2\tau_2)} \quad (1)$$

[1] ADInstruments Pty Ltd. Australia.
[2] Ag/AgCl, F55, Skintact, Leonhard Lang GmbH, Austria.
[3] ADInstruments Pty Ltd. Australia.
[4] ADInstruments Pty Ltd. Australia.

The $c^x_3(\tau_1,\tau_2)$ variable reveals the third order cumulant, which is defined as "Equation (2)":

$$c_3^x(\tau_1,\tau_2) = E\{x(n)x(n+\tau_1)x(n+\tau_2)\} \quad (2)$$

Where E[.] denotes the expectation operation. By setting $n+\tau_1=m$, $n+\tau_2=k$ and substituting "Equation (3)" in "Equation (1)" and splitting the exponent, it can be shown that [10]:

$$B(\omega_1,\omega_2) = E\{X(\omega_1)X(\omega_2)X^*(\omega_1+\omega_2)\} \quad (3)$$

As is evident, we can obviously state that the bispectrum measures the correlation among three frequencies, ω_1, ω_2, $(\omega_1+\omega_2)$ and estimates the phase coupling [13]. The frequency f $(\omega/2\pi)$ may be normalized by sampling frequency to be between 0 and 1. Moreover, due to symmetry properties, knowledge of bispectrum in the triangular region $\omega_2\geq 0$, $\omega_2\geq \omega_1$, $\omega_1+\omega_2\leq\pi$ is sufficient to describe the rest. This region is shaded in Fig. 2 and labelled by 1 and ensures that there is no bispectral aliasing [10,13]. In contrast with the power spectrum which is real valued, non negative and a function of one frequency variable, the bispectrum is a function of two frequencies and complex valued, as a result, it has both magnitude and phase.

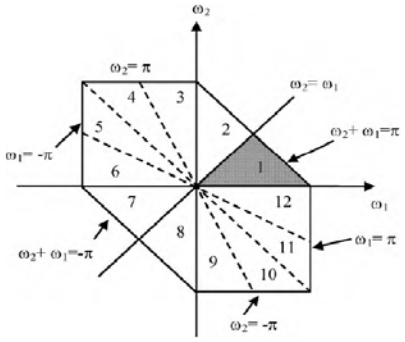

Fig. 2: Symmetry regions of the bispectrum and non-redundant region which is shaded and labeled by 1.

2.3.1 Higher Order Spectral Features

a. Weighted Center of Bispectrum (WCOB)

Although the bispectrum plots enable us to visually differentiate physiological or pathological states, it is not practical to use these plots for automatic pattern recognition by computers. Thus, several features are extracted from the centroid, moments or entropies of the distributions in [10]. In this study, we used WCOB feature set [10,14]. If the bispectrum of the point (x,y) is B_{xy}, then the WCOB(f_{1m},f_{2m}) in the bi-frequency plane is given by:

$$f_{1m} = \frac{\sum_{\Omega} xB_{xy}}{\sum B_{xy}} \quad , \quad f_{2m} = \frac{\sum_{\Omega} yB_{xy}}{\sum B_{xy}} \quad (4)$$

Where x and y are the frequency bin index in the non-redundant region (Ω), defined in Fig. 2. In addition, WCOB is a vector with two variables f_{1m} and f_{2m}, which can be used to indicate the different stages of muscle contraction as well as the fatigue phenomenon [14].

b. Higher Order Statistical Based Entropies

Three bispectral and cumulant based entropies were derived to characterize the regularity or irregularity of sEMG signals during rest, fatiguing 50% MVC, 100% MVC and recovery. These features are similar to spectral entropy [15]. "Equations (5-9)", show formulae for these entropies:

- *Normalized Bispectral Entropy (NBE)*

$$NBE = -\sum_i p_i \log p_i \quad (5)$$

Where

$$p_i = \frac{|B(f_1,f_2)|}{\sum_{\Omega}|B(f_1,f_2)|} \quad (6)$$

- *Normalized Bispectral Squared Entropy (NBSE)*

$$NBSE = -\sum_n p_n \log p_n \quad (7)$$

Where

$$p_n = \frac{|B(f_1,f_2)|^2}{\sum_{\Omega}|B(f_1,f_2)|^2} \quad (8)$$

The mentioned features are calculated within the region (1) defined in Fig. 2, which is equivalent to Ω in the above equations. In addition, the normalization ensures that the entropy is calculated for a parameter which lies between 0 and 1 (as required for probability). As a result, entropies NBE and NBSE are also in the same range.

- *Negentropy*

Negentropy, J, is based on the information- theoric quantity of differential entropy. Negentropy is zero for a Gaussian process, while it is always nonnegative for other distributions. So, it can be used to measure non-Gaussianity of signals. The classical and simple method for approximating negentropy is based on higher order moments. For a zero mean and unit variance random variable x, J is defined as follows:

$$J(x) \approx \tfrac{1}{12} skew(x)^2 + \tfrac{1}{48} kurt(x)^2 \quad (9)$$

Where E[.] is the expectation operation and skew(x) and kurt(x) are the zero- lag third order and forth order cumulants, respectively [7].

3. Results

In order to perform analyses, the raw EMG signals were made zero mean. In addition, to provide uniformity, the signals were normalized with respect to their standard deviation. The bispectrum was estimated using direct method as defined in "Equation (3)", by using Higher Order Spectral Analysis (HOSA) toolbox [16]. This method is similar to the periodogram and is referred to as higher order periodogram [10]. Similarly, it requires the stationarity assumption. The majority of physiological signals are nonstationary in nature. However, it is generally accepted that sEMG signals recorded during rest and isometric contraction, can be considered stationary during a period of less than two seconds. Thus we chose two second period of our data to compute the bispectrum. Then, blocks of 256 samples corresponding to 128ms data with respect to the mentioned sampling frequency with 50% overlap were used to estimate the bispectrum. In this way, we could produce roughly 15 realizations to perform averaging and to satisfy the required smoothness and frequency resolution for our estimation for each trial. Hamming window was used as the analysis window.

Fig. 3(a)-(f) shows the contour maps of bispectrum magnitude at different stages (rest, start point of 50% MVC, mid point of 50% MVC, end point of 50% MVC, 100% of MVC and recovery). According to the symmetry property of bispectrum, its values were evaluated only in the non-redundant region, indicated in Fig. 2. Examining the graphs, we can state that during MVCs the bispectrum maps became smaller compared to rest state. However, during fatigue (end point of 50% MVC), the distribution spread slightly, again. Obviously, the bispectrum of sEMG signals had visible differences at different trials.

Moreover, the blocks of five seconds duration of data were chosen for each trial (rest, 50% MVC, 100% MVC, recovery) and four features were extracted from them to evaluate muscle contraction at various stages, which are also valuable to determine muscle fatigue. TABLE I, summarises the values of the parameters calculated at each stage.

Fig. 4 demonstrates the variations of f_{1m} and f_{2m}-coordinates of WCOB feature at different trials. As can be clearly seen, these two features had a similar trend. In addition, they reached their maximum value at rest. However, these values decreased dramatically during MVCs and increased gently during recovery period. While, f_{1m} and f_{2m} fell in mid point of 50% MVC stage, they rose slightly at the end point of 50% MVC, during which muscle fatigue (exhaustion) occurred. Furthermore, increasing MVC from 50% to 100% led to increase in f_{1m} and f_{2m}. Considering the graph, we can also state that the f_{1m} varied more rapidly than f_{2m}. This means that f_{1m} was more sensitive to variations in muscle force and fatigue.

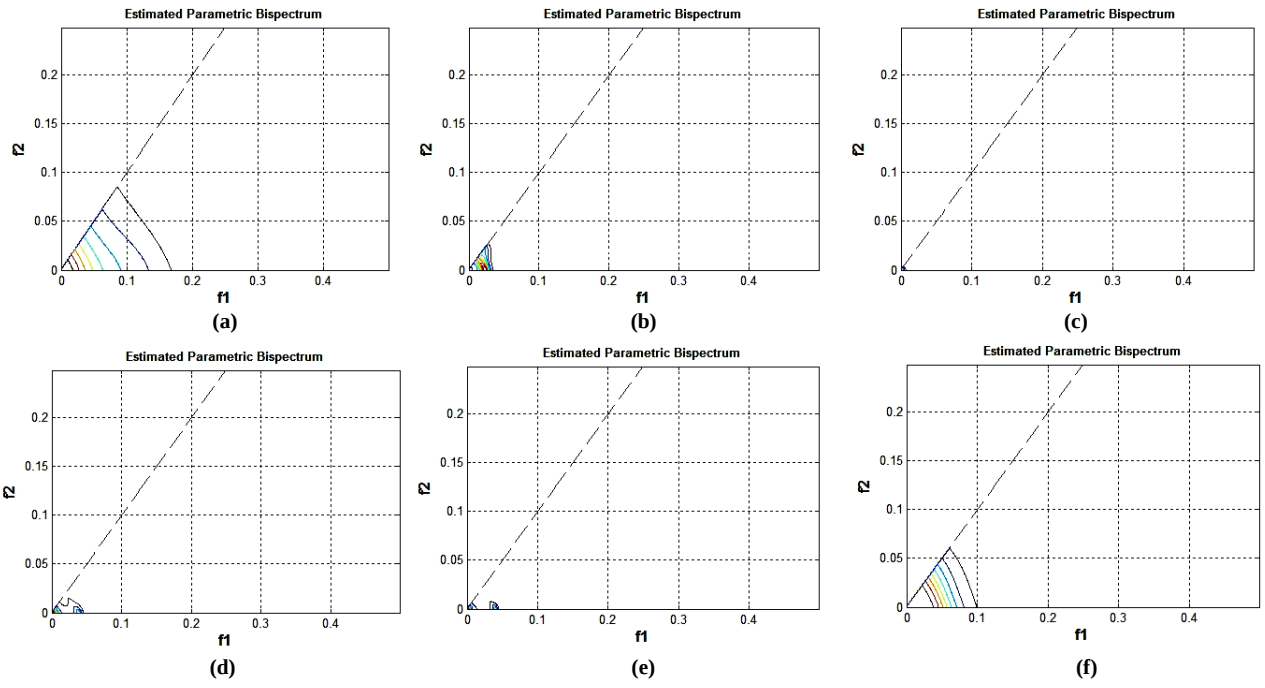

Fig. 3: Bispectrum contour maps of sEMG signals recorded during rest (a), start point of 50% MVC (b), mid point of 50% MVC (c), end point of 50% MVC (d), 100% of MVC (e) and recovery (f).

TABLE I: The Values of the Parameters Analyzed During 4 Trials.

Trial \ Features		f_{1m}	f_{2m}	J	NBE	NBSE
Rest		22.93	14.75	0.004	0.82	0.43
50% MVC	Start	7.80	4.17	0.027	0.58	0.37
	Mid	7.34	3.60	0.026	0.59	0.38
	End	8.75	3.86	0.019	0.58	0.41
100% MVC		9.11	4.67	0.016	0.62	0.40
Recovery		14.79	6.92	0.003	0.79	0.46

Fig. 5 illustrates NBE and NBSE variations during 4 trials. As is evident, entropies decreased with contraction compared to rest and recovery states, indicating less complexity of time series during MVCs. However, the changes were not significant during fatigue and during changes in MVC levels from 50% to 100%.

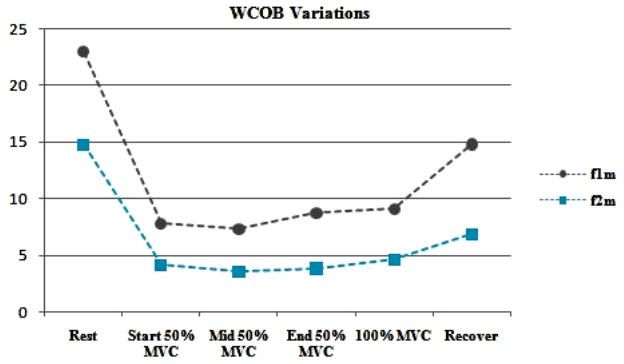

Fig. 4: Variations of f_{1m} (circle) and f_{2m} (square) during rest, fatiguing 50% MVC, 100% MVC and recovery periods.

Fig. 6 represents the results of negentropy, which is a classical method of measuring non-Gaussianity. As is evident, the negentropy has its minimum value during rest and recovery periods, meaning that the signal is more Gaussian. However, it increases dramatically during two MVC trials (50% and 100%). Considering the results reported in TABLE I, we can state that the Gaussianity increases with force level, maybe due to the recruitment of extra motor units. This means that the sEMG is highly non-Gaussian during the start point of 50% MVC. Moreover, the increase (decrease) of Gaussianity (negentropy) during this trial determines that there is a decrease in muscle contraction, indicating muscle fatigue. In another words, when fatigue occurs, the negentropy falls.

4. Discussion

The present study investigated a nonlinear analysis method, named HOSA to evaluate muscle force and fatigue. The use of nonlinear dynamical techniques was motivated by the reason that the physiological signals are nonlinear and chaotic in nature. Neglecting these properties and using inappropriate methods for analyzing such as linear and power spectral methods, may lead to false or misleading results. Thus, higher order statistical methods in time and frequency domains were used to investigate possible relations between variations of sEMG distribution as well as complexity and irregularity and isometric contraction levels and muscle fatigue.

Results obtained from weighted center of bispectrum analysis showed that this vector is sensitive to variations in muscle force and fatigue. The values of f_{1m} and f_{2m} were higher during rest and recovery states, while they decreased during MVCs. However, when fatigue occurred, these parameters increased slightly, again. In addition, the results achieved using Gaussianity test based on negentropy, showed that Gaussianity decreased during voluntary contractions (50% and 100% of MVC) compared to rest and recovery trials. However, it increased during fatigue, indicating the decrease in muscle contraction and change in motor unit recruitment. Our results were in agreement with Hussain et al. [6] achievements, whose study was on sEMG signals recorded from right rectus femoris muscle during 8-trial walk. In contrast, Nazarpour study group [7] reported that sEMG signal indicated non-Gaussian PDF during light contractions (below 30% of MVC) and it tended to a Gaussian process at higher force levels due to central limit theorem. This contradiction may be due to the positioning of the electrodes, which was investigated by Kaplanis et al. [8]. They found that higher order statistical based analysis methods are position dependant, or may be due to clinical variations (anatomical, instrumentation), which is studied by [5]. In addition, the variations in the experimental conditions and recording time, specially fatigue phenomenon can have decisive role [3]. On the other hand, NBE and NBSE features showed the reverse pattern with that of negentropy. These features showed that the complexity decreased during MVCs.

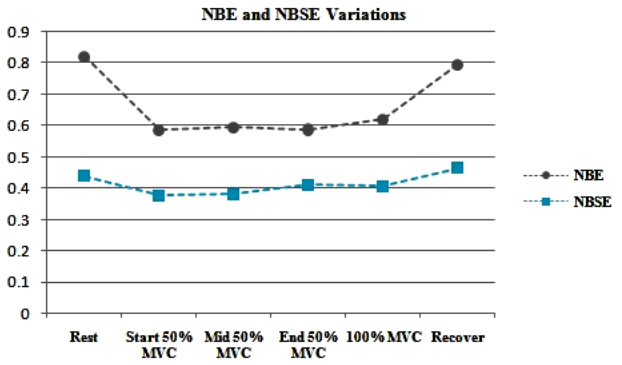

Fig. 5: Variations of NBE (circle) and NBSE (square) during rest, fatiguing 50% MVC, 100% MVC and recovery periods.

Moreover, like [7] we also used negentropy concept to measure the non-Gaussianity of sEMG signals. Because the Gaussianity test based on bicoherence index can only be used to reject the Gaussianity null hypothesis. It means that if the bispectrum index is zero, the full Gaussianity of the process may not be inferred, since fourth or even higher order cumulants and polyspectra would not be necessarily zero.

In addition to quantitative features, which were a great step forward in facilitating automatic machine learning for future studies, we also introduced potential visual aids for the diagnosis of fatigue and the level of force, which are fast and easy to use.

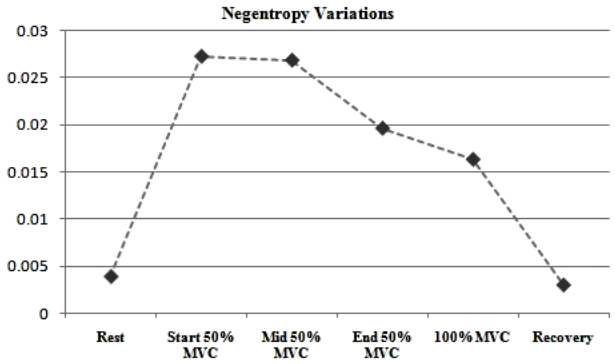

Fig. 6: Variations of negentropy during rest, fatiguing 50% MVC, 100% MVC and recovery periods.

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