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Digital Wavelet Filter for Noise Elimination on Heart Rate Variability Analysis

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Abstract: In this paper, the electrocardiograms measurement circuit boards (produced by ZhongYu Technology Company) was used to measure the signal of heartbeat by pasting electrode patches on the limbs. The heartbeat signal is sampled at 500 Hz with data acquisition card (National Instruments) and recorded in the computer. Since the signals recorded in computer would be deteriorated by noise, we prefer to utilize a digital wavelet filter to replace the General IIR digital filter for the superior noise filtering performance. For the extraction of characteristic values, the So and Chan Method is implemented to find Q wave, R wave and S wave. The interval of two R peaks could be measured and calculated to show the heart rate of human body. HRV (heart rate variability) analysis of the human body can then be performed and regarded as the reference for diagnosis of disease.

Keywords: ECG, wavelet filter, So and Chan Method, R-R Intervals, HRV

1 Introduction

As shown in Fig. 1, the HRV (heart rate variability) [1]parameters obtained by the further analysis of the ECG [2] signal is an important method to assess the autonomic nervous system. The sympathetic nervous system impels rapid heartbeat, pupils dilation , slow gastrointestinal motility, and makes muscle much more powerful to cope with emergency situations. [3] On the other hand, the parasympathetic nervous system induces slow heartbeat, pupils narrowing, rapid gastrointestinal motility, and makes muscle relax and bring the human body into relaxation state. [4] These two nervous systems depend on the physical condition of human body and cooperate in mutually antagonistic balance state. The heartbeat of a normal human is not based on a fixed heart rate in general, and can be triple times of the normal after intense exercise.

After careful measurements, it is found that the interval among heartbeats show small differences in scores within milliseconds, and even at rest state, there is a considerable degree of difference. And such differences in the heartbeat variability can be interpreted as the basis for many heart disease, and thus the analysis of heartbeat variability parameters [5] become the important diagnosis reference.

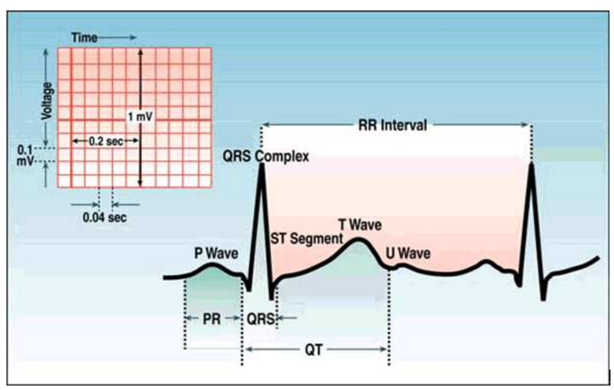

Fig. 1: ECG schematic

The automatic detection of ECG waves is important to cardiac disease diagnosis. A good performance of an automatic ECG analyzing system depends heavily upon the accurate and reliable detection of the QRS complex, as well as the T and P waves. Serval methods[6,7,8,9] to

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detect the QRS complex has been described, Wavelet transform is acknowledged as a very promising technique for timefrequency analysis. By decomposing signals into elementary building blocks that are well localized both in time and frequency, the WT can characterize the local regularity of signals [10]. This feature can be used to distinguish ECG waves from serious noise, artifacts and baseline drift.

In this paper, an algorithm based on the WT for detecting QRS complex, .P and T waves is proposed. A dyadic wavelet transform is used for extracting ECG characteristic points. The local maxima of the WT modulus at different scales can be used to locate the sharp variation points of ECG signals and help the HRV analysis.

2 Analysis of Heartbeat variability

By designing the programs to capture the heartbeat signals, ECG circuit connected to DAQ USB-6008 manufactured by National Instrument Co.. The data acquisition card as shown in Fig. 2 and Fig. 3 will convert analog signals into digital data [11] . To avoid the overflow error caused by inadequate transfer rate due to a substantial amount of data acquisition, and the RAM-Overwrite error, we will adopt FIFO to save digital datas into computers.

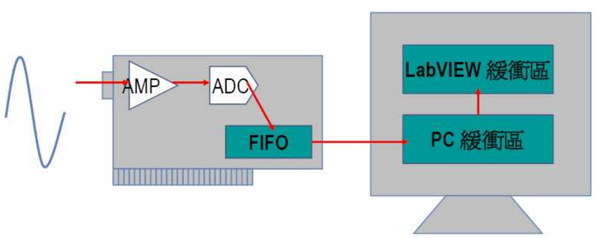

Fig. 2: Signal acquisition diagram

Fig. 3: DAQ USB-6008

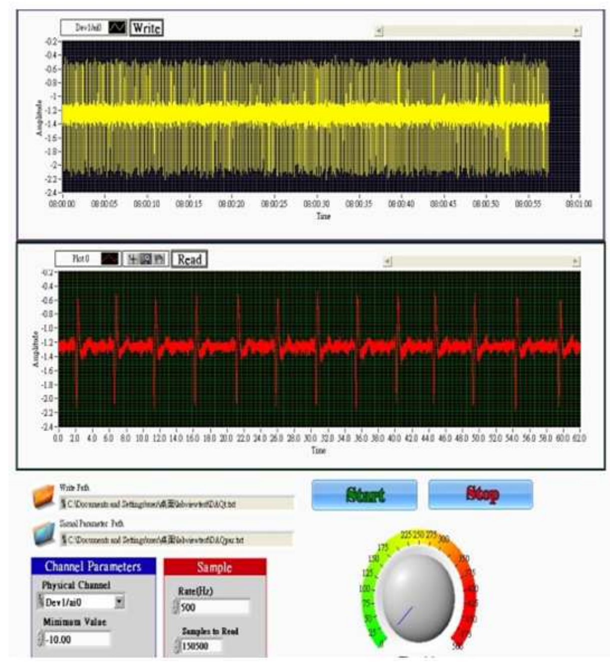

Fig. 4: Heartbeat Signal Capture Platform

According to Nyquist theorem, the sampling rate required to measure is more than twice the signal to avoid the signal distortion. Therefor, the sampling rate is set to 500Hz in this study, which is 5 to 7 times of measuring signals to accurately display a heartbeat signals. The ECG digitized data are stored in the computer and shown in Fig. 4. The program papameters such as sampling rate, data volume, data date, ete could be adjusted to acquire the appropriate datas for the further numerical processing.

2.1 Remove for baseline drift

Since the output signal of DAQ card aiways exhibits baseline drift phenomenon, the general approach will be coupled with a hardware circuitry (0.5Hz high-pass filter) to filter out direct current. However, to save hardware cost, this study is implemented with LabVIEW to solve the probleam of baseline drift.

A certain period of digitized ECG $x[n]$ divided by length from the equation (1) will obtain DC(direct current).

$$dc = \frac{\sum_{n=1}^{L} X[n]}{L} \tag{1}$$

By equation (2), the heartbeat signal $x[n]$ filtered by DC, and then normalized within $\pm 1\%$ can result in normalized signal $y[n]$. Figure. 5 shows the baseline drift before and after improvement where R is the maximun peak for ever repeat intervals.

$$y[n] = x[n] - dc \tag{2}$$

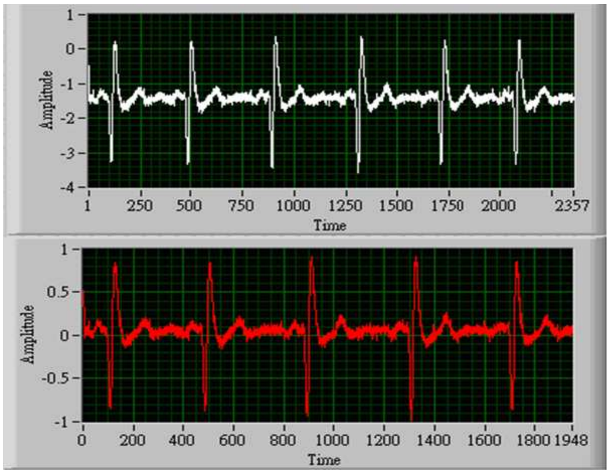

Fig. 5: ECG signal (upper picture) and after base_line removed (lower picture)

2.2 The wavelet filter and IIR filter

Even if the hardware circuitry is used to filter out unwanted noises, filters can only do a certain degree of filtering. If one want to effectively filter noises, the filter needs to be improved to the higher degree, and will increase the hardware cost. Therefore, this study used digital filters to effectively solve noises, and thus reduce hardware costs. In recent years, the wavelet transform [12] is often used in signal decomposition since the wavelet decomposition, a powerful signal analysis tool, is very suitable for noise detections. For any function $f(x)$, its continuous wavelet transform is defined as:

$$w(a,b) = \int_{-\infty}^{\infty} f(t) a^{-}\frac{1}{2} \psi(\frac{x-b}{a}) dt \tag{3}$$

where $\Psi(x)$ is the mother wavelet. And this function can be reconstructed by inver-transform:

$$f(t) = \frac{1}{C_\psi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} w(a,b) a^{-\frac{1}{2}} \psi(\frac{x-b}{a}) \frac{dtda}{a^2} \tag{4}$$

where a and b are referred to as parameters of expansion and contraction, and translation, respectively. Because of the acquired data signals are composed of discrete datas, a discrete wavelet transform is required to analyze these discrete signals. The common method is used to make a and b as $a = a_0^{-m}, b = nb_0 a_0^{-m}$, respectively. The inver-continuous discrete wavelet is transformed into:

$$f(t) = \sum_m \sum_n w_{m,n} \psi_{m,n}(t) \tag{5}$$

In Discrete wavelet transformation, low-resolution coefficients can be calculated by higher-resolution coefficients through a tree structure of the filter bank. [13] Since this method is very efficient, wavelet transform is then widely applied in the digital signal processng. The relationship between the higher and lower wavelet decompositions can be deduced from the most basic wavelet function (6). Assumed that it exists a solution, we will scale and translate the time variable to obtain Equation (7), and then substitute $m = 2k + n$ into Equation (7) to obtain Equation (8).

$$\varphi(t) = \sum_n h(n) \sqrt{2} \varphi(2t - n) \tag{6}$$

$$\varphi(2^j - k) = \sum_n h(n) \sqrt{2} \varphi(2(2^j t - k - n) = \sum_h (n) \sqrt{2} \psi(2^{j+1} t - 2k - n) \tag{7}$$

$$\varphi(2^j - k) = \sum_n h(m - 2k) \sqrt{2} \psi(2(2^{j+1} t - m) \tag{8}$$

If

$$V_j = Span_k \left\{ 2^{\frac{j}{2}} \varphi(2^j t - k) \right\} \tag{9}$$

Then $f(t) \in V_j + 1$, and

$$f(t) = \sum_k c_{j+1}(k) 2^{\frac{(j+1)}{2}} \varphi(2^{j+1} t - k) \tag{10}$$

In the lower scale of resolution, we can re-express it as wavelets

$$f(t) = \sum_k c_j(k) 2^{\frac{j}{2}} \varphi(2^j - k) + \sum_k d_j(k) 2^{\frac{j}{2}} \psi(2^j - k) \tag{11}$$

If $\Psi_{j,k}(t)$ and $\varphi_{j,k}(t)$ are orthogonal, the decomposition coefficients can be derived from the inner product, such as Equation (12). Applying equation (9) into equation (12), thus equation (13) can be derived by swapping the arithmetic operation of summation and integration.

$$c_j(k) = \{f(t), \varphi_j, k(t)\} = \int f(t) 2^{\frac{j}{2}} \varphi(2^j t - k) dt \tag{12}$$

$$c_j(k) = \sum_m h(m - 2k) \int f(t) 2^{\frac{j+1}{2}} \varphi(2^{j+1} t - m) dt \tag{13}$$

Referring to Equation (12), Equation (13) can be obtained as

$$c_j(k) = \sum_m h_0(m-2k)c_{j+1}(m) \quad (14)$$

Similarly the availability of the relation of wavelet coefficients can be obtained such as Equation (15).

$$d_j(k) = \sum_m h_1(m-2k)c_{j+1}(m) \quad (15)$$

If $h_0(-n)$ and $h_1(-n)$ are regarded as the filter coefficients, the lower scale coefficient could be obtained by downSampling convolution results of higher scale coefficient and filter coefficient. By repeat these steps, it will form a group structure of wavelet filters.

Because there are two filters incorporate in the computation process, the numerical data of the input signal is double. However sub-sampling computation will return the numerical data to the original number. That means it is possible to completely re-obtain the original signal without any data loss in this perfect reconstruction for the filter group. [14, 15]

For Equation (10), $f(t)$ is in the signal space of $j+1$ scale, which can be decompose in the signal space of j scale and expressed as

$$\begin{aligned} f(t) &= \sum_k c_j(k)2^{\frac{j}{2}}\varphi(2^j t-k) \\ &+ \sum_k d_j(k)2^{\frac{j}{2}}\psi(2^j t-k) \end{aligned} \quad (16)$$

Substituting Equation (6) into Equation(16), we will obtain Equation(17)

$$\begin{aligned} f(t) &= \sum_k c_j(k)\sum_n h(n)2^{\frac{j+1}{2}}\varphi(2^{j+1}t-2k-n) \\ &+ \sum_k d_j(k)\sum_n h_1(n)2^{\frac{j+1}{2}}\psi(2^{j+1}t-2k-n) \end{aligned} \quad (17)$$

Because all of the base functions are orthonormalized, the Equation (10) and Equation (17) multiplied by $\varphi(2^{j+1}t-k')$ are computed to solve the $c_{j+1}(k)$ as in Equation (18).

$$c_{j+1}(k) = \sum_m c_j(m)h(k-2m) + \sum_m d_j(m)h_1(k-2m) \quad (18)$$

After the signal is proceed by the wavelet algoritm, the signal will be re-building by up-sampling (stretching) method. The up-sampling means inserting a zero value in intervals of the signal so that the length of signal are doubled, and then synthesized to re-build it. Based on the above description, a first-order wavelets are proposed as Figure. 6.

The cell function in the high-order scale would be considered as a impulse function. And, the inner product to decompose the wavelet coefficients is considered just as the sampling work as well. If the sampling frequency is greater than twice the acquired signal (Nyquist Rate) [16], this high-enough sampling points are similar to good Scaling coefficients in wavelet function. This is one of the reasons that wavelet filter is an effective one to perform noise elimination for signal processing.

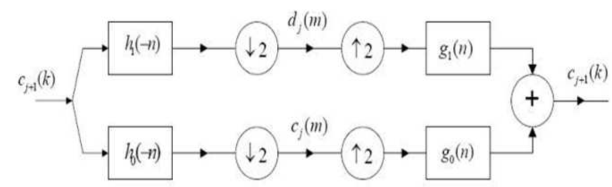

Fig. 6: first-order wavelets filter composed of decompose and synthesis procedure

From the wavelet theory, one can design a wide range of different characteristics of wavelet filters to be suitable for a variety of signals. A quadrature filter must satisfy the following four equations:

$$\sum_n h_0(n) = \sqrt{2} \quad n = 1,\ldots,N \quad (19)$$

$$\sum_n h_1(n) = 0 \quad n = 1,\ldots,N \quad (20)$$

$$h_1(n) = (-1)^n h_0(1-n) \quad n = 1,\ldots,N \quad (21)$$

$$g_0 = h_0, g_1 = h_1 \quad (22)$$

This study used both the traditional IIR low-pass filter and db08-wavelet filter for signal processing, and compare with each other. In Figure. 7, the ECG is shown in the upper diagram at sampling frequency of 500Hz. The middle diagram is the results by using wavelet (db08) filters, and the bottom diagram is the results by using IIR low-pass filters. It is obvious that noise filtering by low-pass filters is limited, and some of R-wave signals in the ECG signal are removed. Wavelets can more effectively eliminate noises and also retain such steep R-wave signals completely.

2.3 So and Chan Method

The algorithm of So and Chan Method [17, 18] is used in this study, and which is based on the slope calculation of signal in time domain. Therefore R-wave peak is accurately positioned to calculate the R-R interval without any signal distortion.

Amplitude is expressed as ECG signal in discrete time n , and the slope of the ECG signal is generated by equation(23), whose threshold value is set according to quation (24). The maximum slope of EGC is taken from

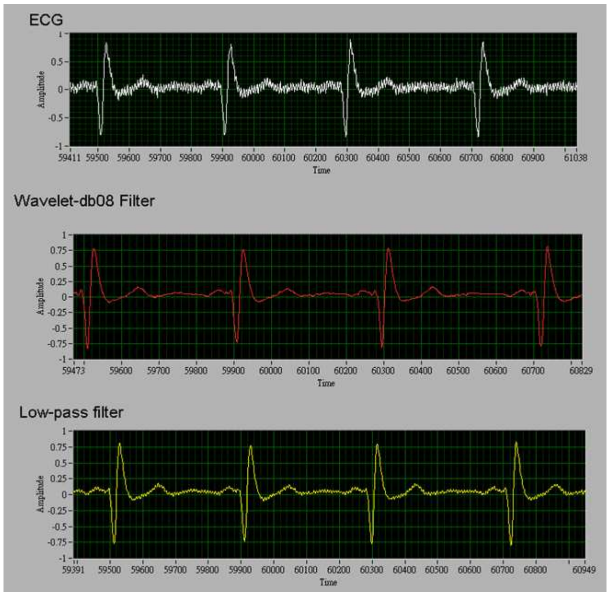

Fig. 7: Comparison of IIR filter and wavelet filter

the previous 260 data as the initial value of $first_{max}i$. If there are two EGC signals whose slopes are greater than the threshold value($slope\_threshold$), then the point located on these ECG signals shall be the starting points of QRS complex waves. However the values taken by $threshold\_parameter$ can be 2,4,8 or 16, and the values taken by parameter can also be 2,4,8 or 16. From test results, the most effective values obtained either by $threshold\_parameter$ or parameter are in the 8 or 16. When the starting position of the QRS complex wave is found, we can shift to next based on the starting point to find the maximum of the QRS complex wave, namely, the R-wave peak. And then based on R-wave as a reference point, the minimum value obtained by shifting forward or backward shall be the Q wave and S wave. Figure. 8 shows the case achieved with LabVIEW.

$$slope(n) = -2x(n-2)x(n-1) + x(n+1) + 2x(n+2) \tag{23}$$

$$slope\_threshold = \frac{treshold\_parameter}{16} \times maxi \tag{24}$$

$$maxi = \frac{first\_maxi - maxi}{parameter} + maxi \tag{25}$$

$$\begin{aligned} first\_maxi = &\ Heigh \quad of \quad R \quad point \\ & -height \quad of \quad QRS \quad onset \end{aligned} \tag{26}$$

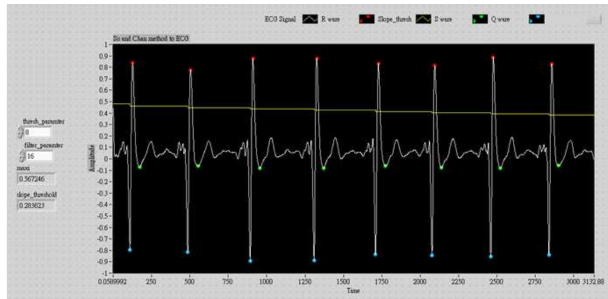

Fig. 8: Results of So and Chan Method

2.4 HRV analysis

The Common methods for calculating heart rate variability are two major categories: one is time-domain statistical analysis, and the other is based on frequency domain spectral analysis.[19]

The main calculation of the ECG signal of finite length in time-domain includes all of the R-R Intervals changes. In Figure. 9, the signals captured in some period can be used to determine the R wave for every heartbeat by the signal processing method, and thus the ECG signal is converted into R-R intervals diagram.

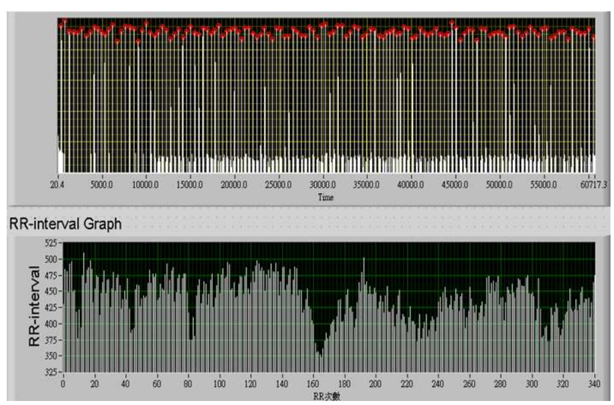

Fig. 9: R-R Intervals Diagram

After obtaining R-R Intervals, one can analyze the different heart rate variability by the different statistical method. With regard to R-R Intervals, the time-domain analysis methods are as follows:

2.4.1 Mean R-R

According to the calculated average of all R-R Intervals, one can judge if the person receiving the test is stable. The MeanRR calculation formula is:

$$MeanRR = \frac{\sum_{i=1}^{n} R_i}{n} \tag{27}$$

2.4.2 SDNN (Std R-R)

This parameter is the standard deviation of R-R intervals. In some literatures, R-R intervals will be referred to as N-N Intervals, so-called SDNN. The calculation formula is:

$$SD = \sqrt{\frac{\sum_{i=1}^{n} (R_i - mean)^2}{n}} \tag{28}$$

2.4.3 CV(coefficient of variation)

CV means the percentage of SDNN and the Mean, as expressed in the following:

$$CV = \frac{SD}{Mean} \times 100\% \tag{29}$$

2.4.4 Rms SD

This parameter is the root mean square of SDNN. The calculation formula is:

$$rmsSD = \sqrt{\frac{\sum_{i=1}^{n-1} (R_i - R_{i+1})^2}{n-1}} \tag{30}$$

The spectral analysis is the energy spectrum distribution corresponding to all R-R intervals by using fast Fourier Transform (FFT). The most widely used power spectral analysis method can be divided into two major categories: parametric method and non-parametric method. This study applies the non-parametric method, the fast Fourier transform to perform short signal analysis.

In the R-R Intervals shown in the frequency spectrum does not represent the true value of heart rate under the spectral analysis structure. Therefore the general practice will increase the frequency of a unilateral spectrum, and re-allocate the spectrum frequencies between 0.0 0.5Hz.

In accordance with reference of HRV Gold Standard [20], short-term signal analysis, in general 3 10 minutes, can be divided into three spectrum blocks as shown in Table (1). Calculating the power in this three regions, one can get the heartbeat activities for the current physical condition. The summation of power under the spectrum area shall be the total power, referred as TP.

The parameters used for the analysis of heart rate variability in this study include: frequency-domain of the LF power, LF/HF ratio, total energy (TP). The time-domain mean is MeanRR, the standard deviation is StdRR, and every beats per minute (BMP) is shown in Figure. 10

Table 1: Fequency Spectrum of HRV

Very low frequency (VLF)	0.00 0.04 Hz
Low frequency (LF)	0.04 0.15 Hz
High frequency (HF)	0.15 0.40 Hz

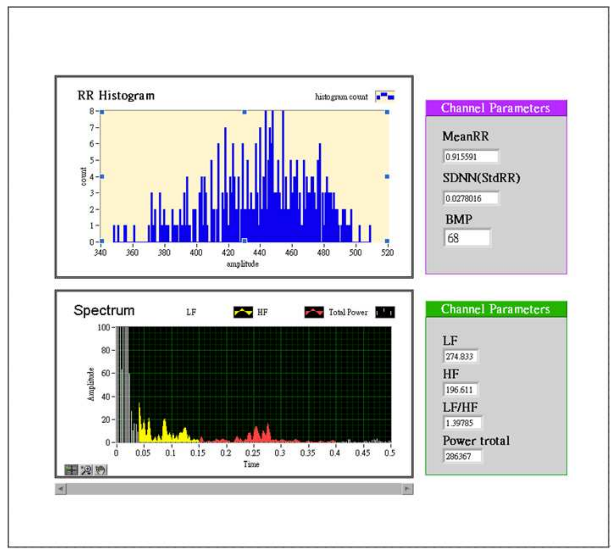

Fig. 10: Results of HRV analysis

3 Conclusions

In this study , wavelet filter is used successfully to replace traditional IIR filters. The performance of Wavelet filter is much better than the traditional one and help the complex analysis for QRS. Instead of the traditional fixed threshold method, So and Chan Method is implemented as a dynamic threshold to set the threshold value of the signal to improve the effectiveness for the QRS characterization. The interactive applications on HRV analysis between time domain and frequency domain seems to provide effective reference for heart diseases diagnosis. The approach we propose to process a biomedical signal could facilitate the further researches in the relevant field.

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