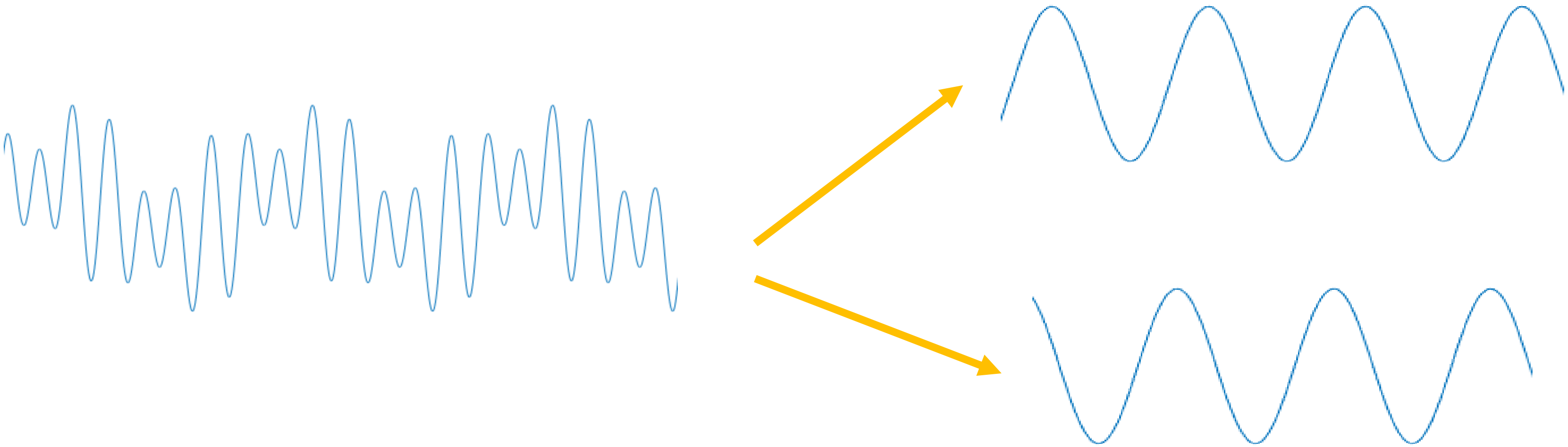
UNIVERSIDAD PERUANA
CAYETANO HEREDIA

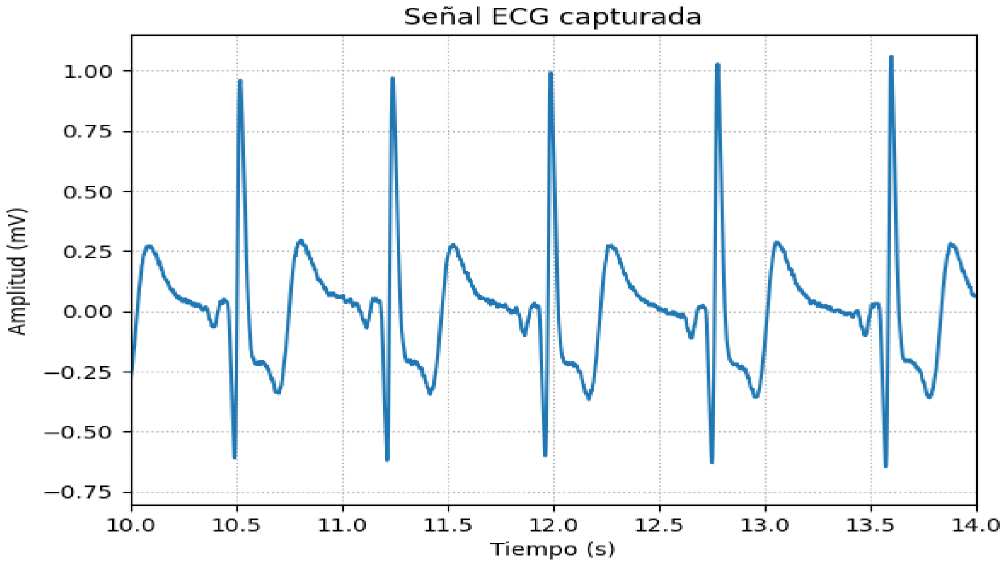
Transformada Wavelet

M.Sc. Lewis De La Cruz; M.Sc. Moises Meza; Ing. Julissa Venancio; Lic. Alonso Cáceres

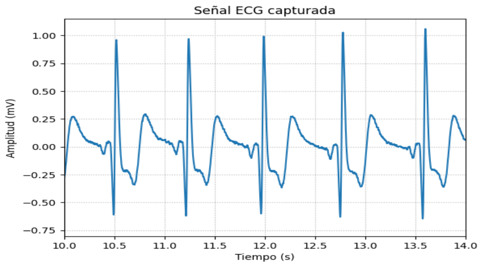
Series de Fourier

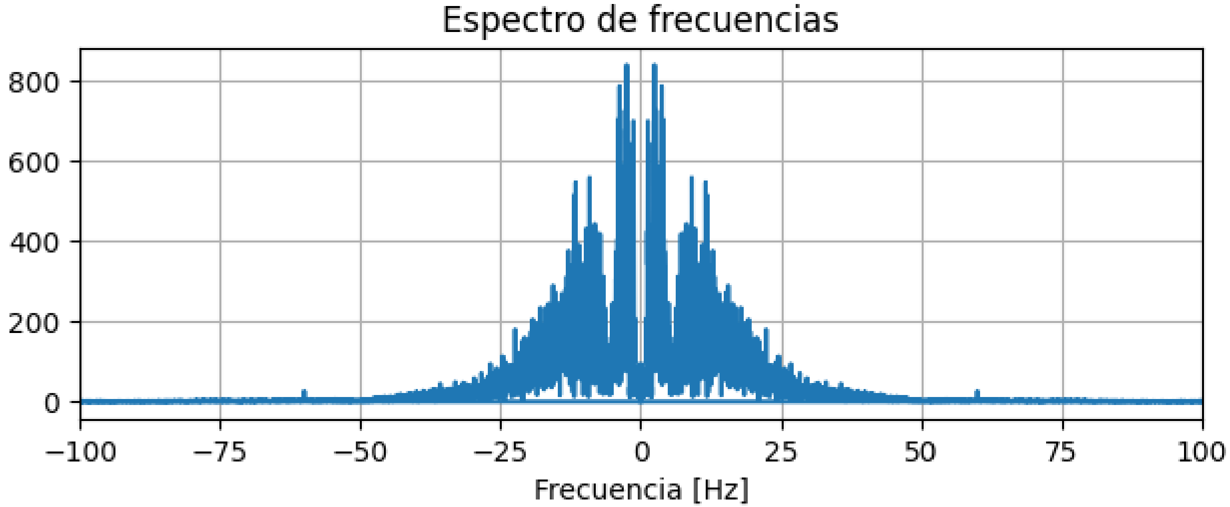


Series de Fourier

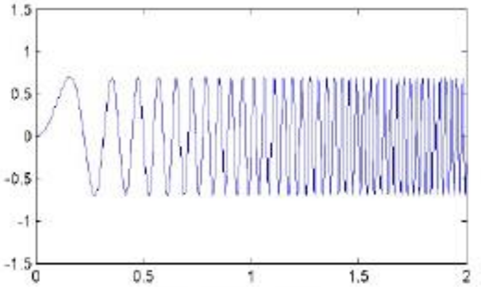


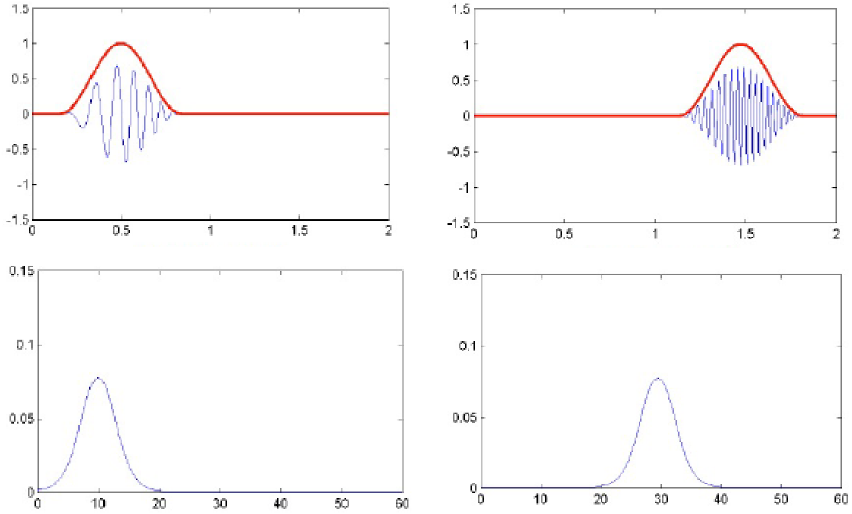
Transformada de Fourier Discreta



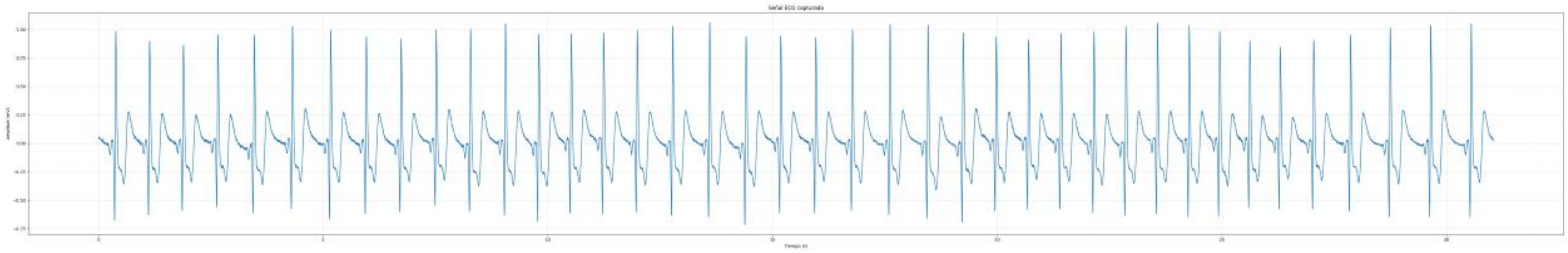


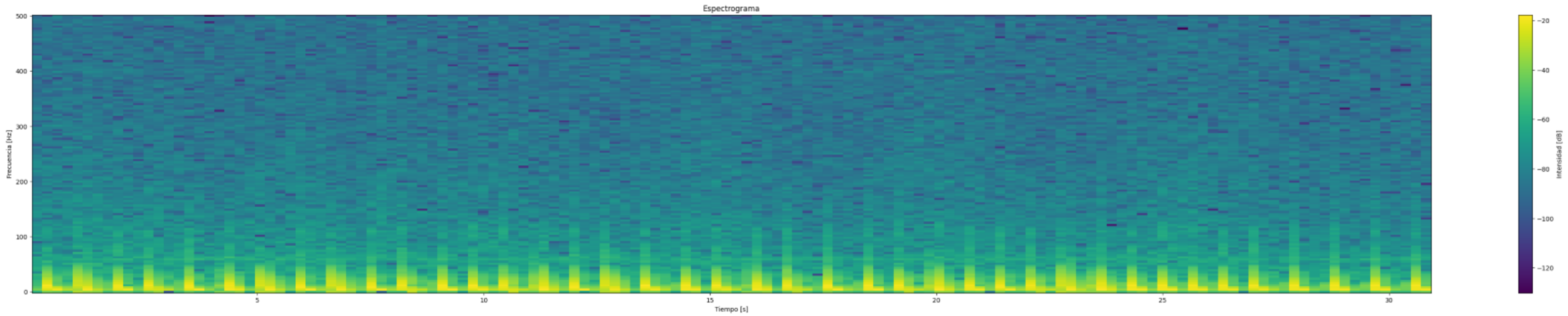
Transformada de Fourier de Tiempo Corto



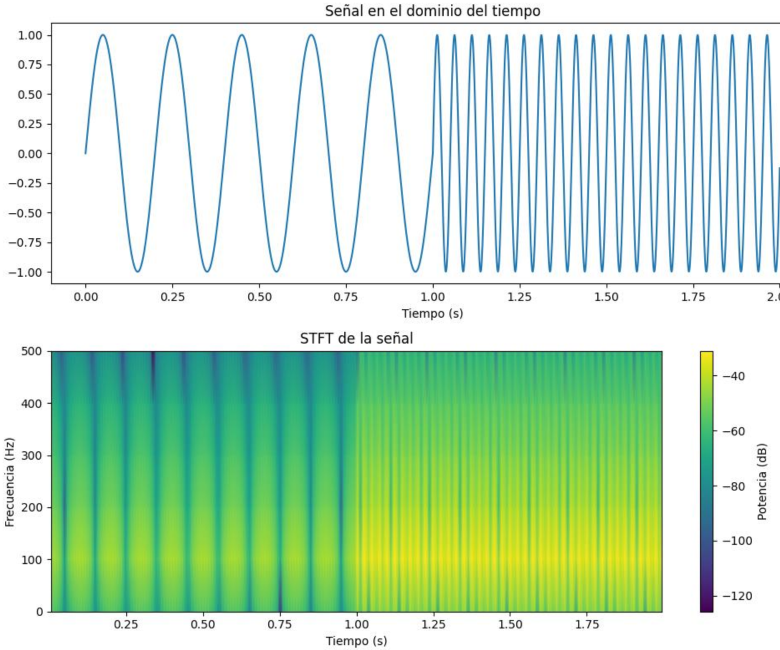


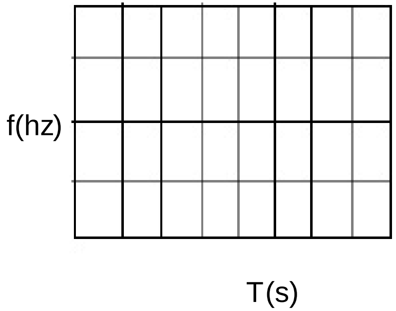
Transformada de Fourier de Tiempo Corto





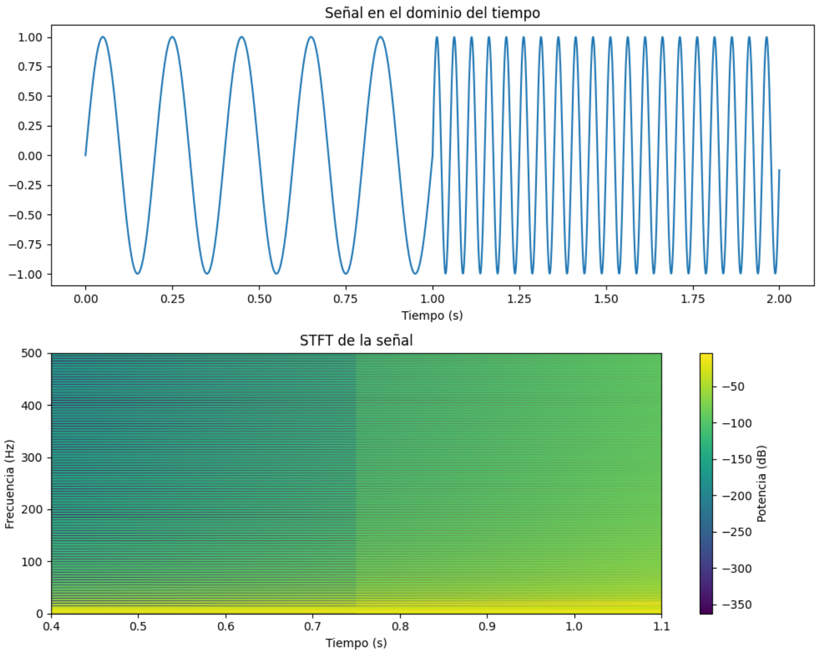
Transformada de Fourier de Tiempo Corto

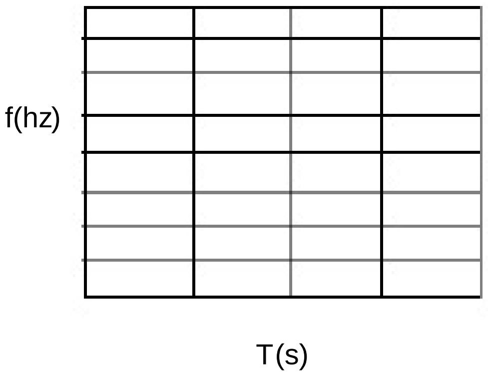




- Ventana pequeña: pobre localización en frecuencia y buena localización en tiempo.

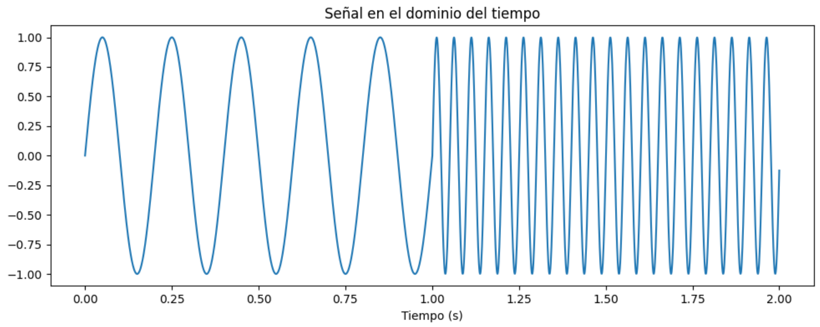
Transformada de Fourier de Tiempo Corto

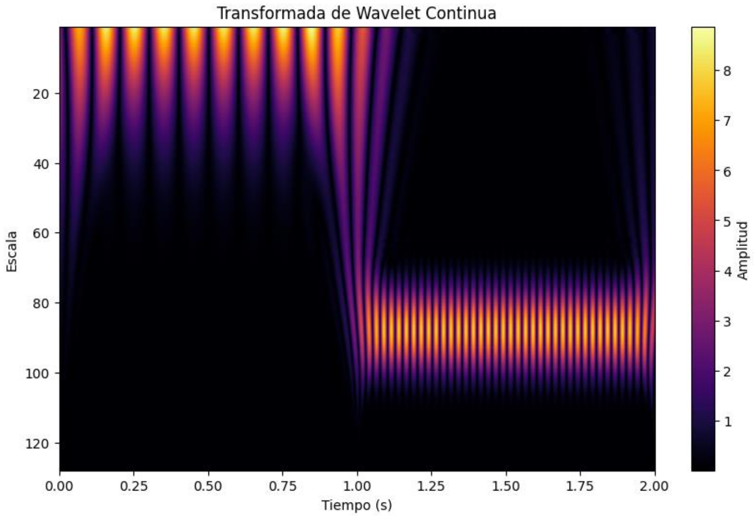


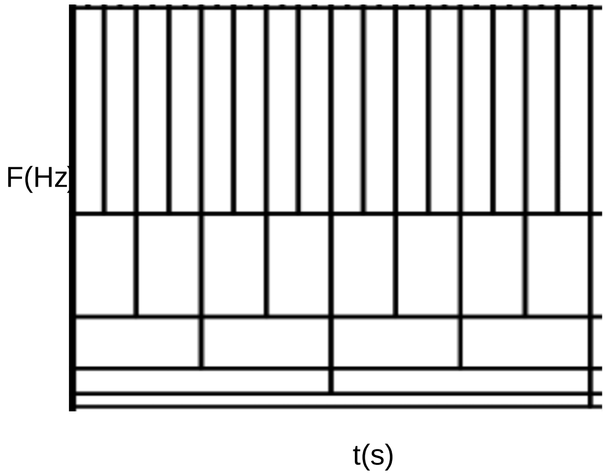


- Ventana grande: pobre localización en tiempo y buena localización en frecuencia.

Transformada Wavelet







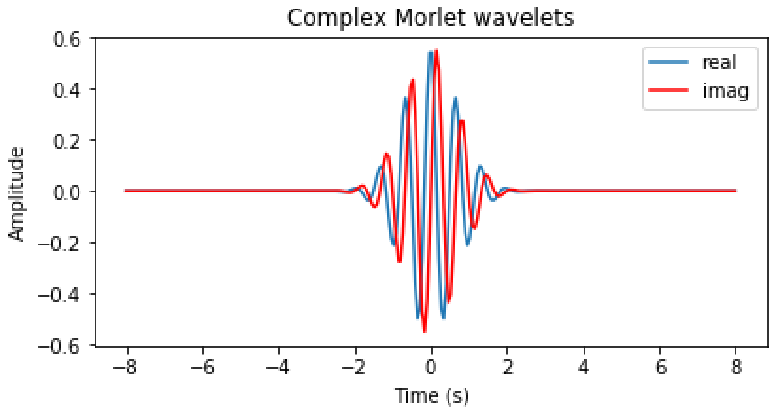
Wavelet

Función con soporte corto en tiempo y frecuencia.
Promedio cero, normalización=1, centrada en t=0.

$$\int_{-\infty}^{\infty} \psi(t)d(t) = 0$$

Contenga M momentos de desvanecimiento para ignorar ciertas tendencias polinomiales, y ser sensitivo a altos grados de oscilaciones

$$\int_{-\infty}^{\infty} t^{l}\psi(t)d(t) = 0, l = 0,1,2,..M - 1$$



Existen varias familias de wavelets y son escogidas de acuerdo a la aplicación y propiedades matemáticas.

Fuente https://github.com/alsauve/scaleogram/blob/master/doc/scale-to-frequency.ipynb

Transformada continua de Wavelet

Correlación de una señal f(t) con una Wavelet madre (ψ) que es escalada y trasladada.

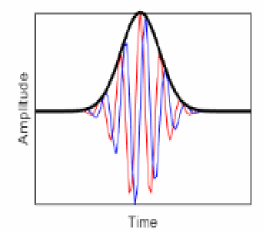
$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\, \psi\left(\frac{t-u}{s}\right)$$

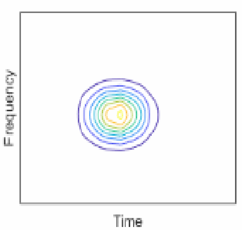
$$W_{u,s} = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{s}}\, \psi^{*}\left(\frac{t-u}{s}\right) dt$$ Análisis

$$f(t) = \frac{1}{C_{\psi}} \int_{0}^{s0} W(\,,s) * \psi_{s}(t) \frac{ds}{s^{2}} + \frac{1}{C_{\psi,s_0}} L(,\, s_0) * \varphi_{s_0} dt$$ Síntesis

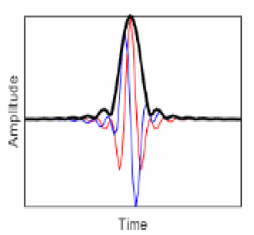
Familia de Wavelet

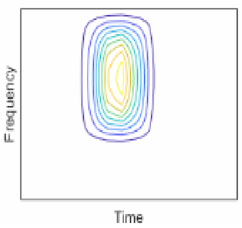
Análisis del Tiempo y Frecuencia





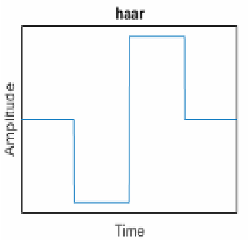
Morlet Wavelet

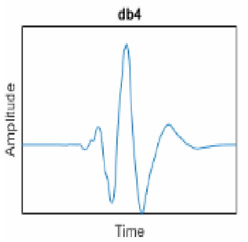


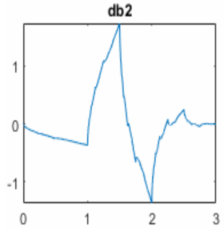


Bump Wavelet

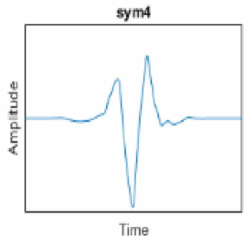
Detección de bordes, features



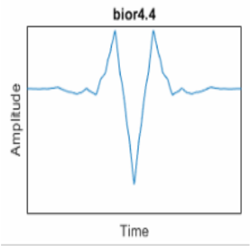




Denoising

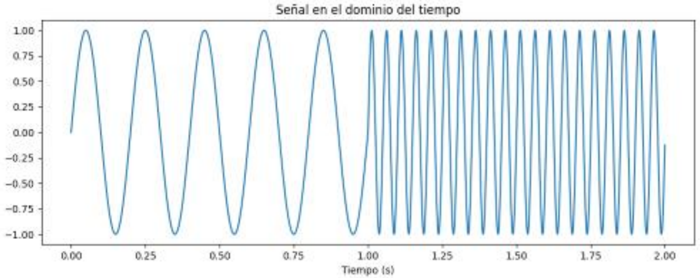


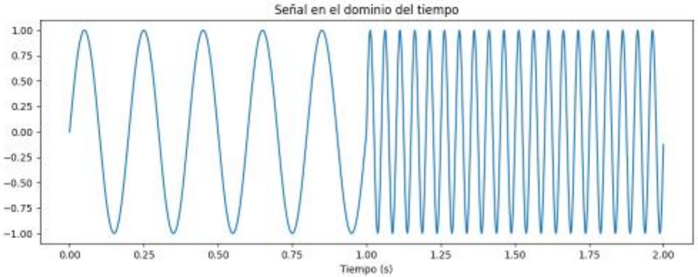
Compresión

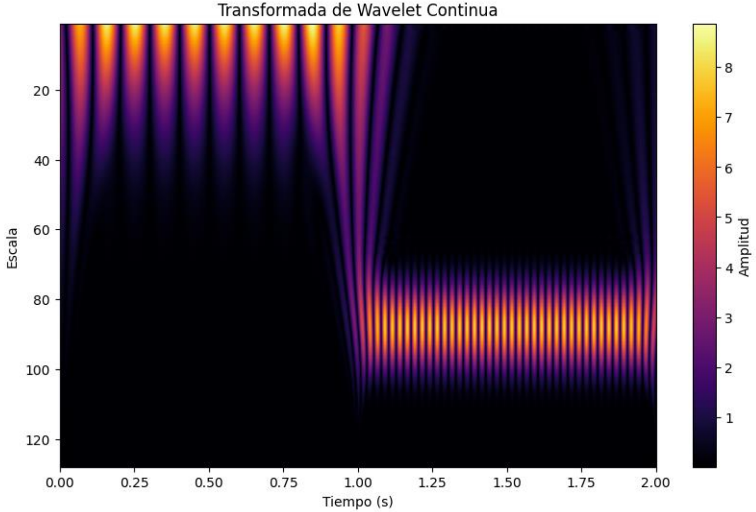


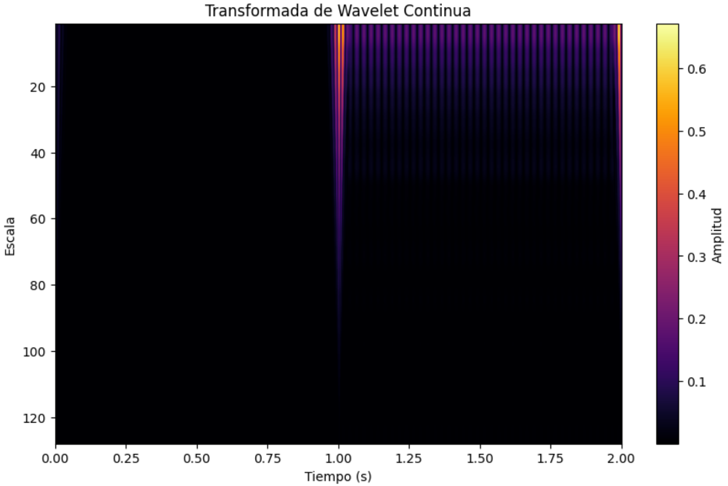
Fuente: https://www.mathworks.com/help/wavelet/gs/choose-a-wavelet.html

Transformada Wavelet









Transformada discreta de Wavelet

Análisis

$$c_{jk} = \langle x(n) | \varphi(n) \rangle$$ Coeficientes de Escala

$$d_{jk} = \langle x(n) | \psi(n) \rangle$$ Coeficientes de Wavelet

Síntesis

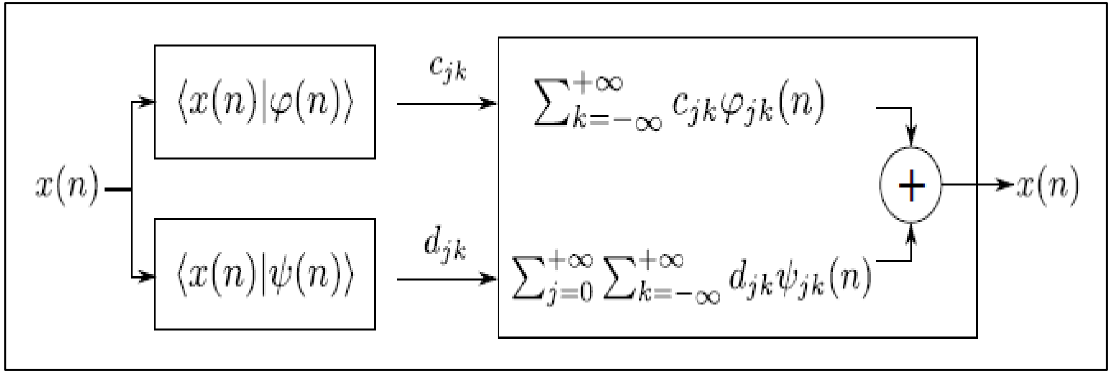
$$x(n) = \sum_{k=-\infty}^{+\infty} c_{jk}\varphi_{jk}(n) + \sum_{j=0}^{+\infty}\sum_{k=-\infty}^{+\infty} d_{jk}\psi_{jk}(n),$$

Función de Wavelet

$$\varphi_{jk}(t) = 2^{j/2}\varphi(2^j t - k) \quad \text{con } j, k \in Z$$

Función de Escala

$$\psi_{jk}(t) = 2^{j/2}\psi(2^j t - k) \quad \text{con } j, k \in Z$$

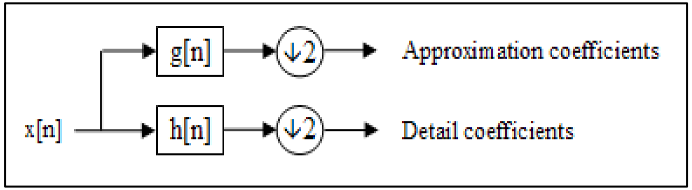


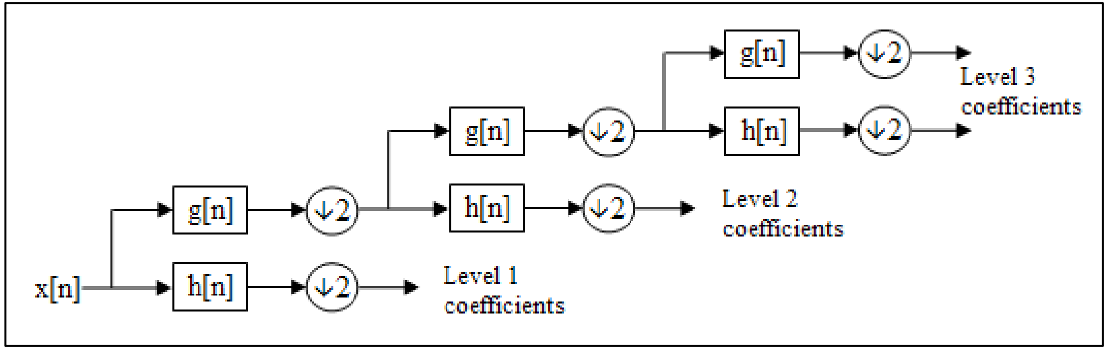
Función de Análisis y Síntesis

Transformada discreta de Wavelet

Si las funciones de wavelet forman unas bases ortonormales, se puede utilizar el concepto de análisis de multiresolución(MRA) y para su implementación se utiliza bancos de filtros que cumplen con los conceptos de Qadrature Mirror Filters y Perfect Reconstruction.

La señal es filtrada recursivamente con filtros pasa bajos, pasa altos y etapas de submuestreo.





https://en.wikipedia.org/wiki/Discrete_wavelet_transform

Transformada discreta de Wavelet

Home › Journal of VLSI signal processing systems for signal, image and video technology › Article

Published: 01 November 1996

Architectures for wavelet transforms: A survey

Chaitali Chakrabarti, Mohan Vishwanath & Robert M. Owens

Journal of VLSI signal processing systems for signal, image and video technology **14**, 171–192 (1996) | Cite this article

https://doi.org/10.1007/BF00925498

Transformada discreta de Wavelet

3. Architectures for the 1-D Discrete Wavelet Transform

3.1. Introduction

The 1-D Discrete Wavelet Transform can be implemented by the Pyramid Algorithm (PA) developed by Mallat [6, 10]. This algorithm can be represented as follows

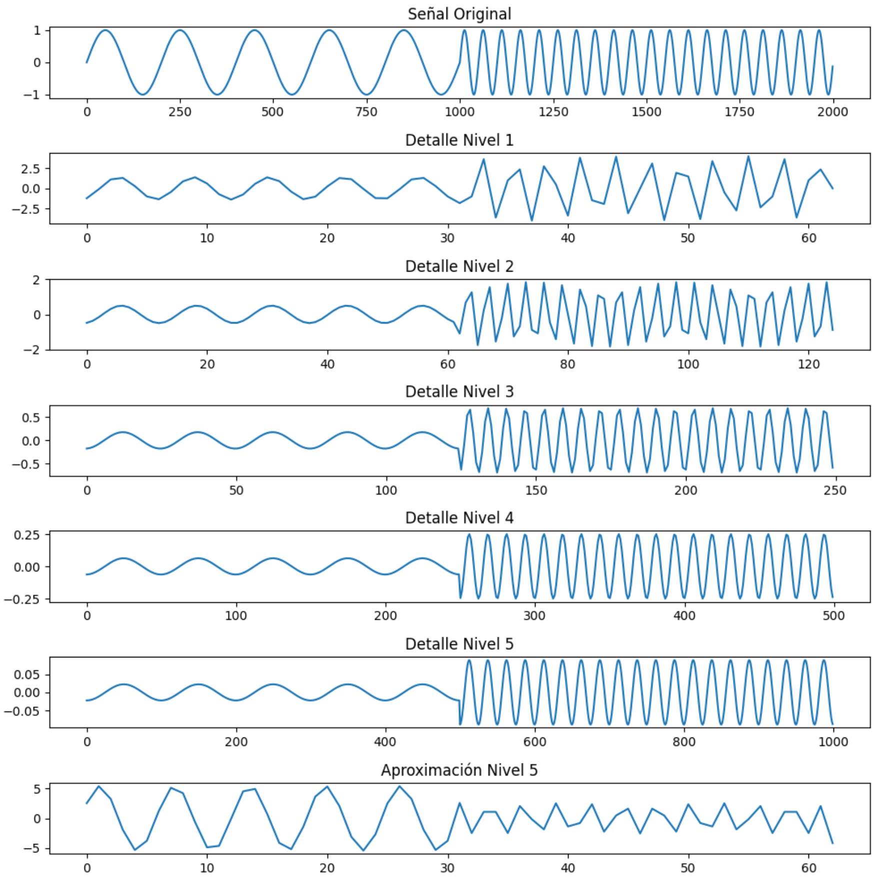
```
begin{Direct Pyramid Algorithm}
  for(j=1 to J)
    for(n=1 to 2^(J-j))
      X[j,n] = Σ_{m=0}^{K-1} X[j-1, 2n-m]w[m]
                                        Low Pass
      Y[j,n] = Σ_{m=0}^{K-1} X[j-1, 2n-m]h[m]
                                        High Pass
end{Direct Pyramid Algorithm}
```

$$X[j,n] = \sum_{m=0}^{K-1} X[j-1, 2n-m]w[m] \quad \text{Low Pass}$$

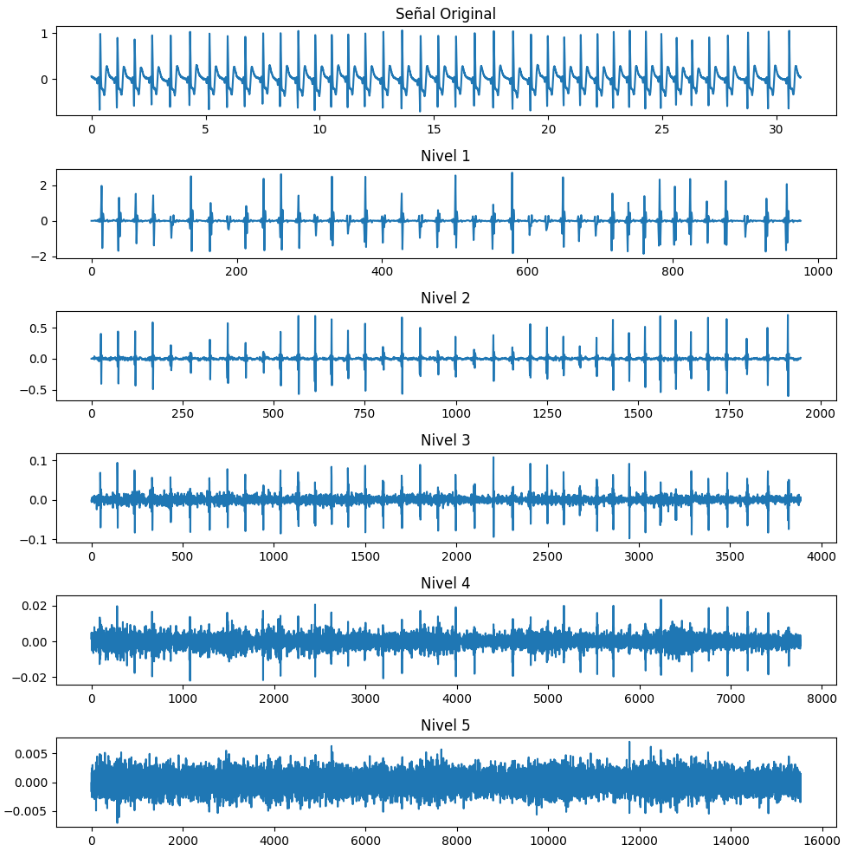
$$Y[j,n] = \sum_{m=0}^{K-1} X[j-1, 2n-m]h[m] \quad \text{High Pass}$$

https://doi.org/10.1007/BF00925498

Transformada Wavelet Discreta



Transformada Wavelet Discreta



¿Cuál es la mejor Wavelet?

Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 132 (2018) 11–21

Procedia Computer Science

www.elsevier.com/locate/procedia

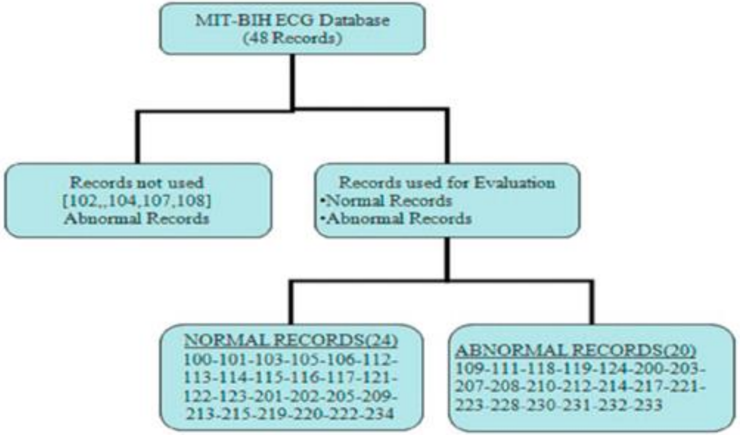
International Conference on Computational Intelligence and Data Science (ICCIDS 2018)

Efficient wavelet families for ECG classification using neural classifiers

Ritu Singh[a,*], Rajesh Mehta[b], Navin Rajpal[a]

[a] USICT,Guru Gobind Singh Indraprastha University,Dwarka, New-Delhi, India
[b] Thapar Institute of Engineering and Technology, Patiala , Punjab, India

https://doi.org/10.1016/j.procs.2018.05.054



Feature Set of each record of patient

Statistical Wavelet Coefficient Based Features

- Average Power
- Standard Deviation
- Variance
- Ratio of the absolute mean value taken from adjacent sub band

(Values of above mentioned parameters are of Detail and Approximate Coefficients in each sub band of 8 level of decomposition)

Morphological Features

Temporal Features

- RR Interval
- PR Interval
- ST Interval
- QT Interval
- QRS Interval
- PR Segment
- ST Segment

Heart Beat Features

- Maximum value of Peaks (Q,R,S,T)
- Number of Peak counts (P,Q,R,S)

Technique / Wavelet	Order	BPN		FNN		RBFNN	
		Acc (%)	T(s)	Acc (%)	T(s)	Acc (%)	T(s)
Daubechie	**db2**	**95.5**	**1.052**	**100**	**3.485**	**100**	**0.798**
	db4	**95.5**	**0.991**	**97.7**	**3.453**	**100**	**0.734**
	db6	95.5	1.039	88.6	2.739	100	0.788
	db8	95.5	1.058	93.2	2.725	100	0.761
Symlet	sym2	95.5	1.002	100	3.186	100	0.771
	sym4	**95.5**	**1.020**	**100**	**2.695**	**100**	**0.782**
	sym6	95.5	1.003	100	3.211	100	0.801
	sym8	90.9	1.023	95.5	2.691	100	0.805
Bior	bior1.5	95.5	1.075	95.5	2.753	100	0.790
	bior2.6	95.5	0.963	95.5	2.218	100	0.729
	bior4.4	**95.5**	**1.001**	**100**	**3.213**	**100**	**0.702**
	bior5.5	95.5	0.959	100	3.224	100	0.724
Rbio	rbio1.5	95.5	1.010	95.5	3.196	100	0.738
	rbio2.6	95.5	0.982	95.5	3.251	100	0.754
	rbio4.4	95.5	0.960	95.5	3.520	100	0.772
	rbio5.5	**95.5**	**0.908**	**97.7**	**3.221**	**100**	**0.712**
Coif	coif2	93.2	0.931	95.5	2.627	100	0.700

Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis

Oliver Faust [1], U Rajendra Acharya [2], Hojjat Adeli [3], Amir Adeli [4]

Affiliations + expand

PMID: 25799903 DOI: 10.1016/j.seizure.2015.01.012

Free article

Abstract

Electroencephalography (EEG) is an important tool for studying the human brain activity and epileptic processes in particular. EEG signals provide important information about epileptogenic networks that must be analyzed and understood before the initiation of therapeutic procedures. Very small variations in EEG signals depict a definite type of brain abnormality. The challenge is to design and develop signal processing algorithms which extract this subtle information and use it for diagnosis, monitoring and treatment of patients with epilepsy. This paper presents a review of wavelet techniques for computer-aided seizure detection and epilepsy diagnosis with an emphasis on research reported during the past decade. A multiparadigm approach based on the integration of wavelets, nonlinear dynamics and chaos theory, and neural networks advanced by Adeli and associates is the most effective method for automated EEG-based diagnosis of epilepsy.

https://doi.org/10.1016/j.seizure.2015.01.012

Conferences > 2023 IEEE XXX International C...

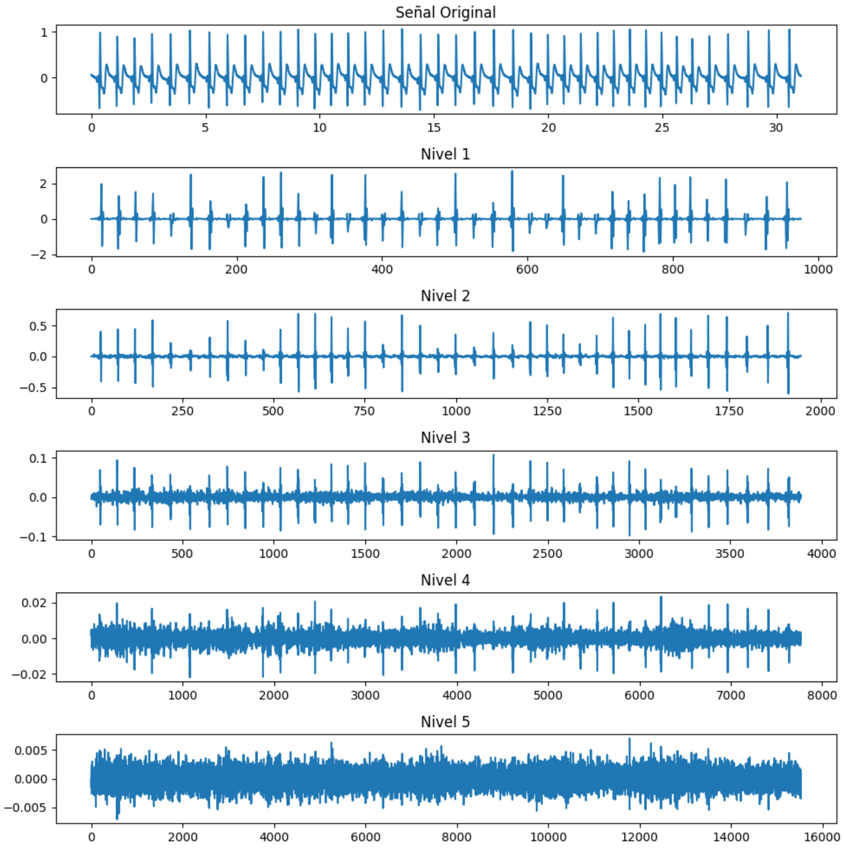
Development of an electrocardiographic signal classifier for bundle branch blocks, applying Tiny Machine Learning

Publisher: IEEE Cite This PDF

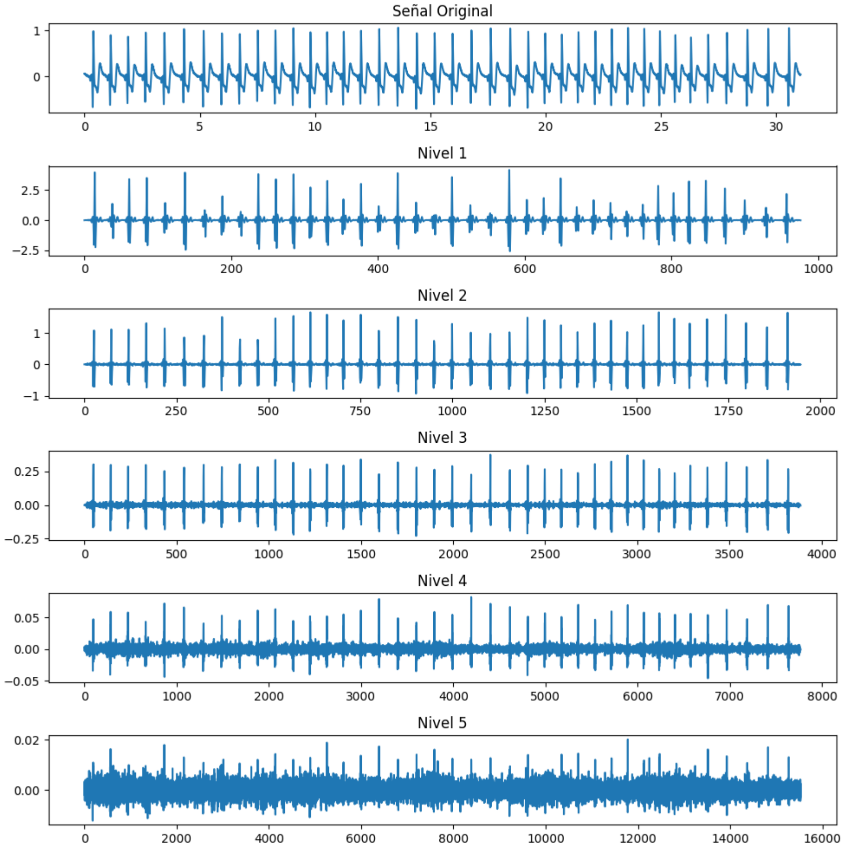
Moises Meza-Rodriguez ; Lewis De La Cruz ; José Alonso Cáceres-DelAguila **All Authors**

Transformada Wavelet Discreta

db4



rbio3.3



> Comput Math Methods Med. 2020 Oct 9;2020:3215681. doi: 10.1155/2020/3215681. eCollection 2020.

Wavelet Scattering Transform for ECG Beat Classification

Zhishuai Liu [1], Guihua Yao [2], Qing Zhang [2], Junpu Zhang [1], Xueying Zeng [1]

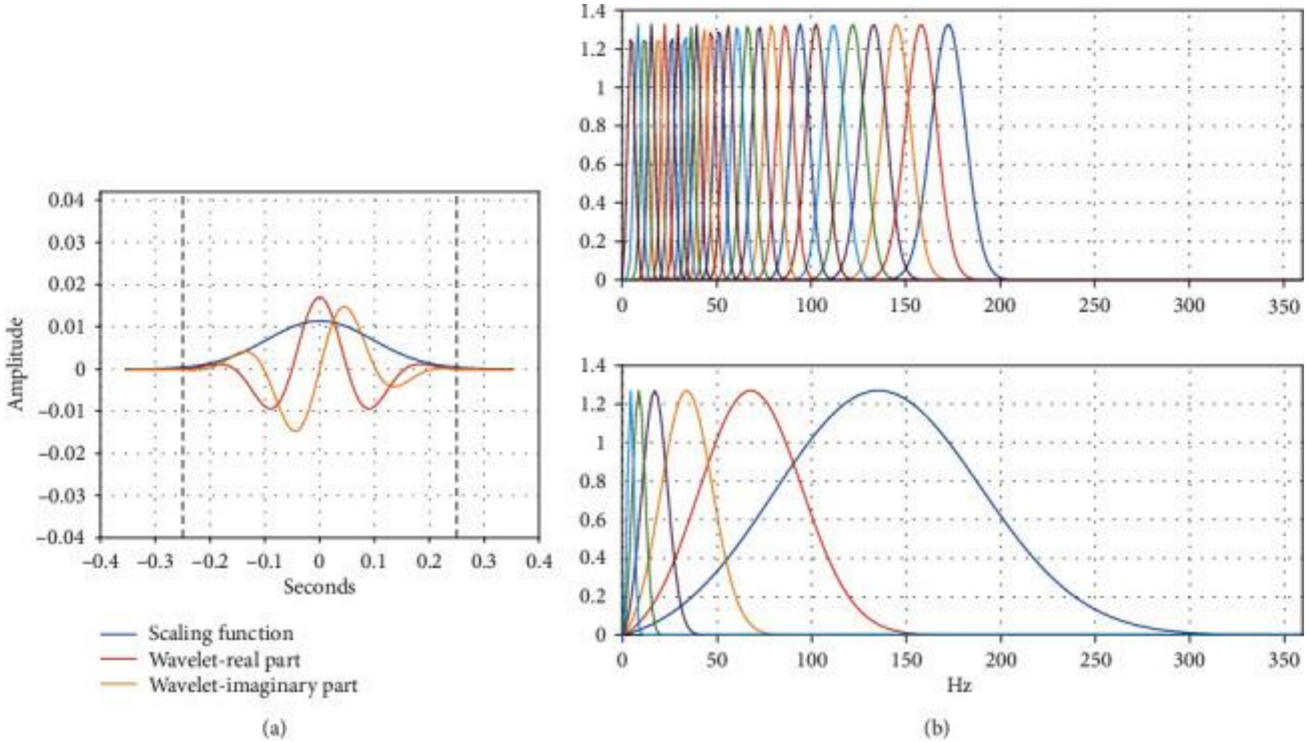
Affiliations + expand

PMID: 33133225 PMCID: PMC7568798 DOI: 10.1155/2020/3215681

Abstract

An electrocardiogram (ECG) records the electrical activity of the heart; it contains rich pathological information on cardiovascular diseases, such as arrhythmia. However, it is difficult to visually analyze ECG signals due to their complexity and nonlinearity. The wavelet scattering transform can generate translation-invariant and deformation-stable representations of ECG signals through cascades of wavelet convolutions with nonlinear modulus and averaging operators. We proposed a novel approach using wavelet scattering transform to automatically classify four categories of arrhythmia ECG heartbeats, namely, nonectopic (N), supraventricular ectopic (S), ventricular ectopic (V), and fusion (F) beats. In this study, the wavelet scattering transform extracted 8 time windows from each ECG heartbeat. Two dimensionality reduction methods, principal component analysis (PCA) and time window selection, were applied on the 8 time windows. These processed features were fed to the neural network (NN), probabilistic neural network (PNN), and *k*-nearest neighbour (KNN) classifiers for classification. The 4th time window in combination with KNN ($k = 4$) has achieved the optimal performance with an averaged accuracy, positive predictive value, sensitivity, and specificity of 99.3%, 99.6%, 99.5%, and 98.8%, respectively, using tenfold cross-validation. Thus, our proposed model is capable of highly accurate arrhythmia classification and will provide assistance to physicians in ECG interpretation.

https://doi.org/10.1155%2F2020%2F3215681



Wavelet filters. (a) The low pass filter with 0.5 s invariance scale. (b) The first filter bank with 8 wavelets per octave and the second filter bank with 1 wavelet per octave.

Fuente: https://doi.org/10.1155/2020/3215681

> Sensors (Basel). 2023 Sep 3;23(17):7643. doi: 10.3390/s23177643.

An ECG Signal Acquisition and Analysis System Based on Machine Learning with Model Fusion

Shi Su [1 2 3], Zhihong Zhu [3], Shu Wan [3 4], Fangqing Sheng [5], Tianyi Xiong [1], Shanshan Shen [1], Yu Hou [1], Cuihong Liu [1], Yijin Li [1], Xiaolin Sun [1], Jie Huang [1]

Affiliations + expand

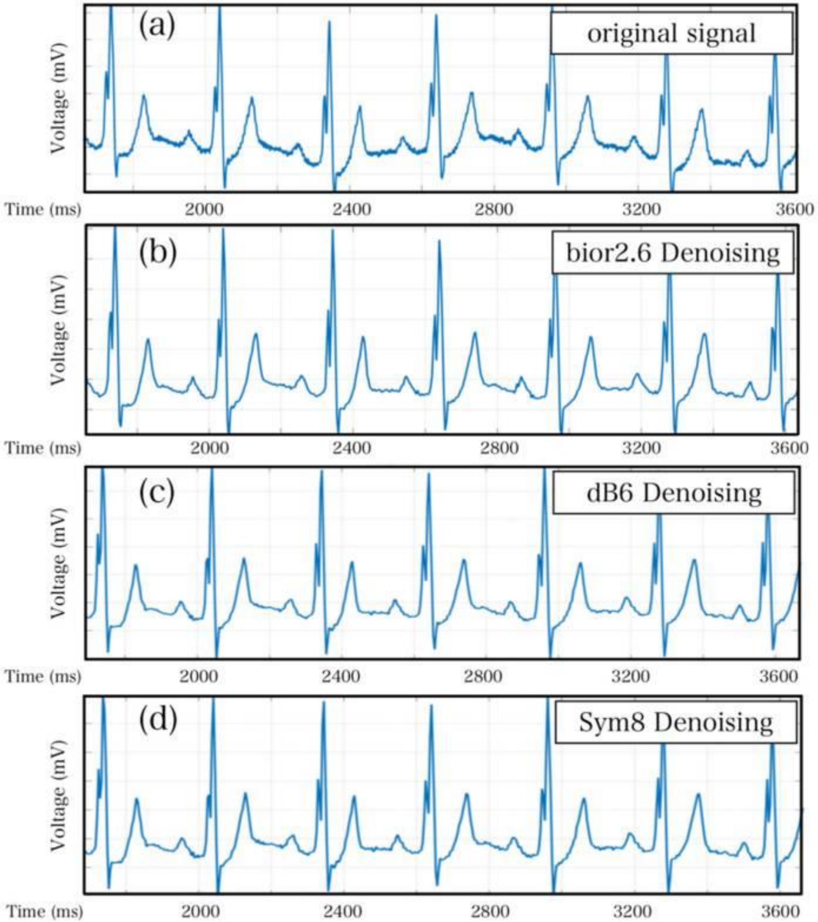
PMID: 37688099 PMCID: PMC10490810 DOI: 10.3390/s23177643

Free PMC article

Abstract

Recently, cardiovascular disease has become the leading cause of death worldwide. Abnormal heart rate signals are an important indicator of cardiovascular disease. At present, the ECG signal acquisition instruments on the market are not portable and manual analysis is applied in data processing, which cannot address the above problems. To solve these problems, this study proposes an ECG acquisition and analysis system based on machine learning. The ECG analysis system responsible for ECG signal classification includes two parts: data preprocessing and machine learning models. Multiple types of models were built for overall classification, and model fusion was conducted. Firstly, traditional models such as logistic regression, support vector machines, and XGBoost were employed, along with feature engineering that primarily included morphological features and wavelet coefficient features. Subsequently, deep learning models, including convolutional neural networks and long short-term memory networks, were introduced and utilized for model fusion classification. The system's classification accuracy for ECG signals reached 99.13%. Future work will focus on optimizing the model and developing a more portable instrument that can be utilized in the field.

Keywords: CNN; ECG; electrocardiogram; machine learning; model fusion.



scientific reports

Article | Open Access | Published: 01 September 2023

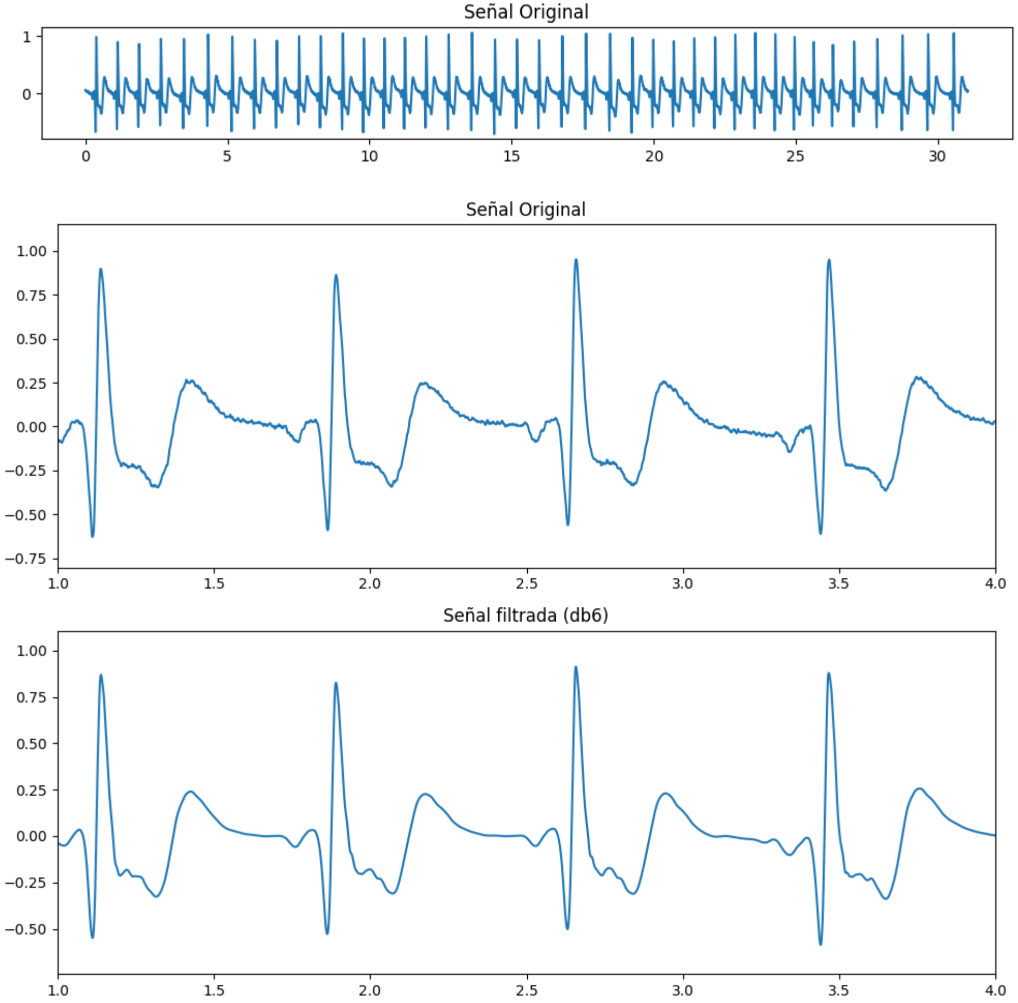
Novel phonocardiography system for heartbeat detection from various locations

Rene Jaros, Jiri Koutny, Martina Ladrova & Radek Martinek

Scientific Reports **13**, Article number: 14392 (2023) | Cite this article

Abstract

The paper presents evaluation of the proposed phonocardiography (PCG) measurement system designed primarily for heartbeat detection to estimate heart rate (HR). Typically, HR estimation is performed using electrocardiography (ECG) or pulse wave as one of the fundamental diagnostic methodologies for assessing cardiac function. The system includes novel both sensory part and data processing procedure, which is based on signal preprocessing using Wavelet Transform (WT) and Shannon energy computation and heart sounds classification using K-means. Due to the lack of standardization in the placement of PCG sensors, the study focuses on evaluating the signal quality obtained from 7 different sensor locations on the subject's chest and investigates which locations are most suitable for recording heart sounds. The suitability of sensor localization was examined in 27 subjects by detecting the first two heart sounds (S1, S2). The HR detection sensitivity related to reference ECG from all sensor positions reached values over 88.9 and 77.4% in detection of S1 and S2, respectively. The placement in the middle of sternum showed the higher signal quality with median of the proper S1 and S2 detection sensitivity of 98.5 and 97.5%, respectively.



Señal Original
1
0
0
5
10
15
20
25
30
Señal Original
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Señal filtrada (db6)
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
1.0
1.5
2.0
2.5
3.0
3.5
4.0