

# Wavelets Packets Analysis for Doppler Effect Detection

E.P. SERRANO, R.O. SIRNE and C.E. D'ATELLIS  
 Escuela Superior Técnica del Ejército "Gral. M.N. Savio"  
 Universidad de Palermo - Fac. de Ingeniería  
 Cabildo 15, (1426) Buenos Aires  
 ARGENTINA

*Abstract* - In this article a method for the parameter estimation of Doppler radar signals is proposed. It is based on the discrete wavelet transform, spline orthogonal wavelets are used from the projection of the mixed signal; wavelet packets analysis play the role of bandpass filter banks with narrowing frequencies ranges. An experimental case is analyzed and the results obtained are discussed.

*Key-Words:* - Wavelets packets, multiresolution, Doppler radar signals.

## 1 Introduction

Assume that  $\tilde{\psi}(\zeta)$  is an orthogonal wavelet with Fourier transform

$$\tilde{\Psi}(f) = j\tilde{\tilde{\psi}}(f)j e^{i\frac{1}{2}f} ; \quad (1)$$

where  $\tilde{\tilde{\psi}}$  is a bandpass filter on  $1=2 \cdot |f| \cdot 1$ .

In this article we use the orthogonal *Lemarié-Battle* cubic spline (OCS) wavelet  $\tilde{\tilde{\psi}}$  ([1],[8]) depicted in Fig. 1.

Figure 2 shows the module of the frequency response  $F(\tilde{\tilde{\psi}})(f) \sim \tilde{\tilde{\psi}}(f)$  corresponding to the OCS wavelet for  $f > 0$ .

We remark that  $j\tilde{\tilde{\psi}}j$  is almost constant on the band; that is, it is not localized at any frequency. For these reasons the wavelet transform give us a time-scale representation of the signal rather than a time-frequency one.

To overcome this disadvantage we can use wavelet packets ([1],[2],[3],[6]), as waveforms well localized

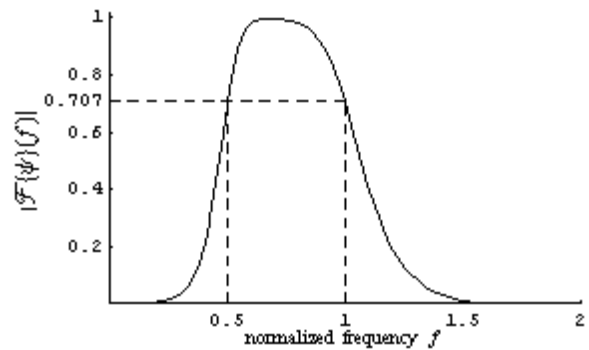


Fig. 2: OCS-bandpass filter with wavelet function.

both in the time and the frequency domains. They become from lineal combination of finite wavelets over common intervals and scales.

Here we will propose a new family of wavelets packets. Following simple ideas, we will implement a localized Fourier transform computed from the wavelet coefficients

$$c_{j;k} = \langle s; \tilde{\tilde{\psi}}_{j;k} \rangle ; \quad (2)$$

In order to our purposes, assume that  $j = 0$ , we also denote

$$W_0 = \text{span} \{ \tilde{\tilde{\psi}}(\zeta - k) ; k \in \mathbb{Z} \} \quad (3)$$

and we recall that if  $s_0 \in W_0$ , then  $s_0$  is localized on  $1=2 \cdot |f| \cdot 1$ .

We observe that for a pure monochromatic signal  $e^{i2\frac{1}{2}f_0\zeta}$ , the wavelet transform is

$$\langle e^{i2\frac{1}{2}f_0\zeta}; \tilde{\tilde{\psi}}(\zeta - k) \rangle = j\tilde{\tilde{\psi}}(f_0)j e^{i\frac{1}{2}f_0(2k+1)} \quad (4)$$

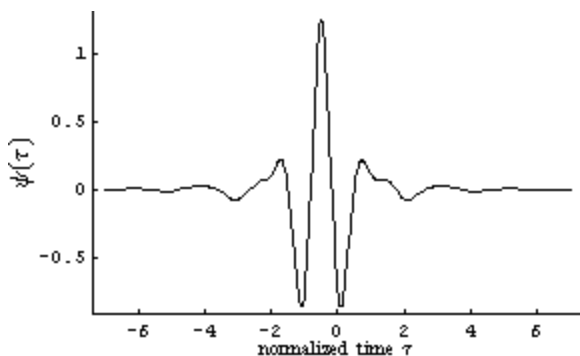


Fig. 1: Orthogonal cubic spline (OCS) wavelet.

for any  $f_0 \in [1/2; 1]$  and  $k \in \mathbb{Z}$ .

Of course, since  $\tilde{A}(f) \approx \text{cte}$  in the passband of the filter, the specific information of the frequency parameter  $f_0$  must be contained in the sequence  $e^{i \frac{1}{2} f_0 (2k+1)}$ .

Moreover, for particular choices of  $f_0$  these sequences will be periodic and this gives the key for the detection.

We use the following notation:

- $t$  : the time.
- $\Delta t$  : the sampling rate interval.
- $\tilde{t} = t/\Delta t$  : the normalized time, with  $t$  and  $\Delta t$  in the same unit (e.g.: sec.).
- $\omega$  : the frequency.
- $\omega_s = 1/\Delta t$  : the sampling rate frequency.
- $f = \omega/\omega_s$  : the normalized frequency, with  $\omega$  and  $\omega_s$  in the same unit (e.g.: Hz).

## 2 Method Description

Let  $N \in \mathbb{Z}$  an even integer and define the frequencies

$$f_n = \begin{cases} 1 + n/N & \text{if } 1 \leq n \leq N/2 \\ n/N & \text{if } N/2 + 1 \leq n \leq N \end{cases}; \quad (5)$$

we remark that

$$\begin{cases} f_{N-n} = 1 - f_n & \text{if } n > 0 \\ f_{N/2} = 1/2 & \text{if } n = N/2 \end{cases}$$

that is, they are localized on  $1/2 \leq f \leq 1$ . Also note that  $f_{N-n} = 1 - f_n$ .

We denote the basic functions

$$e_{N;n} = \frac{1}{\sqrt{N}} e^{i \frac{1}{2} f_n (2k+1)} \quad 0 \leq k < N \quad (6)$$

for  $1 \leq n \leq N/2$ .

We easily check that the family

$$f e_{N;n} ; 1 \leq n \leq N/2$$

is an orthogonal basis (ONB) for  $\mathbb{C}^N$ .

Finally, fixed  $N$ , we define the wavelets packets as

$$\mathcal{E}_{N;n}(\tilde{t}) = \sum_{k=0}^{N-1} e_{N;n}[k] \tilde{A}(\tilde{t} - k) \quad (7)$$

with  $1 \leq n \leq N/2$ ; this is an ONB for the subspace

$$\text{span} \{ \tilde{A}(\tilde{t} - k) ; 0 \leq k < N \} \subset W_0$$

and the family

$$f \mathcal{E}_{N;n}(\tilde{t} - rN) ; r \in \mathbb{Z}$$

is a ONB for  $W_0$ .

In general, if  $q$  divides  $N$ ,

$$f \mathcal{E}_{N;n}(\tilde{t} - rN/q) ; r \in \mathbb{Z}$$

is a frame for  $W_0$ .

First we remark that these are complex wavelet packet functions. The wavelet coefficients for a given signal  $s$  are

$$c_{0;k} = \langle s(\tilde{t}) ; \tilde{A}(\tilde{t} - k) \rangle \quad (8)$$

The orthogonal *wavelet packet transform* in  $W_0$  is defined as

$$d_{0;n;r} = \sum_{k=0}^{N-1} e_{N;n}[k] c_{0;k+rN} \quad (9)$$

for  $1 \leq n \leq N/2$  and  $r \in \mathbb{Z}$ .

For real signals, the values  $|d_{0;n;r}|^2 + |d_{0;N-n;r}|^2$  represent the contribution of the frequency  $f_n$  on the interval  $(rN, (r+1)N)$ .

Note that, if  $s(\tilde{t}) = e^{i 2 \frac{1}{2} f_p \tilde{t}}$ , then

$$d_{0;n;r} = \begin{cases} a & \text{if } n = p \\ 0 & \text{if } n \neq p \end{cases}; \quad a = \text{constant}$$

The extension to other subspaces

$$W_j = \text{span} \{ \tilde{A}(2^j \tilde{t} - k) ; k \in \mathbb{Z} \}$$

is analogous; here we remark that we can choose a different integers  $N_j$  for each scale  $j$ .

In summary, the values

$$(d_{j;n;r})_{j \in \mathbb{Z}; n \in [1; N_j=2; N_j=2]; r \in \mathbb{Z}}$$

give us a time-frequency transform.

## 3 Implementation

In this article we applied the method described in the previous section to calculate the radial velocity  $v$  of a target, detected by the frequency shift (Doppler effect) between the delayed received signal (echo)  $s_r$  and the emitted signal  $s_e$  for a continuous wave (CW) radar system.

In the theoretical case that  $s_e$  and  $s_r$  (without noise) are sinusoidal signals, this shift  $\omega_0$  is the frequency (beat note) of the sinusoidal signal  $s_B$  obtained when the radar receiver mixes  $s_r$  with  $s_e$  and passes the output through a lowpass filter.

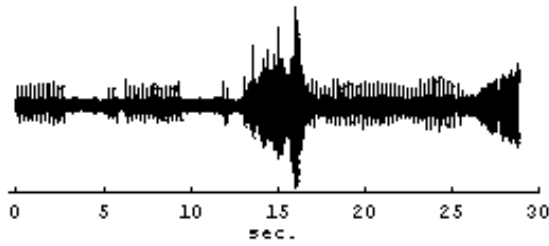


Fig. 3: Signal  $s_B(t)$ ;  $0 \leq t \leq 28.8$  sec.

It can be demonstrated ([4],[5],[7]) that the absolute value of the radial velocity  $v$  of the target result

$$|v| \approx \frac{c \cdot \Delta f}{2 \cdot f_0} ; \quad (10)$$

with relative error  $\epsilon_v = (c \cdot \Delta f) / (2 \cdot f_0 \cdot |v|)$ .

We use a CW radar with  $f_0 = 10^{10}$  Hz. Then, knowing  $\Delta f$  and assuming  $c = 3 \cdot 10^8$  m/sec, with (10) we can estimate  $|v|$  in Km/h using

$$|v| \approx 0.054 \cdot \Delta f ; \quad (11)$$

with relative error less than  $9.26 \cdot 10^{-8}$  for velocities less than 100 Km/h.

So, the precision of the obtained  $|v|$  value will depend on the frequency approach.

In this work we considered, specially, small shifts  $\Delta f$  produced by velocities between 40 and 100 Km/h of a car moving along a linear trajectory toward the radar.

Figure 3 shows the signal  $s_B(t)$  to be analyzed; it was sampled with  $f_s = 44100$  Hz.

The magnitude of the signal spectrum, obtained with FFT, is depicted in Fig. 4;  $|s_B(f)|$  is maximum for  $f_0 = 1247.5$  Hz corresponding to a velocity  $|v| \approx 67.4$  Km/h along an interval of 28.8 sec. of the signal.

In this work, we propose to analyze the signal  $s_B$  in three steps:

1. First step: in the multiresolution framework with OCS, we proceed with the wavelets analysis

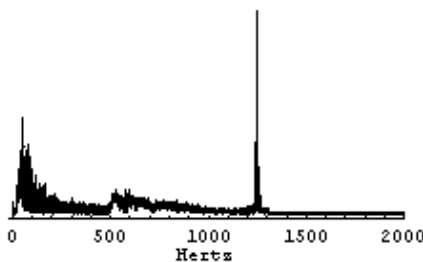


Fig. 4: Magnitude of  $s_B(t)$  spectrum,  $|s_B(f)|$ .

using the Mallat algorithm ([6],[9]), for the resolution levels  $j = 1; 2; \dots; 10$ .

Table 1 shows for each resolution level, the frequency bands

$$[2^{j-1} \Delta f_s ; 2^j \Delta f_s] ; j = 1; \dots; 10$$

and the corresponding –using (11)– velocity intervals

$$[0.054 \cdot 2^{j-1} \Delta f_s ; 0.054 \cdot 2^j \Delta f_s] ; j = 1; \dots; 10:$$

level j	frequency Hz		velocity Km/h	
	min	max	min	max
1	11025:00	22050:00	595:35	1190:70
2	5512:50	11025:00	297:68	595:35
3	2756:25	5512:50	148:34	297:68
4	1378:13	2756:25	74:42	148:34
5	689:06	1378:13	37:21	74:42
6	344:53	689:06	18:60	37:21
7	172:27	344:53	9:30	18:60
8	86:13	172:27	4:65	9:30
9	43:07	86:13	2:33	4:65
10	21:53	43:07	1:16	2:33

Table 1: Frequency bands and velocity intervals for each multiresolution level  $j$ .

2. Second step: We compute the energy of the signal in each multiresolution frequency band; this energy results

$$E_j = \sum_k |c_{j,k}|^2 ; j = 1; \dots; 10: \quad (12)$$

Table 2 shows the greatest values  $100 \cdot E_j / E_t$  observed, where  $E_t = \sum_j E_j$ ; the more important (38%) corresponds to  $j = 5$ , in accord with the real velocity of the car.

level j	energy	velocity	
	%	min -Km/h-	max
4	6	74:42	148:84
5	38	37:21	74:42
6	10	18:60	37:21
9	26	9:30	18:60

Table 2: Percentual values of energy.

3. Third step: We applied wavelet packets in the level  $j = 5$ , the more significant energy level (see Table 2).

In this level we analyze 77 consecutive groups of 512 coefficients  $c_{j,k}$ , corresponding to 77 nonoverlapping adjacent intervals with  $512 \cdot 2^5 = 16384$  samples ( $16384 = 44100 \text{ Hz} \approx 0.37$  sec.) of the signal.

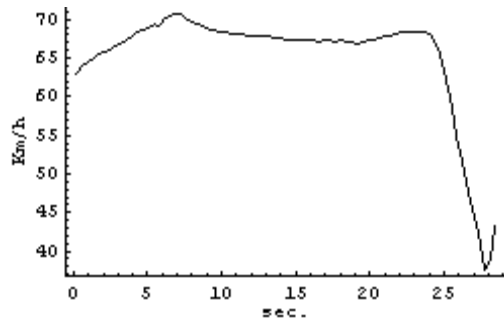


Fig. 5: Car velocity v function of time t.

Working with 512 coefficients in the frequency band [689:06; 1378:13] Hz, we can estimate  $\bar{v}_0$  with

$$j\hat{v}_0j = \frac{1378:13 - 689:06}{512=2} \text{Hz} < 2:7 \text{ Hz};$$

corresponding to a velocity precision

$$j\hat{v}j < 0:15 \text{ Km/h} :$$

Then, we can estimate  $j\hat{v}j$  each 0:37 sec.; Fig. 5 shows the car velocity as function of time. The mean velocity in the interval [0;28:8] sec. results

$$j\bar{v}j = 65:2 \text{ Km/h}:$$

The advantage of methods based on wavelets and wavelet packets, in comparison with standard spectral methods (which give, in this case, similar results;  $j\bar{v}j = 65:4 \text{ Km/h}$ ) are two. In the first place, to adjust the accuracy in time and frequency; in the second, the use of minimum number of entries (the wavelet coefficients) diminish the computational burden.

*Acknowledgments:*

This work was partially supported by Fundación Antorchas, Proyecto N° 13900-2, Buenos Aires, Argentina.

The authors want to thank the collaboration of J. Guglielmone, E. Tiscornia, M. Arena and A. Popovsky for the useful discussion about the subject and the preparation of the experience and data recording.

*References:*

[1] Chui C.K., *An Introduction to Wavelets*, Academic Press, 1992.  
 [2] Coifman R.R., Y. Meyer, M.V. Wikerhauser, *Wavelet Analysis and Signal Processing*, Jones and Barlett – B. Ruskai et al. eds.,1992.

[3] Daubechies I., *Ten Lectures on Wavelets*, SIAM,1992.  
 [4] Kaiser G., *Physical Wavelets and Radar - A Variational Approach to Remote Sensing*, *IEEE Antennas and Propagation Magazine*, 1996.  
 [5] Kaiser G., *A Friendly Guide to Wavelets*, Birkhäuser, 1994.  
 [6] Mallat S., *A Wavelet Tour of Signal Processing*, Academic Press, 1998.  
 [7] Serrano E., R.O. Sirne, M. Fabio, A.D. Popovsky, C.E. D’Attellis, *Doppler Detection in HF Radars Using Wavelets*, *WSEAS Transactions on Signal Processing*, Issue 3, 2, 2006, pp. 372-375.  
 [8] Unser M., A. Aldroubi, M. Eden, A family of polynomial spline wavelet transforms, *Signal Processing, Elsevier Science Publishers*, 30, 1993, pp. 141-162.  
 [9] Unser M. and T. Blu, *Fractional Spline and Wavelets*, *SIAM Rev.*, Vol.42, No.1, Jan 2000.