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## ► To cite this version:

Luis Espinosa, Jan Bacca, Flavio Prieto, Philippe Lasaygues, Loïc Brancheriau. Accuracy on the Time-of-Flight Estimation for Ultrasonic Waves Applied to Non-Destructive Evaluation of Standing Trees: A Comparative Experimental Study. 2018. hal-01769820

**HAL Id: hal-01769820**

**<https://hal.science/hal-01769820>**

Preprint submitted on 18 Apr 2018

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# Accuracy on the Time-of-Flight Estimation for Ultrasonic Waves Applied to Non-Destructive Evaluation of Standing Trees: A Comparative Experimental Study

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## 1 Summary

Time-of-flight measurement is a critical step to perform ultrasonic non-destructive testing of standing trees, with direct influence on the precision of defect detection. Aiming to increase the accuracy on the estimation, the characteristics of the ultrasonic measurement chain should be adapted to the constraints of wood testing in living condition. This study focused on the excitation signal parameters, such as shape, temporal duration, and frequency response, and then the selection of a suitable time-of-flight determination technique. A standing plane tree was tested, placing ultrasonic receivers at four different positions, with five different excitation signals and three time-of-flight detection methods. The proposed ultrasonic chain of measurement resulted in high signal-to-noise ratios in received signals for all configurations. A time-frequency analysis was used to determine the power distribution in the frequency domain, showing that only chirp signal could concentrate the power around the resonant frequency of the sensor. Threshold and Akaike information criterion method performed similar for impulsive signals with decreasing uncertainty as sensor position approached to the radial direction. Those two methods failed to accurately determine time-of-flight for Gaussian pulse and chirp signals. Cross-correlation was only suitable for the chirp signal, presenting the lower uncertainty values among all configurations.

## 1 Introduction

Modern techniques can be used to minimize the risk associated with tree failure. Significant advances in this field include decay detection equipments, formu-

las and guidelines for assessing hazardous trees [1, 2].

Standing tree quality can be evaluated using different techniques [3]. First, a visual inspection is privileged, but can be insufficient to detect inner decay. The use of specialized tools include micro-drill resistance measurements [4], a widely used technique consisting on drilling through the tree trunk following a straight path while measuring the penetration resistance. Basically, defects such as decay and cracks present a reduced resistance to the drill, a pattern that can be detected. However, this technique is limited by the selected orientation, it is difficult to assure going through the defect.

Other group of techniques uses stress waves timing to evaluate wood quality and trees inner state. The basic consideration is that decay inside wood will have an influence in the propagation of elastic waves: at low velocity regions, such as decay, velocity decreases and signal attenuation increases [5]. For standing trees testing, commercial approaches include the IML Impulse Hammer, the Fakkop 2D Microsecond Timer and the Sylvatest [6]. Wood mechanical properties can be estimated using the measured velocities, for example, using the Christoffel equation [7, 8, 9]. Accuracy on the time-of-flight estimation is crucial to perform a correct wood evaluation. Additionally, resonance-based methods present an alternative for velocity detection based on the analysis of the stress waves natural frequencies, traveling through the wood [10, 11].

Considering 2D imaging, ultrasonic tomography is one of the techniques used for non-destructive control of standing trees [12, 13, 14, 15, 16, 17, 18]. This method consists on cross-sectional imaging from the tree trunk using either reflection or transmission wave propagation data. Usually, the parameter used to

70 build the image is the time-of-flight (TOF) taken by  
 71 the ultrasonic wave from the transmitter to the mul-  
 72 tiple receivers. Thus, TOF determination is a critical  
 73 step to perform image reconstruction [19]; image qual-  
 74 ity is highly dependent on the precision of the TOF  
 75 measurement.

76 Considering conventional ultrasonic testing, the ob-  
 77 ject is excited with a pulse, and TOF measurement  
 78 rely on the estimation of the signal instantaneous  
 79 power by determining the first arrival above a noise  
 80 threshold, defined by the user [20, 21]. Also, a pulse  
 81 train can be used to boost the transmitted energy  
 82 for a specific frequency [22]. Automatic methods for  
 83 detecting first arrivals have been proposed, including  
 84 pickers based on the Akaike information criteria (AIC)  
 85 [23, 24] and the Hinkley criteria [25]. Alternatives in-  
 86 clude the transmission of encoded waveforms, such  
 87 as the chirp-coded excitation method, where a recog-  
 88 nizable signature is sent through the media and the  
 89 TOF is estimated using a cross-correlation function  
 90 [26, 27, 28]. In consideration of the wide range of sig-  
 91 nals and TOF detection techniques, the choice of pa-  
 92 rameters for standing tree ultrasonic testing demands  
 93 an evaluation of the accuracy of the aforementioned  
 94 methods.

95 This study aimed to compare several signal shapes  
 96 and TOF detection methods, for setting up an ul-  
 97 trasonic chain of measurement in order to perform  
 98 non-destructive evaluation of standing trees. Impul-  
 99 sive and encoded signals were tested, combined with  
 100 three different methods for TOF estimation: Thresh-  
 101 old, AIC method and cross-correlation. First, ex-  
 102 perimental setting is presented, including electrical  
 103 specification for the ultrasonic chain, the excitation  
 104 signal parameters and a description of the TOF de-  
 105 tection methods. Then, energy and signal-to-noise  
 106 ratios are computed for all configurations. A time-  
 107 frequency analysis using the Gabor transform is per-  
 108 formed, aiming to inspect energy distribution. Lastly,  
 109 wave transit times are reported, computing dispersion  
 110 among experiments repetition, to establish which set-  
 111 ting leads to highest accuracy.

## 112 2 Materials and methods

113 A standing plane tree (*Platanus × acerifolia* (Aiton)  
 114 Willd) was tested (Figure 1). Probes distance above  
 115 the ground was 120 cm. The trunk diameter was  
 116 23 cm, with a regular cross-section. Tests were con-  
 117 ducted in dormancy period (winter). Two ultrasonic  
 118 pair of sensors were used: Physical Acoustics Corpo-  
 119 ration R3 $\alpha$  and R6 $\alpha$ . Sensor R3 $\alpha$  has a main resonant  
 120 frequency at 36 kHz and two secondary resonant fre-  
 121 quencies at 22 kHz and 95 kHz; operating frequency  
 122 range indicated by the manufacturer is from 25 to 70  
 123 kHz. Sensor R6 $\alpha$  has a main resonant frequency at  
 124 60 kHz and two secondary resonant frequencies at 37



Figure 1: *Platanus* standing tree tested.

kHz and 97 kHz; operating frequency range indicated  
 by the manufacturer is from 35 to 100 kHz. These  
 sensors are intended for general purpose ultrasonic  
 testing, presenting a solid stainless steel body with  
 a flat ceramic face. A fluid couplant was used. The  
 position of the sensor acting as transmitter was fixed;  
 the receiver position changed in 4 equidistant points  
 at angles located along half the trunk circumference:  
 45°, 90°, 135° and 180°.

### 2.1 Ultrasonic measurements

Ultrasonic chain of measurement is presented in Fig-  
 ure 2. Electrical signal generator and oscilloscope cor-  
 responded to a Picoscope 2000 (emission sample rate 1  
 MHz, reception sample rate 4 MHz), with an interface  
 to a personal computer for data acquisition. Input  
 amplifier reference was FLC Electronics Single Chan-  
 nel High Voltage Linear Amplifier A800 (bandwidth  
 DC to 250 kHz, 40 dB amplification). Output ampli-  
 fier was Physical Acoustics Corporation AE2A/AE5A  
 wide bandwidth AE amplifier (bandwidth up to 2  
 MHz, internal 40 dB preamplifier).

This chain of measurement acts as a continuous lin-  
 ear stationary causal filter, then the input signal  $s(t)$   
 and the output signal  $y(t)$  are related by a convolution  
 function:

$$y(t) = ((h_t^* * s) * h_m)(t), \quad (1)$$

where  $h_m$  is the response of the tree,  $s(t)$  is the  
 electrical generated signal, and  $h_t^*(t)$  is the equivalent  
 electro-acoustic pulse response. The electro-acoustic  
 pulse response  $h_t^*(t)$  is the auto-convolution of the  
 transducers impulse response  $h_t(t)$ , including the re-  
 sponse of the amplifier, and considering the transmit-  
 ter and receiver transducers responses with coupling  
 to be identical.

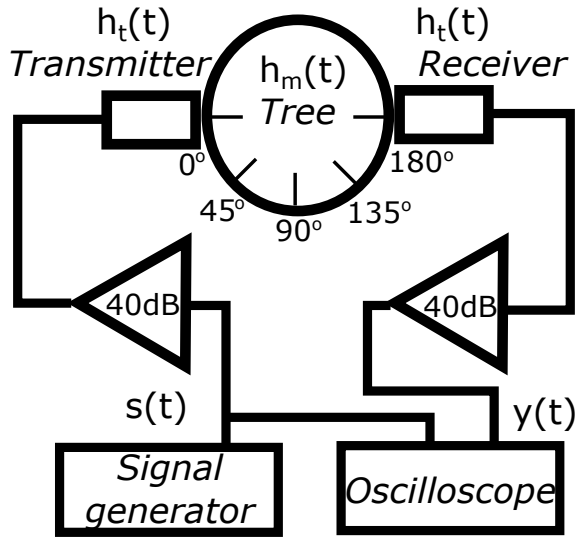


Figure 2: Ultrasonic chain for measurements.

158 The five signal shapes tested were an impulse (short  
 159 duration rectangular pulse), pulse train, Gaussian  
 160 pulse, half-Gaussian pulse and chirp (Figure 3). The  
 161 short duration rectangular pulse, pulse train and half-  
 162 Gaussian pulse present a fast impulsive start, result-  
 163 ing in a large band frequency response, with several  
 164 resonant lobes in the case of the pulse train and a soft  
 165 power decay for the half-Gaussian pulse. The Gaus-  
 166 sian pulse and chirp signal have a sinusoidal shape,  
 167 multiplied by a Gaussian window, resulting in a con-  
 168 centrated power spectrum around a central frequency  
 169 (resonant peaks for the sensors), with a narrower  
 170 bandwidth for the chirp signal. Parameters fixed for  
 171 the signals are presented in Table 1. Peak voltage for  
 172 all signals was set to 2V (maximum for signal gener-  
 173 ator). Signals repetition period was fixed to  $T = 8ms$ .

174 For every sensor position and signal shape, ultra-  
 175 sonic measurement was repeated 10 times, removing  
 176 and replacing the transducers. For the signal ampli-  
 177 tude measurements, the root mean square voltage  
 178 (RMS) and the signal-to-noise ratio (SNR) were com-  
 179 puted. RMS voltage was obtained as:

$$V_{RMS}(y) = \sqrt{\frac{1}{N} \sum_{n=1}^N |y_n|^2}, \quad (2)$$

180 with  $N$  as the signal length. SNR was computed  
 181 as:

$$SNR(y) = 20 \log \left( \frac{V_{RMS}(y)}{V_{RMS}(\eta)} \right), \quad (3)$$

182 where  $\eta$  is the noise, estimated by selecting the first  
 183 signal portion before the arrival time.

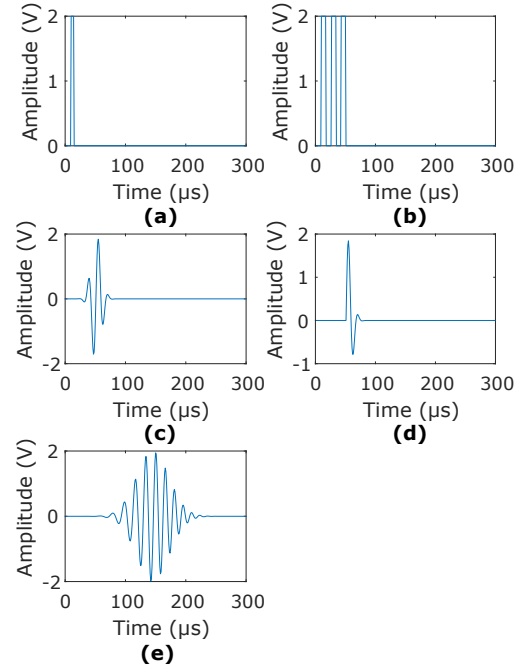


Figure 3: Signal shapes tested: (a) impulse, (b) pulse train, (c) Gaussian pulse, (d) half-Gaussian pulse and (e) chirp signal.

Table 1: Signal parameters.  $T_s$  presents the duration of signal portion.  $F_c$  indicates the central frequency of every signal.  $F_{co}$  indicates the cut-off frequency range (-3 dB points around central frequency). For chirp signal,  $\Delta F$  presents the bandwidth, around the central frequency.

Parameters R3 $\alpha$	Parameters R6 $\alpha$
Impulse	
$T_s$ : 5 $\mu s$	$T_s$ : 5 $\mu s$
$F_{co}$ : [0 90.159] kHz	$F_{co}$ : [0 90.159] kHz
Pulse train	
$F_c$ : 36 kHz	$F_c$ : 60 kHz
$T_s$ : 83 $\mu s$ (3 Periods)	$T_s$ : 50 $\mu s$ (3 Periods)
$F_{co}$ : [29.39 40.20] kHz	$F_{co}$ : [49.75 68.01] kHz
Gaussian pulse	
$F_c$ : 36 kHz	$F_c$ : 60 kHz
$T_s$ : 139 $\mu s$ (5 periods)	$T_s$ : 83 $\mu s$ (5 periods)
$F_{co}$ : [26.46 45.54] kHz	$F_{co}$ : [44.09 75.90] kHz
Half Gaussian pulse	
$F_c$ : 36 kHz	$F_c$ : 60 kHz
$T_s$ : 69 $\mu s$ (2.5 periods)	$T_s$ : 42 $\mu s$ (2.5 periods)
$F_{co}$ : [24.20 55.28] kHz	$F_{co}$ : [24.50 81.38]
Chirp signal	
$F_c$ : 36 kHz	$F_c$ : 60 kHz
$\Delta F$ : 28kHz	$\Delta F$ : 48kHz
$T_s$ : 45 $\mu s$ (10 periods)	$T_s$ : 27 $\mu s$ (10 periods)
$F_{co}$ : [32.57 40.04] kHz	$F_{co}$ : [54.55 67.22] kHz

## 2.2 Time-of-flight detection methods

### Threshold

Threshold level for the received signal had to be defined above the noise level [16]. The threshold level is defined to be  $m$  times the standard deviation of the noise, with  $m$  as a user-defined parameter. For the experiments, this value was constant and fixed by trial and error to 8. TOF is then selected to be the first time point where signal is above the threshold level.

### AIC method

This method assumes that signal can be divided into two local stationary segments, before and after the onset time, each one modeled as an autoregressive process. The time instant where the Akaike information criterion (AIC) is minimized, corresponds to the optimal separation between noise and signal, this is, the onset time [22]. For a signal divided at point  $k$  into two segments  $y_1$  (before  $k$ ) and  $y_2$  (after  $k$ ), the AIC criterion is computed as:

$$AIC[k] = k \log(\sigma^2(y_1)) + (N - k) \log(\sigma^2(y_2)). \quad (4)$$

TOF value is obtained by founding the time point where the AIC criterion reach the global minimum.

### Cross-correlation

When a recognizable signature is sent through the media, such as chirp signal, input and output signals delay time can be obtained using cross-correlation [26, 27, 28]. The maximum value for the cross-correlation function between two signals indicates their delay time. Normalized cross-correlation function is:

$$r_{sy}[l] = \frac{1}{\sqrt{E_s E_y}} \sum_{k=0}^N s[k] y[k-l], \quad (5)$$

where  $E_s$  and  $E_y$  correspond to the signals energy and  $N$  is the signal length.

## 3 Results

### 3.1 Signal amplitude measurement

Figure 4 presents the root mean square voltage (RMS) mean and standard deviation values, for the received signals, for all the experiment configurations. Correspondingly, Table 2 summarizes the RMS values for the five signals, sorting by the RMS mean value in descending order. Except for pulse train signal, almost all configurations that used sensor R6 $\alpha$  resulted in larger RMS values than the R3 $\alpha$  counterpart. Receiver angles with larger RMS values were those located at 90° and 135°. For the R3 $\alpha$  sensor, the signals

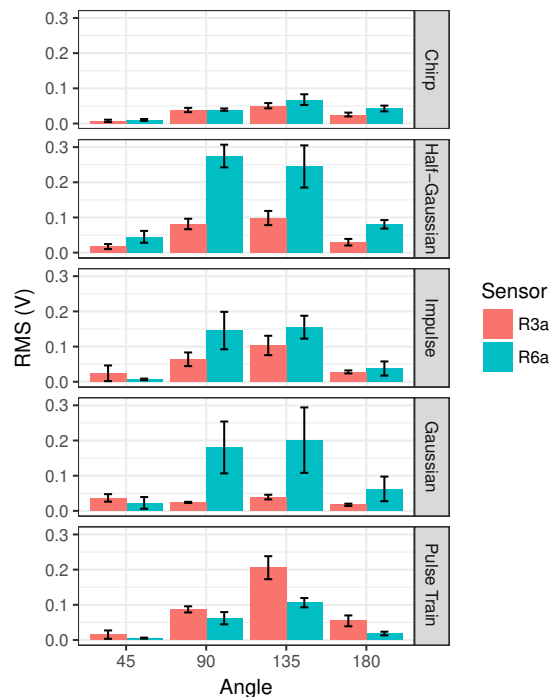


Figure 4: Mean values for RMS for all configurations. Error bars present  $\pm\sigma$ .

presenting an impulsive behavior (pulse train, half-Gaussian pulse and impulse) resulted in more energetic received signals. Chirp signal received for both cases ranked in the last positions.

Table 3 presents the output/input ratio for the RMS voltage applied and received at the transducers on the tree. Input RMS voltage corresponds to the excitation signal  $s(t)$  after the 40 dB amplifier applied to the US transmitter; output RMS voltage corresponds to the signal  $y(t)$  before the 40 dB amplifier and obtained in the US receiver. It is important to consider that the transducer impulse response will modify the signal applied to the tree. Using the chirp signal resulted in a lower RMS ratio for both sensors,

Table 2: Mean and standard deviation of RMS values for received signals, sorted from higher to lower.

Sensor	Signal	$\mu(RMS)$ [mV]	$\sigma(RMS)$ [mV]
R3 $\alpha$	Train	90.6	74.4
	Half Gaussian	56.7	37
	Impulse	54.8	37.8
	Chirp	30.5	17.1
	Gaussian pulse	29.4	11.1
R6 $\alpha$	Half Gaussian	161.3	106.8
	Gaussian pulse	116.6	97.4
	Impulse	86.3	73.1
	Train	47.9	41.6
	Chirp	40.1	22.4

Table 3: Ratio between output ( $y(t)$  before 40dB amplification) and input ( $s(t)$  after 40dB amplification) RMS values for all signals, sorted from higher to lower.

Sensor	Signal	$s(t)$ $V_{RMS}$ [mV]	$y(t)$ $V_{RMS}$ [mV]	Out/In Ratio [dB]
R3 $\alpha$	Impulse	50.0	54.8	-79.2
	Half-Gaussian	54.9	56.7	-79.7
	Train	139.6	90.6	-83.7
	Gaussian pulse	78.5	29.4	-88.6
	Chirp	141.9	30.5	-93.6
R6 $\alpha$	Half-Gaussian	45	161.3	-68.9
	Gaussian pulse	60.8	116.6	-74.3
	Impulse	50.0	86.3	-75.2
	Train	109.5	47.9	-87.1
	Chirp	109.4	40.1	-88.6

Table 4: Mean and standard deviation of SNR values for received signals, sorted from higher to lower.

Sensor	Signal	$\mu(SNR)$ [dB]	$\sigma(SNR)$ [dB]
R3 $\alpha$	Train	33.11	6.48
	Impulse	32.67	5.31
	Gaussian pulse	29.77	5.08
	Half-Gaussian	29	7.09
	Chirp	27.58	7.21
R6 $\alpha$	Train	41.71	10.85
	Impulse	40.52	12.35
	Gaussian pulse	35.02	11.75
	Half-Gaussian	30.51	6.9
	Chirp	21.81	6.53

241 and signals such as the half Gaussian pulse and the  
242 impulse resulted in the larger ratios.

243 Figure 5 presents the signal-to-noise ratio (SNR)  
244 mean and standard deviation values. Table 4 sum-  
245 marizes the SNR values, sorting by SNR mean value  
246 in descending order. Average SNR values over all re-  
247 ceiver angles ranged between 20 and 40 dB, indicating  
248 low presence of noise. Only exception correspond to  
249 chirp signal when using the R6 $\alpha$  located at 45 $^\circ$ , where  
250 mean SNR was around 10 dB. As obtained for the  
251 RMS measurements, SNR values for the sensor R6 $\alpha$   
252 were higher than those obtained for R3 $\alpha$ . Impulsive-  
253 like signals, as the pulse train and impulse, presented  
254 the highest SNR ratios.

### 255 3.2 Time-frequency analysis

256 As the frequency contents of the received signals var-  
257 ied over the time, we used a time-frequency analysis  
258 to obtain a representation of the input and output  
259 signals behavior for the ultrasonic chain of measure-  
260 ment. From several alternatives to perform the time-  
261 frequency analysis, the Gabor transform was used  
262 [29, 30].

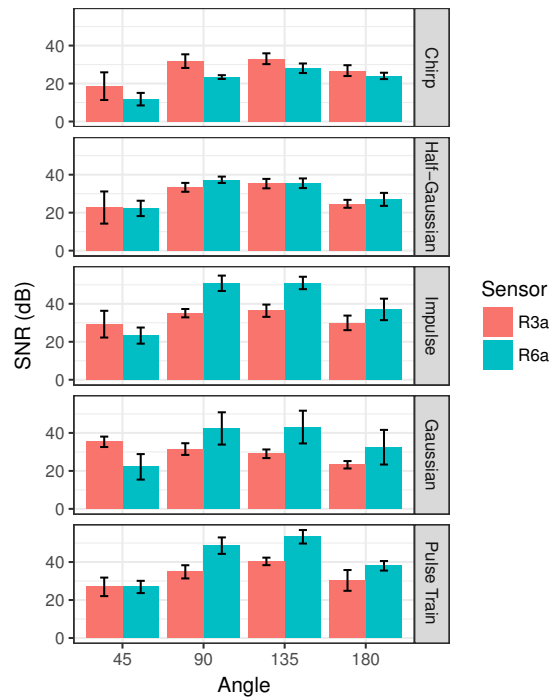


Figure 5: Mean values for SNR for all configurations. Error bars present  $\pm\sigma$ .

For this study, resolution in time was set to 0.1 ms  
and resolution in frequency was set to 5 kHz. The  
receiver angle selected for the analysis was 135 $^\circ$ , con-  
sidering it presents the most energetic signals, with  
higher SNR ratios.

Figure 6 and Figure 7 present first the input and  
output signals on time domain, then their frequency  
spectrum and finally the input and output spectro-  
grams, for sensors R3 $\alpha$  and R6 $\alpha$  respectively.

Chirp is the only signal able to concentrate the en-  
ergy around the central frequency for both sensors on  
the output signal. Gaussian pulse presented power  
concentration at frequencies near to the excitation  
central frequencies only for sensor R3 $\alpha$ ; mean power  
frequencies did not correspond for sensor R6 $\alpha$  where  
energy dissipated at different frequencies from 60 kHz  
(mainly 37 kHz and 97 kHz). The other signals pre-  
sented energy concentration mainly on the other sen-  
sor resonant peaks: for R3 $\alpha$  at the third resonant  
peak (95 kHz), and for R6 $\alpha$  in first and third re-  
sonant peaks (37 kHz and 97 kHz).

### 3.3 TOF determination

Time-of-flight was obtained for all the experiment  
configurations, using the Threshold and AIC method.  
Cross-correlation was used exclusively for the chirp  
signal, given that is the only excitation signal with  
a similar shape on the output for both sensors, and  
therefore, chirp signal results are studied separately.

For the sensor R3 $\alpha$ , Figure 8 shows the mean and

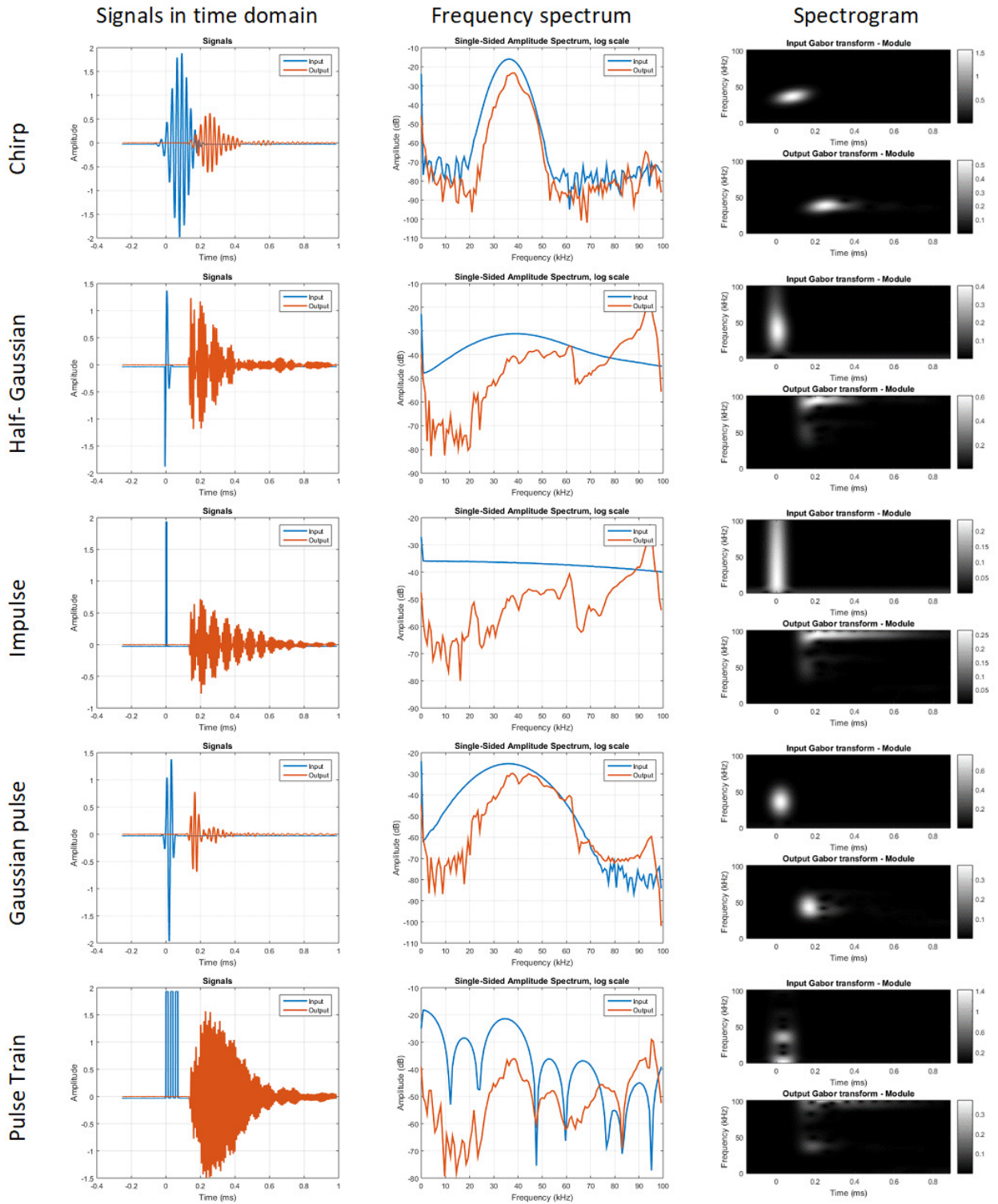


Figure 6: Time-frequency analysis for sensor R3a: input and output signals in time domain (left), frequency spectrum (center) and spectrogram (right).

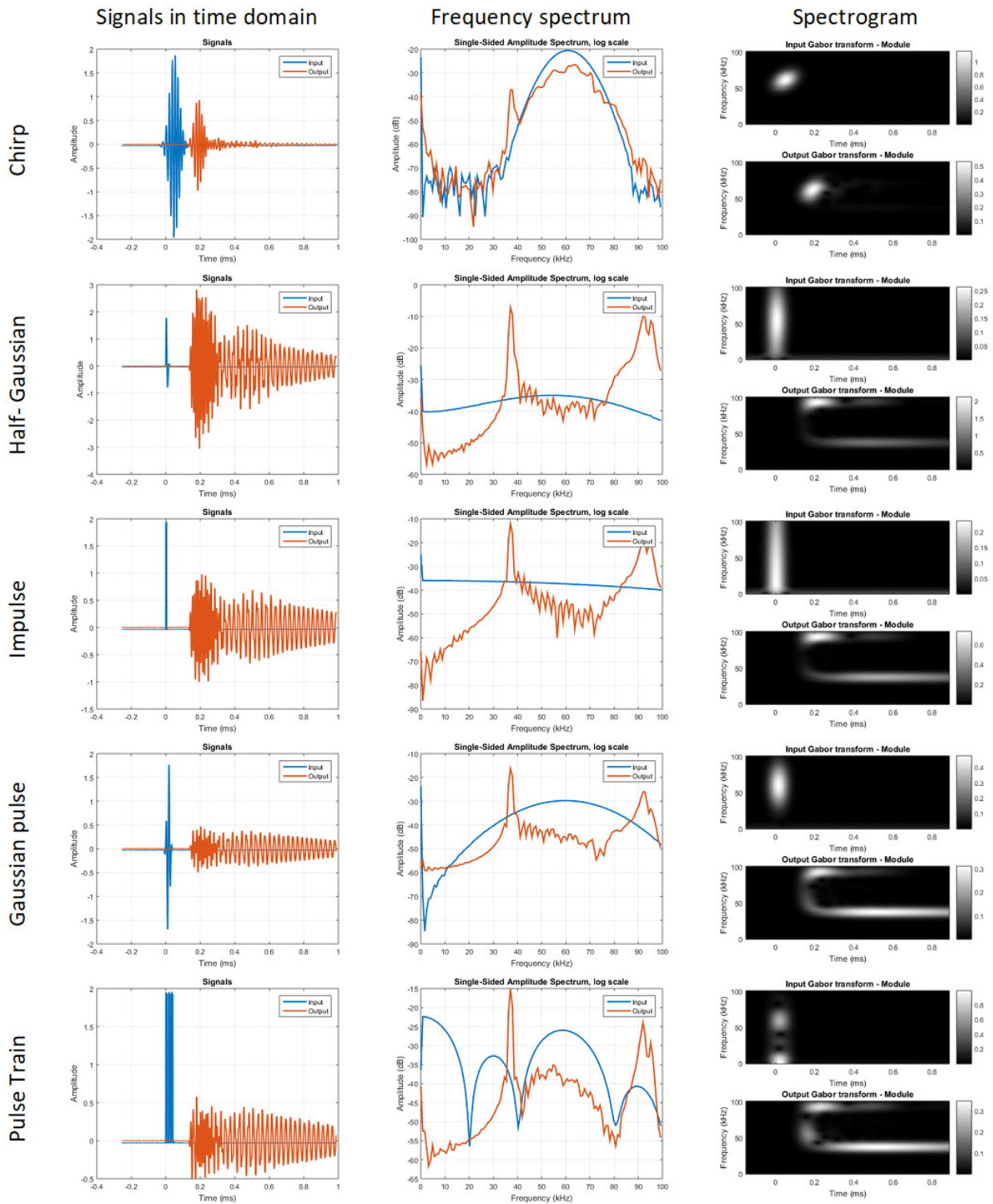


Figure 7: Time-frequency analysis for sensor R6 $\alpha$ : input and output signals in time domain (left), their frequency spectrum (center) and spectrogram (right).



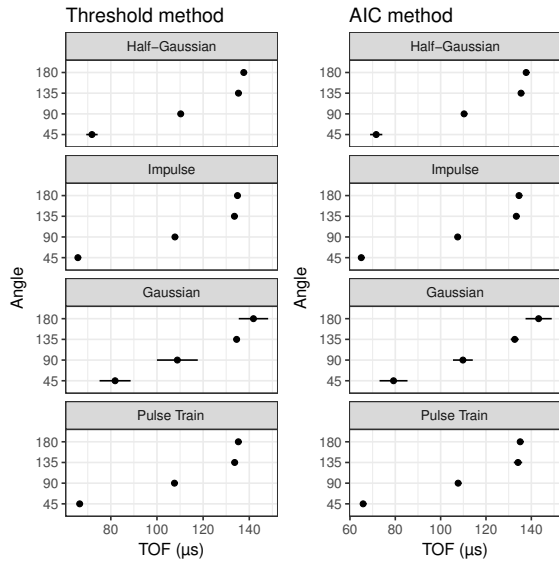


Figure 8: Mean TOF values using the Threshold method (left) and AIC method (right) for  $R3\alpha$ . Error bars present  $\pm\sigma$ .

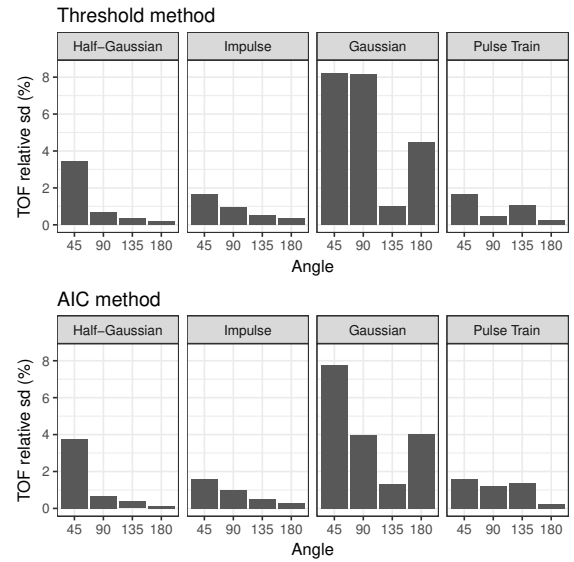


Figure 9: Relative standard deviation for TOF values using the Threshold method (up) and AIC method (down) for  $R3\alpha$ .

292 standard deviation values for the TOF estimated using  
 293 the threshold technique and AIC methods, for all  
 294 signals except chirp. Mean TOF values ranged be-  
 295 tween  $65 \mu\text{s}$  to  $143 \mu\text{s}$ . Difference in mean values es-  
 296 timated with the two methods was always inferior to  
 297  $1.4 \mu\text{s}$ . Standard deviation ranged between  $0.3 \mu\text{s}$  to  
 298  $8.8 \mu\text{s}$  for threshold method and  $0.2 \mu\text{s}$  to  $6.7 \mu\text{s}$  for  
 299 AIC method. To obtain a clearer view of variability  
 300 on the mean TOF estimation, Figure 9 presents the  
 301 relative standard deviation (coefficient of variation),  
 302 computed as the standard deviation divided by the  
 303 corresponding mean value, and presented as a per-  
 304 centage. Concerning the angle, variations were larger  
 305 when sensor position angle was  $45^\circ$ , and decreased as  
 306 this angle approached to  $180^\circ$ , this is the sensor lo-  
 307 cated opposed at radial direction. Lower variability  
 308 was obtained for impulse signal, with coefficients of  
 309 variation ranging from 0.33% to 1.67%. Gaussian signal  
 310 presented the larger variability, considering that the  
 311 AIC and threshold method work better with initial  
 312 impulsive signal.

313 In the case of the sensor  $R6\alpha$ , Figure 10 presents the  
 314 mean and standard deviation values for the TOF es-  
 315 timated using the threshold technique and AIC meth-  
 316 ods, for all signals except chirp. Mean TOF values  
 317 ranged between  $66 \mu\text{s}$  to  $143 \mu\text{s}$ , equivalent to the val-  
 318 ues for sensor  $R3\alpha$ . Difference in mean values es-  
 319 timated with the two methods was always inferior to  
 320  $1 \mu\text{s}$ . Standard deviation ranged between  $0.5 \mu\text{s}$  to  
 321  $5.2 \mu\text{s}$  for threshold method and  $0.5 \mu\text{s}$  to  $5.7 \mu\text{s}$  for  
 322 AIC method, slightly lower than the difference for sen-  
 323 sor  $R3\alpha$ . Figure 11 shows the relative standard devia-  
 324 tion presented as a percentage. For the receiver posi-  
 325 tion angle, variations were larger when sensor position  
 326 angle was  $45^\circ$ , and decreased as this angle approached

327 to  $180^\circ$ . Coefficients of variation obtained for half- 327  
 328 Gaussian, impulse and pulse train signals were simi- 328  
 329 lar, always inferior to 3% for both AIC and threshold 329  
 330 approaches. Gaussian signal presented the larger vari- 330  
 331 ability again, reaching a 7% when sensor was located 331  
 332 at  $180^\circ$ . 332

333 TOF values for chirp signal were obtained using the 333  
 334 three detection methods, including cross-correlation. 334  
 335 Figure 12 presents the mean and standard deviation 335  
 336 values for both sensors. Mean TOF values for  $R3\alpha$  336  
 337 ranged between  $85 \mu\text{s}$  to  $152 \mu\text{s}$  using cross-correlation 337  
 338 and  $120 \mu\text{s}$  to  $160 \mu\text{s}$  for the other two methods; 338  
 339 for  $R6\alpha$  ranged between  $94 \mu\text{s}$  to  $150 \mu\text{s}$  with cross- 339  
 340 correlation and  $90 \mu\text{s}$  to  $150 \mu\text{s}$  with the other two 340  
 341 methods. Standard deviation for  $R3\alpha$  ranged be- 341  
 342 tween  $0.48 \mu\text{s}$  to  $0.79 \mu\text{s}$  using cross-correlation and 342  
 343  $5.7 \mu\text{s}$  to  $33 \mu\text{s}$  for AIC and threshold methods; for 343  
 344  $R6\alpha$  ranged between  $0.31 \mu\text{s}$  to  $3.69 \mu\text{s}$  using cross- 344  
 345 correlation and  $3.34 \mu\text{s}$  to  $19 \mu\text{s}$  for AIC and threshold 345  
 346 methods. Chirp signal presents small amplitude vari- 346  
 347 ations at the beginning, an ill-favored condition when 347  
 348 using AIC and Threshold methods, where a first en- 348  
 349 ergetic arrival is expected; therefore the method pre- 349  
 350 senting less variation is the cross-correlation method. 350  
 351 Figure 13 presents the relative standard deviation val- 351  
 352 ues, where the large difference for cross-correlation 352  
 353 compared to the other two methods is clearly ob- 353  
 354 served: for  $R3\alpha$  sensor the coefficient of variation us- 354  
 355 ing cross-correlation was smaller than 1% while for 355  
 356 the other two methods ranked between 3.8% to 27%; 356  
 357 similarly for  $R6\alpha$ , using cross-correlation resulted in a 357  
 358 coefficient of variation ranking between 0.2% to 3.9% 358  
 359 compared to a range going from 3% to 12.7% for AIC 359  
 360 and threshold methods. 360

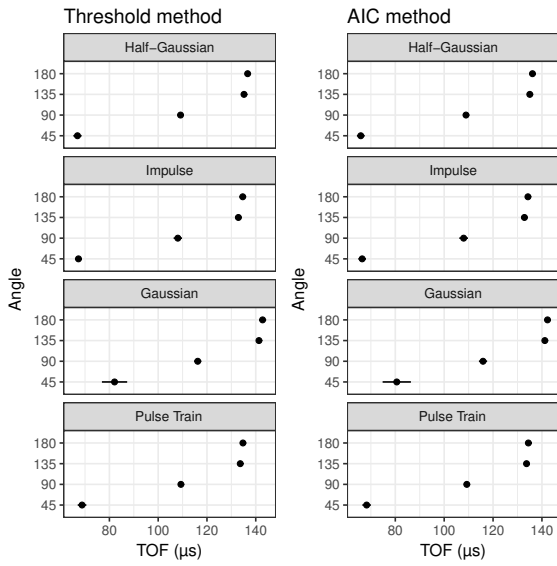


Figure 10: Mean TOF values using the Threshold method (left) and AIC method (right) for R6 $\alpha$ . Error bars present  $\pm\sigma$ .

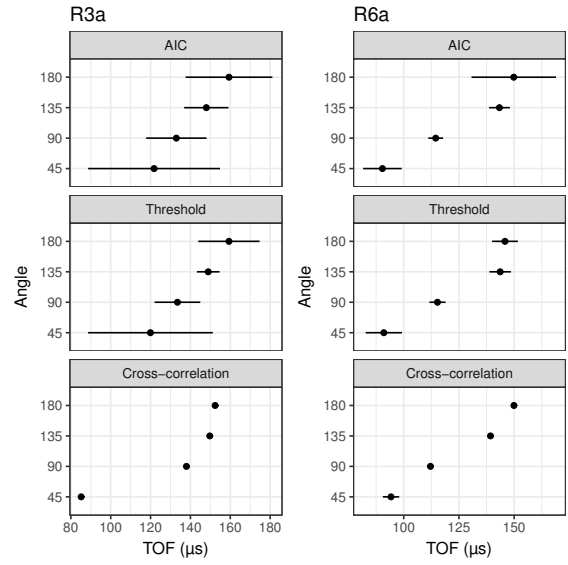


Figure 12: Mean TOF values for the chirp signal using the Threshold, AIC and cross-correlation methods for R3 $\alpha$  (left) and R6 $\alpha$  (right). Error bars present  $\pm\sigma$ .

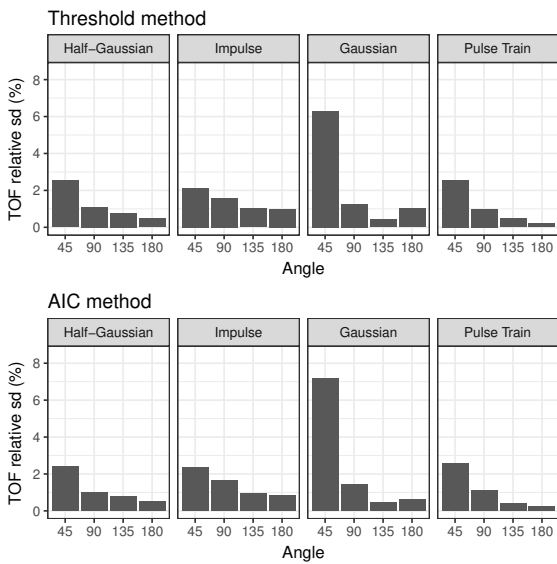


Figure 11: Relative standard deviation for TOF values using the Threshold method (up) and AIC method (down) for R6 $\alpha$ .

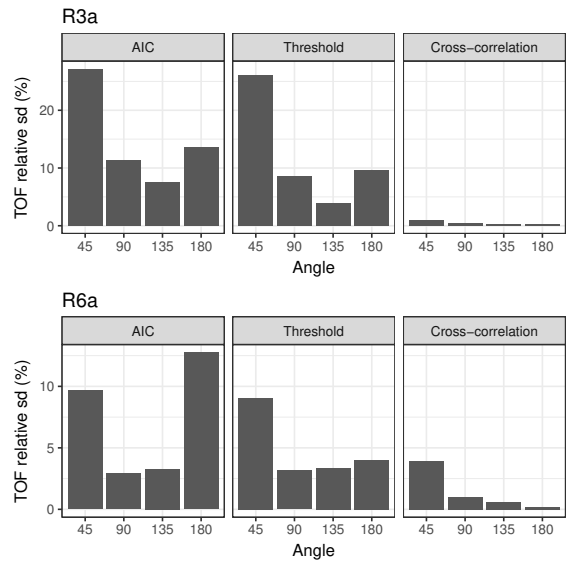


Figure 13: Relative standard deviation for TOF values for the chirp signal using the Threshold, AIC and cross-correlation methods for R3 $\alpha$  (up) and R6 $\alpha$  (down).

## 4 Discussion

Signal energy received in angle  $45^\circ$  was significantly lower than those obtained for the other angles, even if this position implies the shorter distance between transmitter and receiver tested. The transmitter placed at  $135^\circ$  resulted generally in the larger signal energy received. Ultrasonic beams for these sensors are affected by the transducer directivity pattern, resulting in a higher radiation intensity in the frontal direction of the sensor, that is orientated in radial direction in the experiments. Other effect is related to the propagation of waves in wood: wood anisotropy affects wave propagation, including a curvature of ray paths from transmitter to receivers, with respect to straight line paths for an isotropic case. [31, 32].

Signals with an initial impulsive response (impulse, pulse train and half-Gaussian pulse), resulted in larger energy received, but this energy was spread over several frequency bands, as seen on the time-frequency analysis, where the only signal able to concentrate the energy around the sensor central frequency was the chirp, the same one that presented a lower received energy. So, the compromise implies higher received energy but widely spread frequency spectrum or lower received energy but well concentrated frequency spectrum.

Threshold and Akaike methods for TOF detection presented highly similar results, as observed in a previous study [33], where it was shown that those two methods performed in agreement when the received signals presented SNR ratios above 20 dB. However, Akaike method presents as advantage that it does not need user-defined parameters, like the  $\alpha$  value in threshold case, which variation will result in a different TOF estimation. Inaccuracy increases using AIC method when the SNR is very low, i.e. below 10 dB.

For the chirp signal, the method that presented the lower variations was the cross-correlation. Among the other signals, the combination AIC-Impulse presented best results. Figure 14 presents the comparison between the relative standard deviation values, for the Impulse-AIC setting and the chirp-cross-correlation. For most cases, the chirp-cross-correlation setting resulted in lower variation for TOF estimation. The only case where chirp-cross-correlation combination was inferior than Impulse-AIC corresponded to the sensor R6 $\alpha$  located at  $45^\circ$ . In that case, signal-to-noise ratio was the lower for all configurations, near to 10 dB, while impulse presented a SNR with a mean value of 25 dB.

When comparing the difference between the TOF mean values obtained with the R3 $\alpha$  and R6 $\alpha$  sensors, the AIC-Impulse combination resulted in a lower difference, as presented in Table 5. A dispersion effect became noticeable when using the chirp signal, that could affect the TOF measurements. When the medium is dispersive, wave propagation velocity de-

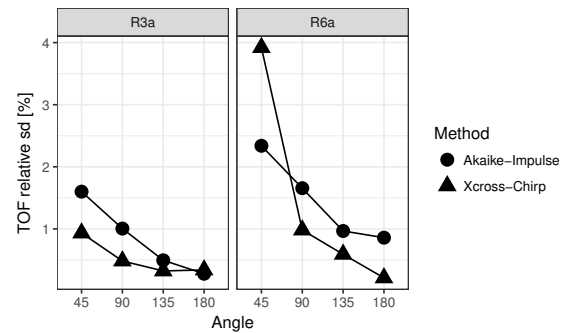


Figure 14: AIC-Impulse and Chirp-Cross-correlation comparison for TOF relative standard deviation values.

Table 5: Absolute mean differences between TOF obtained with R3 $\alpha$  and R6 $\alpha$  sensors.

Angle [°]	$\Delta$ Impulse [ $\mu s$ ]	$\Delta$ Chirp [ $\mu s$ ]
45	1.45	9.08
90	0.47	25.9
135	0.54	10.4
180	0.29	2.50

pend on the frequency, resulting in an output signal that spreads out in time. To visualize this effect, the peaks of the Gabor transform were obtained for both input and output chirp signals, giving an idea of instantaneous frequency for different time instants, as shown in Figure 15 for the case of the sensor R6 $\alpha$  located at  $135^\circ$ . Input frequencies present a linear distribution on time, however, the instantaneous output frequencies delayed more for higher frequencies.

## 5 Conclusions

For standing tree non-destructive evaluation using ultrasonic waves, setting up the chain of measurement for *in situ* testing is a crucial step. Accuracy on the time-of-flight determination leads to a correct defect identification. However, several factors influence this measurement: the excitation signal characteristics in energy and frequency, the transducer frequency response, the wood inner variability, the coupling between the sensor and the tree including the bark influence, the effect of the SNR on the TOF estimation, among others. In this article, *in situ* testing was performed comparing five different excitation signals, two different transducers with resonant frequencies at 36 kHz and 60 kHz, 4 different receiver positions around the tree and three TOF detection methods. Among all configurations, the one presenting less variation on the TOF measurements was the combination of an encoded excitation signal, such as chirp signal, with cross-correlation to measure the time delay. Chirp signals deserve attention considering that this signal was adjusted to the transducer response

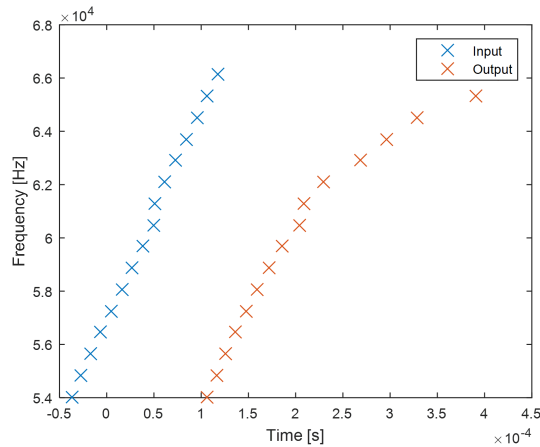


Figure 15: Chirp dispersion effect for the case of sensor R6 $\alpha$  and the receiver located at 135 $^\circ$ : instantaneous frequency from Gabor transform for input and output signals.

449 and the received signals concentrated energy in fre-  
 450 quency bands around the resonant frequency of sensors.  
 451 The sensor position affected the consistency on  
 452 time measurements: as the sensor position angle ap-  
 453 proached to the radial direction, the TOF values pre-  
 454 sented less variation. Considering the variability of  
 455 the tree and the limited operating band of the sensors,  
 456 it is difficult to have full control of the excitation sig-  
 457 nal. Even when an given signal is generated with the  
 458 electrical signal generator, this signal is filtered by the  
 459 transfer functions of the emitting transducer, the tree  
 460 and the receiving transducer. To continue with this  
 461 work, a study of the energy transference considering  
 462 the transducer properties, the transducer-bark cou-  
 463 pling, the bark properties and the presence of decay  
 464 would be necessary.

## 465 Acknowledgement

466 This work has been carried out in the framework of a  
 467 project (C16A01) funded by the ECOS Nord program  
 468 and is a part of Luis Espinosa Ph.D. thesis (grant from  
 469 COLCIENCIAS - Departamento Administrativo de  
 470 Ciencia, Tecnología e Innovación, Colombia).

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