seems promising in terms of the calculation times, and allows the use of the same paradigm for the simulation of hybrid models.

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Performance comparison of four time-of-flight estimation methods for sonar signals

B. Barshan and B. Ayrulu

Performances of four methods of time-of-flight estimation for sonar signals are compared in terms of their bias, standard deviation and complexity: thresholding, curve fitting, m-out-of-N sliding-window, and correlation detection. Whereas correlation detection represents the theoretical optimum, simpler and faster suboptimal methods can offer acceptable performance at much lower cost. The experimental results are in close agreement with the simulations.

Introduction: Most sonar systems depend on reliable *time-of-flight* (TOF) estimates for accurate target localisation. The target range r is related to the TOF t_o by the speed of sound: $r = ct_o/2$.

This Letter compares the performances of four methods of TOF estimation, three of which are suboptimal but are fast and simple to implement in real time: thresholding, sliding-window, and curve fitting. These are compared to the optimum *correlation detection method* which maximises the signal-to-noise ratio (SNR). A comparison of the methods is based on their bias, standard deviation, and complexity.

Time-of-flight estimation: In *simple thresholding*, the estimated TOF is the time t_o at which the echo amplitude first exceeds a preset threshold τ (Fig. 1). The TOF estimate thus obtained is usually larger than the actual TOF, which corresponds to the onset of the echo signal. This bias on the thresholding estimate is difficult to model or describe analytically since it is a function of the threshold level, target location, and type.

Another practical TOF estimation method is *curve fitting* in which an iterative nonlinear least-squares procedure is employed to fit a parabola to the onset of the sonar echo. The vertex of the fitted parabola is taken as an estimate of the TOF (Fig. 1). This estimate usually falls to the left of the thresholding estimate, and reduces the bias considerably [1].

The third suboptimal method considered is the *sliding window*, which has not been applied to sonar signals before. It originates from the m-out-of-N (or double thresholding) detection method, first used for radar signals [2]. A window of length N is slid through the echo signal one sample at a time. At each window position, the number of samples exceeding the preset threshold τ is counted. If this number exceeds a second threshold m, then a target is assumed to be present and a TOF estimate is obtained. The advantage of this method is its robustness to noise spikes of total duration $< m$, since the target detection is based on at least m samples exceeding the threshold, instead of a single one as in simple thresholding. We have considered three variations of this method where the TOF estimate is taken as: (i) the first sample exceeding τ within the window, (ii) the sample at the centre of the window, and (iii) the $(N - m)$th sample of the window. The performance of the sliding window depends on the window length N, the second threshold value m, and the variation used.

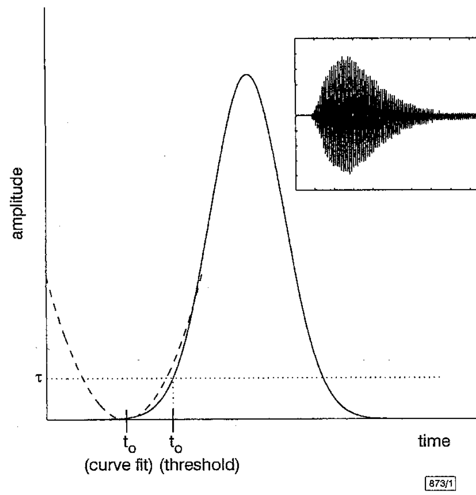

Fig. 1 *Envelope of sonar echo and TOF estimation by thresholding and curve fitting*

Inset: Typical real sonar waveform

The *classical optimum correlation detection* method for TOF estimation is also unbiased, and maximises the SNR. It employs a matched filter that contains a replica of the echo waveform to determine its most probable location in the received signal. Since the echo shape varies with target location and type, a large number of reference templates are required for the correlation operation.

Simulation results: For a target at range r and azimuth θ in the far zone of the transducer, the received time signal can be modelled by

$$s_{r,\theta}(t) = k(r) e^{-\frac{\theta^2}{2\sigma_\theta^2}} e^{-\frac{(t-t_o-\frac{1.8}{f_o})^2}{\sigma_t^2}} \sin[2\pi f_o(t-t_o)] \quad (1)$$

Here, $k(r)$ is a function of the target type and range r [1]. The angular beam profile is modelled as a zero-mean Gaussian with suitably chosen variance σ_θ^2 [3]. This model for the echo signal is capable of representing observed signals for a wide variety of target types and locations [3].

First, the problem of finding suitable values for the window length N and the second threshold value m in the sliding-window method is considered. Different N and m values in the range $5 \leq N \leq 50$ and $1 \leq m \leq N$ have been tried when $r = 0.3, 0.5, 0.7, 1.0$m and $\theta = 0°, \pm 10°, \pm 20°$. Choosing $N = 40$ and $m = N/4$ results in the smallest bias in the TOF estimate in most cases. Thus these values of N and m are used for the sliding-window method throughout this study. The first threshold τ is taken as five times the noise standard deviation in all the suboptimal methods.

In the simulations, the values $r = 0.3, 0.5, 0.7, 1.0$m, $\theta = 0°, \pm 10°, \pm 20°$, $f_o = 40$kHz, $c = 343.5$m/s, $\sigma_\theta = 27°$, and $\sigma_t = 0.0003$s are used. To estimate the bias and the standard deviation, 100 realisations are generated by adding zero-mean white Gaussian noise to the signal. For the correlation method, an average over 100 simulated signals is computed to produce the echo template. A comparison among the four TOF estimators is made in Table 1 in terms of their biases and standard deviations. We have considered the three processing options: the original time signal modelled by eqn. 1 (O), the rectified signal (R), and its envelope (E). Since the performances of R and O are comparable, only the results for O and E are presented in the Table. The data for all combinations of r and θ are not presented due to space limitations. We have, however, observed that the effect of increasing r and $|\theta|$ is to degrade the estimation accuracy. This is mostly caused by the decreasing SNR as the signal amplitude decreases with increasing r and $|\theta|$ (eqn. 1).

When the *envelope* of the signal is processed with the suboptimal methods, minimum bias is obtained with curve fitting. However, the variance obtained with this method is the largest. As expected, bias performance of this method degrades when the *original* signal is used, due to the fluctuations of the waveform around the onset of the signal. When the original signal is processed curve fitting is even worse than simple thresholding.

Table 1: Results for r = 0.5m, θ = 0° and SNR = 20dB

Method		Simulation		Experiment	
		Bias	$\sigma_{\hat{t}_o}$	Bias	$\sigma_{\hat{t}_o}$
		s	s	s	s
THD	O	1.81×10^{-4}	3.07×10^{-5}	1.82×10^{-4}	2.49×10^{-5}
	E	1.41×10^{-4}	2.77×10^{-5}	1.41×10^{-4}	2.40×10^{-5}
SW (i)	O	1.71×10^{-4}	1.59×10^{-5}	1.69×10^{-4}	1.73×10^{-5}
	E	1.65×10^{-4}	2.22×10^{-5}	1.60×10^{-4}	2.04×10^{-5}
SW (ii)	O	2.09×10^{-4}	1.59×10^{-5}	2.07×10^{-4}	1.73×10^{-5}
	E	1.97×10^{-4}	1.84×10^{-5}	1.94×10^{-4}	1.74×10^{-5}
SW (iii)	O	2.39×10^{-4}	1.59×10^{-5}	2.37×10^{-4}	1.73×10^{-5}
	E	2.27×10^{-4}	1.84×10^{-5}	2.24×10^{-4}	1.74×10^{-5}
CUF	O	2.14×10^{-4}	1.49×10^{-4}	2.02×10^{-4}	1.53×10^{-4}
	E	1.34×10^{-4}	2.98×10^{-5}	1.34×10^{-4}	2.50×10^{-5}
COR	O	9.04×10^{-7}	2.62×10^{-18}	1.19×10^{-5}	1.71×10^{-5}
	E	2.36×10^{-6}	2.62×10^{-6}	4.96×10^{-6}	1.37×10^{-6}

THD: thresholding, SW: sliding window, CUF: curve fitting, COR: correlation, O: original, E: envelope

In terms of variance, the sliding-window method always outperforms the thresholding and curve-fitting methods. However, its bias performance depends on the SNR and the variation of the method used. Although not presented here, we have investigated the effect of varying the SNR from 12dB to infinity. The conclusion is that variation (i) gives the smallest bias when the SNR is low. Performance of variation (ii) is slightly worse, and (iii) is the worst. For a larger SNR, the situation is reversed: variation (iii) performs best, and (ii) and (i) have worse performance in the given order. This result is due to the variation of the threshold with noise; when the noise standard deviation is small (large SNR), τ is chosen small. Then, the samples of the signal exceed the threshold level τ at the tail of the Gaussian envelope which occurs within the second half of the time window. Therefore, variations (ii) and (iii) perform better. For high noise standard deviations (low SNR), the threshold is chosen larger, and the bias between the actual TOF and the point at which the threshold is exceeded becomes larger. In this case, the beginning of the time window is closer to the actual TOF, and variations (ii) and (iii) perform better. The transition between the low and high SNR cases occurs around SNR = 35dB.

In order of increasing computational complexity, the methods can be sorted as thresholding, sliding-window, curve fitting, and correlation detection. For the processing of a single echo, the required CPU times on a SUN SPARC 20 workstation are 5.6, 8.3 and 11.1ms, respectively, for the first three methods. The classical correlation detection method would require many orders of magnitude greater time.

Experimental results: Experiments have been performed with wide-beam f_o = 40kHz transducers [4]. A planar target is positioned at r = 0.5m and θ = 0°. Data acquisition from the sonars is accomplished by using a DAS-50 A/D card with 12bit resolution and 1MHz sampling frequency. Starting at the transmit time, 10,000 samples of each echo signal have been collected. A typical waveform obtained from the real sonar system is shown as the inset of Fig. 1. As in the simulations, an average over 100 noisy sonar waveforms is computed to produce the correlation template. Experimentally obtained biases and standard deviations for all four methods, computed over 100 echo waveforms, are tabulated in Table 1. The results are in very good agreement with the corresponding simulations.

Conclusion: Four TOF estimation methods are compared on the basis of bias error, standard deviation, SNR dependence and complexity. Three of the methods are suboptimal but fast and simple to implement. The fourth method, correlation detection, is optimal but computationally more complex, with certain disadvantages in a real-time implementation. It has been included mainly as a reference in this study. When the signal envelope is processed, minimum bias is obtained with the curve-fitting method, which is, however, computationally more complex and more difficult to implement than the two other suboptimal methods. In terms of standard deviation, the sliding-window method always outperforms the thresholding and curve-fitting methods. Its bias performance is dependent on the SNR and the variation of the method used. Overall, the three simpler, suboptimal methods discussed provide a variety of attractive compromises between accuracy and system complexity.

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