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Signal Processing Methods and Poly-Pulse Waveforms for Laser Vibrometry in Pulsed Mode

J. Totems¹, V. Jolivet¹, J.-P. Ovarlez¹, N. Martin²

¹ONERA, The French Aerospace Lab, Chemin de la Hunière, 91761 Palaiseau Cedex, France
julien.totems@onera.fr, veronique.jolivet@onera.fr, jean-philippe.ovarlez@onera.fr

²Gipsa-Lab, 961 rue de la Houille Blanche, Domaine Universitaire BP 46, F-38402 Saint-Martin d'Hères, France
nadine.martin@gipsa-lab.inpg.fr

Abstract

We present our work to jointly optimize modulation waveforms and signal processing for long range vibration sensing using a heterodyne coherent laser radar in pulsed mode. The performance of various existing Instantaneous Frequency (IF) estimators is compared through simulation, taking into account Continuous Wave (CW) and pulse-pair waveforms, and for the first time poly-pulse waveforms. A new estimator, based on a pseudo time-frequency representation of the IF's likelihood function, was developed in response to the specific noise conditions encountered in laser radar. In agreement with theoretical calculations, our simulations show that, for pulsed mode, poly-pulse waveforms and our IF Likelihood (IFL) processing outperform the classical pulse-pair waveform in case of dominant speckle noise. With the same available laser power for the various operating modes, CW mode often demonstrates the best signal-to-noise ratio, given the strong speckle noise conditions and the vibration bandwidth considered here. Yet, pulsed mode with IFL processing proves to be more robust when the analysis bandwidth is increased and allows better demodulation, at low carrier-to-noise ratio.

1. Introduction

Coherent laser radars can measure the small amplitude vibrations of remote surfaces targeted with the laser, by determining the Doppler shift of the back-scattered wave. The interference between this scattered wave and an artificially shifted local oscillator, on a detector, is the source of a heterodyne signal around this artificial frequency shift, with an additional shift which is proportional to the scattering surface's radial velocity. This technique has been successfully applied to the detection of structural damage in buildings¹, and target recognition for military purposes². In both cases, the aim is to identify the vibration's modal frequencies, after frequency demodulating the signal.

Today, one of the major goals is to lengthen the range of these instruments. To this end, a pulsed mode has been developed³, which allows the signal's peak power to be increased, for the same mean laser power. But until now, the performance of this operation mode, which usually works with pulse pairs, was limited by its sensitivity to phase noise and Doppler ambiguities that appear for poorly chosen pulse separations⁴. Gatt et al.⁵ have shown the potential of poly-pulse waveforms to counter these problems, but did not describe the best suited signal processing. We compare various non-parametrical processing strategies for these waveforms, and evaluate their interest in regard to the classical CW and pulse-pair operating modes, in the context of long range identification of moving targets.

2. Signal model

This study is based on the following expression of the signal, in a complex form:

$$i_s(t) = \mu(t).i_{het}(t) + i_b(t) = \mu(t).i_0.m(t).\exp(j\phi_{vib}(t)) + i_b(t) \quad (1)$$

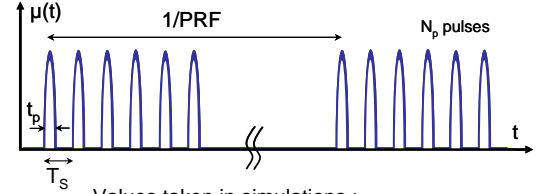
where $\mu(t)$ is an amplitude modulation applied to the laser emission ($\mu(t) = 1$ in CW mode), $i_{het}(t)$ is the heterodyne current, with a mean amplitude i_0 , $m(t)$ is a complex multiplicative noise (speckle noise), gaussian valued, circular and centered, with a variance set to 1, $\phi_{vib}(t) = 4\pi.x_{vib}(t)/\lambda$ is the phase modulation caused by the targeted surface vibration $x_{vib}(t)$ for the laser wavelength λ , and $i_b(t)$ is an additive complex noise (detector / photon noise), white, gaussian valued, circular and centered, with variance σ_b^2 .

This simplified model is valid only if we assume that any global Doppler shift has previously been removed, and if we neglect the phase effects of atmospheric turbulence and laser frequency noise (which can be mitigated by decreasing optical path difference between local oscillator arm and measuring arm) in regard to speckle noise, which is mostly due to the coherent scattered figure, from the target's rough surface, moving in front of the reception aperture when the target rotates. Thus the multiplicative noise is directly linked to the characteristics and dynamics of so-called speckles.

15th Coherent Laser Radar Conference

The two main noise parameters are B_m , the inverse of the multiplicative noise's coherence time, so that its autocorrelation function is: $\Gamma_m(\tau) = \exp(-B_m^2 \tau^2)$, and the Carrier to Noise Ratio (CNR), defined by $\langle |i_{het}|^2 \rangle / \langle |i_b|^2 \rangle = i_0^2 / 2\sigma_b^2$. B_m will be chosen of a few kiloHertz, close to the modulation bandwidth created by the vibration (which corresponds to mm/s order vibration velocities). Such values are consistent with the actual parameters expected for long range moving vehicle identification (previous studies³ considered speckle noise with lower bandwidth, few hundred Hertz). We remind that the goal is to determine $v_{vib}(t) = dx_{vib}(t)/dt = \lambda/2 f_{inst}(t)$, which is equivalent to a frequency demodulation in the presence of strong additive and complex multiplicative noises.

Pulsed waveforms are created by modulating the amplitude with $\mu(t)$, which takes values 0 or μ . Their parameters are defined in figure 1. Our comparison between various waveforms assumes in particular an equal mean laser power; the peak value μ is thus $\sqrt{1/(N_p t_p PRF)}$. We also suppose that we have previous knowledge of the target's distance, and know precisely which samples contain signal. In practice, the radar that was used to detect the target can provide us with telemetry accurate enough for this purpose.



Values taken in simulations :
 $t_p = 2 \mu s$, $T_s = 50 \mu s$, $PRF = 500 \text{ Hz}$, $N_p = 2 \text{ or } 6$
 Figure 1: Poly-pulse waveform parameters

3. Instantaneous frequency estimators

We present various IF estimators that we developed, adapted, or found in laser radar or signal processing literature:

Table 1 : Summary of studied IF estimators

| | | | |
|-----------------|---------------------------|--|--|
| CW mode | Autocorrelation First Lag | $\hat{f}_{inst}(t) = \frac{1}{2\pi\Delta t} \arg\left(\sum_{k=1}^K i_s(t+k\Delta t) i_s^*(t+(k-1)\Delta t)\right)$ | |
| | SpectroGram Centroid | $\hat{f}_{inst}(t) = \frac{B}{2\pi} \arg\left(\int_B SG(t, f) \cdot \exp\left(j2\pi \frac{f}{B}\right) df\right)$ | (B: analysis bandwidth) |
| | Lee's Spectral Matching | $\hat{f}_{inst}(t) = \arg \max_f (S_{ref}(f) * SG(t, f))$ | (S_{ref} : reference spectrum) |
| PP mode | Pulse-Pair | $\hat{f}_{inst}(t = k / PRF) = \frac{1}{2\pi T_s} \arg(\langle i_s \rangle_{k,2} \langle i_s \rangle_{k,1}^*)$ | ($\langle i_s \rangle_{k,i}$: mean signal on pulse #1 of waveform #k) |
| Poly-Pulse mode | Poly Pulse-Pair | $\hat{f}_{inst}(t = k / PRF) = \frac{1}{2\pi T_s} \arg\left(\sum_{l=2}^{N_p} \langle i_s \rangle_{k,l} \langle i_s \rangle_{k,l-1}^*\right)$ | |
| | Correlation FT | $\hat{f}_{inst}(t = k / PRF) = \arg \max_f \left(\left \int \Gamma_{i_s,k}(\tau) \cdot f(\tau) \cdot \exp(-j2\pi f \tau) d\tau \right \right)$ | |
| | Poly-Pulse Spectrum | $\hat{f}_{inst}(t = k / PRF) = \arg \max_f \left(\left \int_{\text{Multiplet } k} i_s(t) \cdot \mu(t) \cdot \exp(-j2\pi f t) dt \right \right)$ | |
| | IF Likelihood | $\hat{f}_{inst}(t = k / PRF) = \arg \max_f \left(- (i_{s,k} e^{-j2\pi f t})^H \cdot Q^{-1} \cdot (i_{s,k} e^{-j2\pi f t}) \right)$ | ($Q = Q_m + Q_{ib}$, sum of covariance matrices of multiplicative and additive noises) |

For CW mode, we have implemented three popular estimators in literature: the short term « coherent average » of phase difference between consecutive samples (Autocorrelation First Lag³, AFL), the centroid of a spectrogram's columns (with a circular mean, in order to avoid bias from the non-zero-mean noisy background) (SpectroGram Centroid⁵, SGC), and a short-term spectrum matching, also on the spectrogram (Lee's Spectral Matching⁶, LSM).

Pulse Pair mode is processed by calculating the phase difference between each pair of pulses (Pulse-Pair, PP).

This method is also implemented in Poly-Pulse mode: the phase difference between consecutive pulses is coherently averaged here again (Poly Pulse-Pair, PPP). But various works like Youmans⁶ insist on the benefit of differentiating phase over non-consecutive pulses, in which case the problem boils down to linear regression of the autocorrelation's phase, i.e. the search of its Fourier Transform's (FT) maximum. That is why we consider a second class of estimators for Poly-Pulse

mode, which we call “spectral”. The first one is based on the FT of the autocorrelation function, after a proper windowing to select relevant samples and lags (Correlation Fourier Transform, CFT). Another one, theoretically equivalent to the latter, uses the spectrum of the received waveform multiplied by the emitted waveform (Poly-Pulse Spectrum, PPS). This corresponds to radar matched filter, which is optimal when dealing with additive white noise. In case of multiplicative noise, though, PPS is not optimal, and we propose a new estimator based on the likelihood function of the poly-pulse’s instantaneous frequency (Instantaneous Frequency Likelihood, IFL, using a variable change from Ghogho et al.⁷). It does require prior knowledge of noise characteristics (CNR and B_m , which can be evaluated on the signal), and remains sensitive to deviations from the given signal model, but it is theoretically the best estimator for this model. For these spectral estimators, we also propose to build a pseudo Time-Frequency Representation (TFR), by juxtaposing in columns the function we need to maximize for each poly-pulse. In case of strong additive noise, peak tracking between columns – between poly-pulses– can help discriminate the peak at the true signal IF from the transitory peaks due to strong noise. We implemented a simple temporal smoothing on the TFR in order to show the potential of this option (we then call the processing methods: PPS-s, CFT-s and IFL-s). The same smoothing is applied to CW mode TFRs for a fair comparison (SGC-s, LSM-s).

4. Poly-pulse waveforms theoretical performance

Before applying these estimators to vibrometry, we study the error on the velocity estimate over a single waveform, in the case of pulse-pair and poly-pulses. We evaluated numerically the theoretical Cramér-Rao Lower Bound (CRLB) on this error (Q only on non-zero samples):

$$\sigma_v \geq [\text{tr}((\frac{\partial Q}{\partial f})^2 Q^{-1})]^{-1/2} \text{ with } Q(t, u) = \mu^2 i_0 e^{-B_m^2(t-u)^2} e^{j2\pi ft} + \sigma_b^2 I \quad (2)$$

We had to add the effect of CNR variation in time (so-called fading) to better predict velocity error. On figure 2, we see that theory and simulation agree on better precision with waveforms containing six pulses rather than only two, as predicted by Gatt et al.⁵. Also, we notice that our IFL estimator almost reaches optimum precision when CNR is high, whereas PP and PPP estimators are limited by multiplicative noise. On the other hand, the CRLB cannot account for the degradation seen at low CNR; only simulation can help qualify waveforms and estimators in case of strong additive noise.

5. Simulation results

Using our heterodyne signal simulator, we have qualified all presented estimators, on the criterion of Signal-to-Noise Ratio (SNR), which is evaluated on the vibration spectrum, as the ratio of the power spectral density at the modal frequency over the power spectral density of the noise floor. The simulated vibration had 5 modal frequencies between 20 and 120 Hz, with maximum velocities around 1 mm/s. The retained SNR value is the average of the 5 individual SNRs. The multiplicative noise bandwidth B_m is set to 5 kHz. For each given result, we average the SNR of 200 runs.

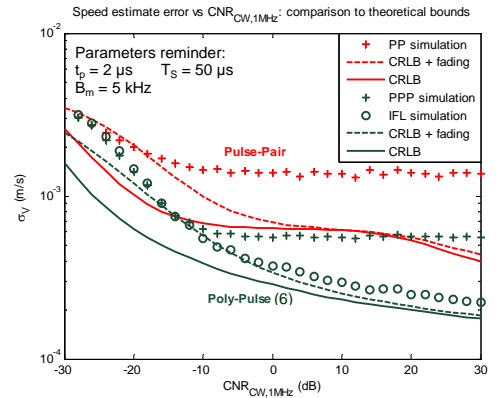


Figure 2: Comparison of theoretical and simulated velocity precisions over a single waveform in pulsed mode

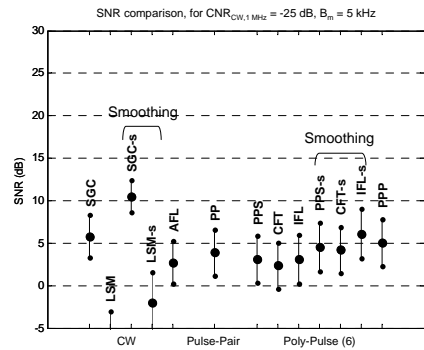


Figure 3: SNR results of estimators under strong additive noise

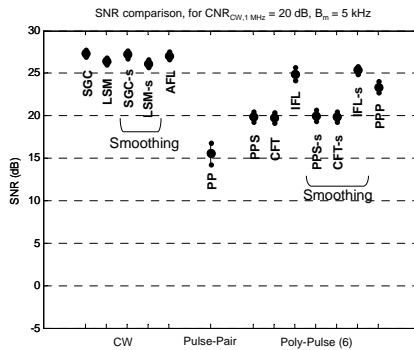


Figure 4: SNR results of estimators under predominant multiplicative noise

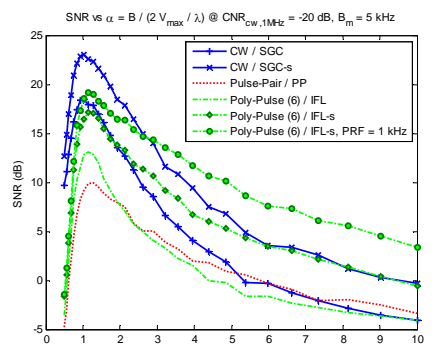


Figure 5: SNR results in case of analysis bandwidth mismatch

15th Coherent Laser Radar Conference

In pulsed mode, with a strong additive noise (CNR = -25 dB in 1 MHz, cf. figure 3), our IFL estimator with a temporal smoothing of the RTF performs a little better than other processing methods. CW mode obtains equivalent SNR, unless smoothing is applied to the spectrogram, in which case SNR increases by about 5 dB, thanks to background noise mitigation.

When multiplicative noise is predominant (CNR = 20 dB in 1 MHz, cf. figure 4), CW mode also yields much higher SNR, thanks to an efficient phase noise averaging allowed by numerous measurements. In pulsed mode, the IFL estimator allows a 5 dB gain compared with estimators that are only adapted to additive noise, and a 10 dB gain compared with pulse-pair mode. Our objective to improve the robustness of pulsed mode against speckle noise is met, with a computing time comparable to the one in CW mode.

For the previous results, it was assumed that the analysis bandwidth, defined by the filter used in CW mode or $1/T_s$ in pulsed mode, was closely adjusted to the frequency modulation bandwidth due to target vibration : $B = 1/T_s = 4 v_{\text{vib,max}} / \lambda$. Yet in practice, without prior knowledge of vibration maximum velocity, a larger analysis bandwidth has to be chosen. We show that, in case of strong additive noise, temporal smoothing allows TFR-based processing to be much less sensitive to bandwidth enlargement (cf. figure 5). With the chosen PRF, CW mode still yields higher SNR, but if the PRF is increased in pulsed mode, so as to better average phase noise, poly-pulse waveform with IFL processing allows over 3 dB gain, despite the loss in peak CNR due to the greater number of pulses. An optimum is found at PRF = 1500 Hz, which depends on relative strength of multiplicative and additive noises.

6. Conclusion

We have simulated and compared performance of various IF estimators for signal processing for coherent laser radar vibrometry, in a long range, moving target identification context. Our results indicate that the estimator we proposed, which is based on a pseudo time-frequency representation of the IF likelihood, is better than the other estimators available today for poly-pulse waveforms in pulsed operation mode. We confirm the advantage of this waveform over the classical pulse-pair, particularly for its robustness against the complex multiplicative noise encountered. CW mode remains generally more efficient, when dealing with large bandwidth vibration-induced frequency modulation and comparably large bandwidth multiplicative noise. Yet, pulsed mode as we implemented it can be better in practice, without prior knowledge of the target's vibration speed. It is also intrinsically relevant in applications that require monostatic instruments and work with slow targets, since neither optical path isolation nor difference in carrier frequency can shield reception from noise due to signal parasitic reflections. Our future works will involve development of peak tracking techniques for optimal extraction of the vibration from the time-frequency representation, study of the effects of other perturbations like high frequency motor vibrations, and laboratory experimentation of poly-pulse vibrometry.

Acknowledgments

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