SNR lidar signal improovement by adaptive tecniques

Aimè Lay-Ekuakille[1], Antonio V. Scarano[2]

Dipartimento di Ingegneria dell'Innovazione, Univ. Degli Studi di Lecce – via Arnesano, Lecce
[1]aime.lay.ekuakille@unile.it
[2]scarano.antonio@virgilio.it

Abstaract - Image filtering by Richardson-Lucy algorithm show an iterative solution for monodimensional signal deconvolution. In this paper the performance of this algorithm will verified when LIDAR signals are pre- filtere by an adaprive low-pass filter. Most intresting results, for real-time deconvolution and filtering of lidar signal, will also showed.

I. Introduction

A LIDAR observation may be considered an 1x N image that by Richardsoin-Lucy algorithm, is submitted to a deconvolution process. The measured signal Pm(t) is taken as the initial guess $P^{TM}(1)$ for the iteration and negative values due to noise have to be set to zero in order to guarantee its convergence. In complex environment at lidar signal is superposed noise *N(t):*

$$P_m(t) = P(t) + N(t) = (R(t) \times P_\delta(t)) + N(t) \quad (1)$$

were *P(t)* is lidar observation after deconvolution process, strongly dependent on geometrical and optical characteristics of the sensor, and $P_\delta(t)$ is ideal observation when the response funtion of lidar sensor is a Diràc distribution, like ideal laser pulse. From (1), the additive noise term *N(t)* makes a direct deconvolution impossible.
In general, deconvolution process with *R(t)* show a low-pass characteristic, and this operation intensifies the range of higher frequencies, were *N(t)* contributions are relevant. Consequently a pre-low-pass filtering of observed data can be very useful in some cases. The aim of this paper is to propose a new filtering scheme whit an Adaptive Noise Canceller (ANC), that with knowing of a-priori noise statistic and lidar prifile, optimeze a set of digital filter coefficients to adapt its impulse response to improove SNR. The choice for adaptive algorithm in an N-LMS (Normalized-Least Mean Square) that update filter weight looking-up to input signal power, making a fine tuning of impulse response.

II. System description

The aim of this work is to evaluate the performance of the system like below

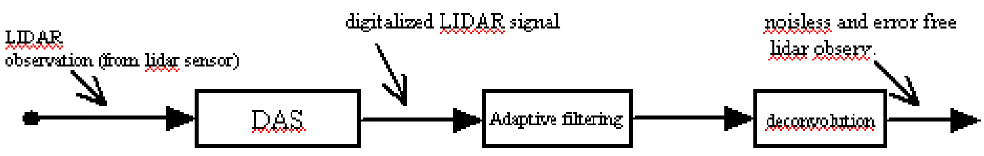

Fig. 1 System structure

were DAS is the system that perform the data acquisition that in any case may be considered "all-in one" with the lidar bulk. DAS will guarantee a "non demolition" extraction of information, performing an electrical de-coupling between sensor and processing unit. After acquisition, adaptive filtering is performed to lock the filter response on the noisy component of observation. Deconvolution process now is error free due to pre-filtering (low-pass).
In this paper was designed the filter structure: filter length (number of taps) and various filter parameter like forgetting factor and learning step (gain constant).

After, system performance will be investigated and specific results outlined.

III. The Adaptive Noise Canceller (ANC)

A system of these need a couple of input signal: lidar observation, and a noisless reference signal input. Neverthless, noisless signal is the goal, so the schema in figure summarize a choice for reference input obtained from primary input signal by a delay.

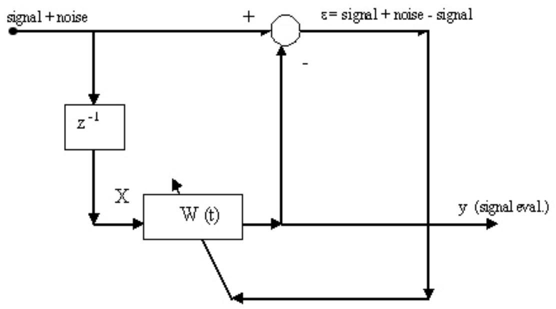

Fig. 2: Adaptive Noise Canceller (ANC)

This delay allow a decorrelation between signal and noise, so at the filter input there is only signal component over filter lock-in.
Signal that drive filter learning is ε=s+n-y, squaring will be: $\varepsilon^2=s^2+(n-y)^2+2s(n-y)$; expected value of booth member give

$$E[\varepsilon^2]=E[n^2]+E[(s-y)^2]+2E[n(s-y)]=E[n^2]+E[(s-y)^2]$$

(2)

So, the minimum error power will be

$$E_{\min}[\varepsilon^2]=E[n^2]+E_{\min}[(s-y)^2] \qquad (3)$$

when filter will become optimum filter for that specific lidar observation, $E[\varepsilon]$ will be minimized reaching minimum value on a L-dimensional iper-quadratic surface, whit L taps for filter.

IV. N-LMS algorithm

Like Newton's method and the syeepest-descent method, for descending toward the minimum on the performance source, even this approach need to know the gradient of function to minimize. N-LMS (Normalized-Least Mean Square) algorithm is an easy way to descende the performance surface that uses a special estimate of the gradient, suitable for the ANC scheme described above. It does not require off-line gradient estimation, so it is simple to implemenmt in real- time applications.
The transversal filter presentend in fig.1 with label *W(t)* may be rappresented as an Adaptive Linear Combiner

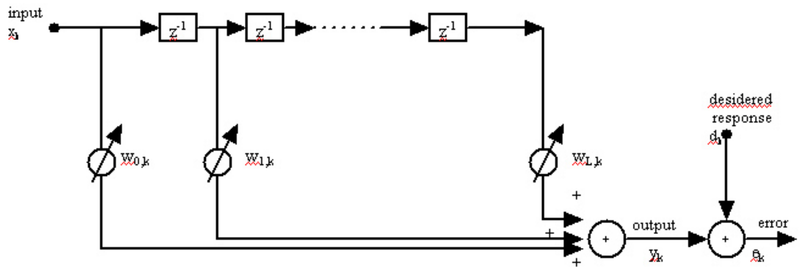

Fig. 3 The Adaptive Linear Combiner as a transversal filter

Where the combiner output, $y_{k,}$ is a linear combination of the input samples, so

$$\varepsilon_k = d_k - \underline{X}_k^T \underline{W}_k \quad (3)$$

where $\underline{X}_k^T$ is th evector of input samples.

To develop an adaptive algorithm using the previous methods, we would estimate the gradient of $\xi_k = E[\varepsilon_k^2]$ with ε_k^2, taking itself as an estimate of ξ_k.

At each iteration in the adaptive process, the gradient estiamtion in performed like this

$$\nabla_k = \begin{bmatrix} \frac{\partial \varepsilon^2_k}{\partial w_0} \\ \cdot \\ \cdot \\ \frac{\partial \varepsilon^2_k}{\partial w_L} \end{bmatrix} = 2\varepsilon_k \begin{bmatrix} \frac{\partial \varepsilon_k}{\partial w_0} \\ \cdot \\ \cdot \\ \frac{\partial \varepsilon_k}{\partial w_L} \end{bmatrix} = -2\varepsilon_k \underline{X}_k \quad (4)$$

with this simple esitimate of the gradient, we can now specify a steepest type of adaptive algorithm. In detail,

$$\underline{W}_{k+1} = \underline{W}_k - \frac{\mu}{\sigma^2}\nabla_k = \underline{W}_k - 2\frac{\mu}{\sigma^2}\varepsilon_k \underline{X}_k \quad (5)$$

this is the N-LMS algorithm with μ as gain constant that regulates the speed and stability of adaption, and σ^2 is the input signal power.

A choice for μ is $\frac{1}{\lambda_{\max}} > \mu > 0$ that guarantes the convergence. If [R] is the input correlation matriw, $\lambda_{\max}$ cannot be greate than the trace of [R]; thus convergence of the weight-vector mean is assured by:

$$0 < \mu < \frac{1}{(L+1)\sigma^2} \quad (6)$$

with $\lambda_{\max}$ the maximum eigenvalue of [R] and σ^2 is the input signal power.

V. Misadjustment in adaptive process

Misadjustement in adaptive process is defined as the ratio of the excess mean-square error to the minimum mean-square error, and is thus a measure of how closely the adaptive process tracks the true analitical solution, that is a measure of the "cost od adaptability". The excess mean square error is defined as

$$excessMSE = E[\underline{V}_k^{',T} \Lambda \underline{V}'_k] \quad (7)$$

where $V_k^{'}$ is the weight vector at istant k, and Λ is the diagonal eigenvalue matrix of [R].

In terms of sum:

$$excessMSE = \sum_{n=0}^{L} \lambda_n E[v'^2_{n,k}] \quad (8)$$

If the adaptive transient has died out and therefore that the sqared error is near the minimum value, may be assumed the approximation.

$$excessMSE \approx \mu\xi_{\min}\sum_{n=0}^{L} tr[\underline{R}] \quad (9)$$

so, the form of misadjustement may be now computed

$$M = \frac{excessMSE}{\xi_{\min}} \approx \mu tr[\underline{R}] \quad (10)$$

Is clear that M is directly proportional to the adaptive gain constant, μ.Thus there is a trade-off between the misadjustement and the rate of adaption.In fact the time constant ofthe n-mode of learning curve is

$$(\tau_{mse})_n = \frac{1}{4\mu\lambda_n} \quad (11)$$

VI. Simulation results

Matlab® system simulation will be now presented.
First step was been the construction of a tipical output lidar profile

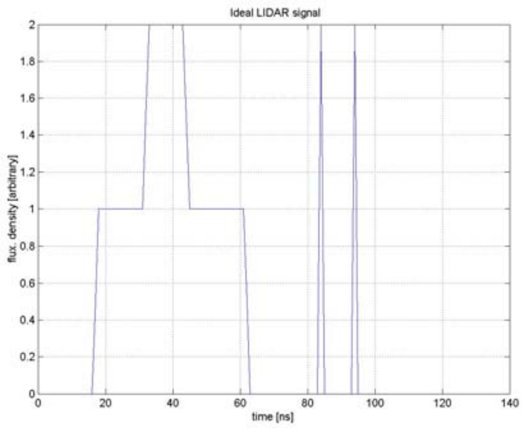

Fig. 4 Tipical ideal LIDAR profile

Superposing a zero mean gaussian noise whit σ^2 =0.08 will obtaine

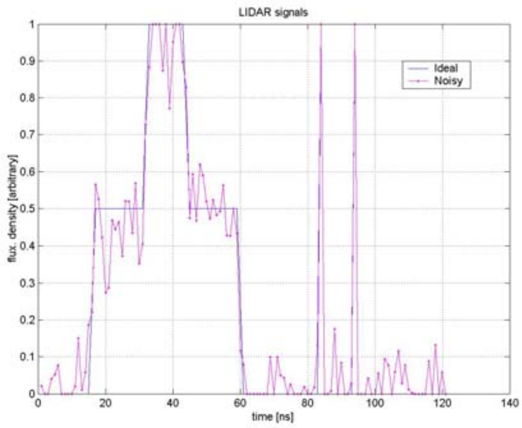

Fig. 5 Comparision: ideal and noisy lidar signal

After low-pass filtering with ANC

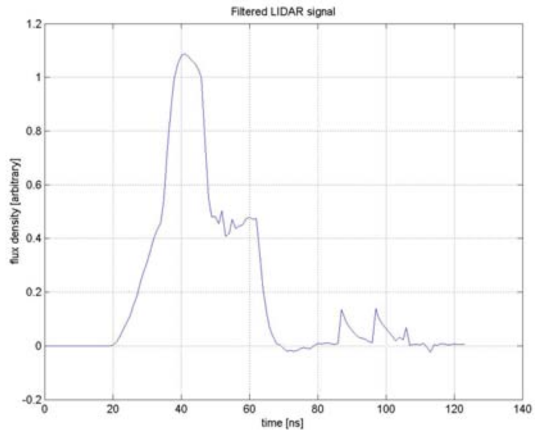

Fig. 6: LIDAR signal filtered by ANC

And after deconvolution process by Richardson-Lucy algorithm

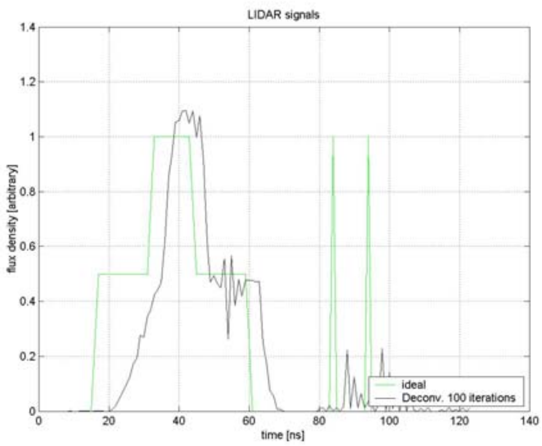

Fig. 7 Comparision between ideal and reconstructed LIDAR signals

ANC system performs a low-pass filtering on noisy lidar signal and its effects could be seen by filter frequency response that show a low-pass characteristic

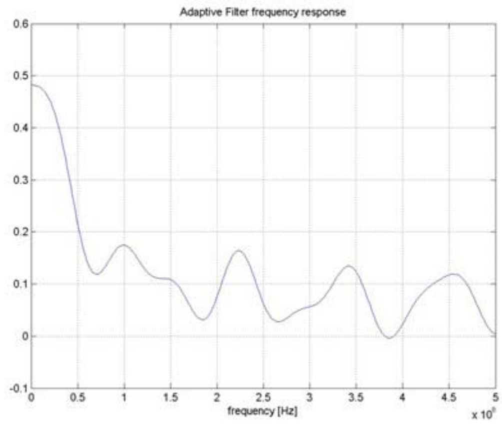

Fig. 8 Low-Pass characteristic of adaptive filter

These results was obtained by an ANC system with 16 taps and a gain factor (μ) of 0.01.

VII. Conclusion

Adaptive tecniqes will be used to filter a noisy lidar signal before convolution process by Richardson_lucy algorithm.
Real time characteristics of entire process of filtering and deconvolution make it very suitable for complex environment measurements.
No more knowing about noise characteristics, i.e.: noise band, amplitude,...) make possible to determine the cut off frequency more exactly by the adaptive automatic process.

References

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