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Nonlinear adaptive noise-induced algorithm and its application in penetration signal

Zongbao Liu [a,b,*], Shiqiao Gao [a], Haipeng Liu [a], Dongmei Zhang [a], Lei He [b]

[a] State Key Laboratory of Explosion Science and Technology, Beijing Institute of Technology, Beijing 100081, China
[b] Department of Electrical Engineering, University of California, Los Angeles, CA 90095, USA

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ABSTRACT

A nonlinear adaptive noise induced algorithm with nonlinear weights was proposed to extract rigid body deceleration during penetration events; it has 3rd-order nonlinear weight, which ensures deceleration curve is smooth everywhere (not only continuous) and avoids sharp points (crucial for targets detection). In addition, an autocorrelation algorithm was improved by applying moving window method to be compared with the proposed nonlinear adaptive algorithm. By calculating penetration depth and Power Spectrum Density (PSD) of 4 deceleration time series, we show that the nonlinear adaptive algorithm more effectively reduces noise in deceleration for striking velocities between 538 and 800 m/s compared with Adaptive Panta Criterion, moving window autocorrelation and wavelet algorithms. It is further shown that the proposed adaptive algorithm is of the same order as the other 3 methods in terms of computational complexity.

1. Introduction

The objective of penetration signal processing is to extract the characters of deceleration during penetration events for the optimization of the projectiles' burst points and determination of the materials impacted (concrete, soil, sand, etc.), which could enhance the weapons' performance. From Refs. [1–4], penetration deceleration has mainly 3 physical components: rigid body deceleration, high frequency vibrations from the accelerometer and projectile and high frequency noise.

Filtering is the first step to characterize deceleration, detect multi-layer targets and explode the projectile precisely. In a broad class of filtering methods for projectile deceleration we can identify three major subclasses: filter circuits, frequency based methods and time-frequency based methods [3–5].

Filter circuits inevitably increase the size of earth penetrator instrumentation, which is crucial for the miniaturization of penetrator [5–7]. Because the rigid body deceleration of a projectile is a nonstationary random signal (overlapping frequency bands), frequency based implementation fails to reveal the time-varying characteristics of the signal. The averaging process inherent in the frequency methods (mostly Fourier Transform) smears the time varying spectral features [8]. To deal with the nonstationary nature of penetration signals, the customary practice is to invoke the use of adaptive filtering [9]. The adaptive filters (nonlinear systems) are time varying since their parameters are continually changing in order to meet a performance requirement.

In this paper, an adaptive algorithm (adaptive filter) with nonlinear weight is introduced to remove noise in penetration deceleration. Additionally, a moving window autocorrelation algorithm is proposed to reduce noise effectively. Comparison of the two proposed algorithms and two previous algorithms are performed for striking velocities between 538 and 800 m/s and shows better

* Corresponding author at: State Key Laboratory of Explosion Science and Technology, Beijing Institute of Technology, Beijing 100081, China.
E-mail address: lzbucla@gmail.com (Z. Liu).

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Nomenclature

Notation

$f(x)$	fitted polynomial of time series
K	order of polynomial
a_i	coefficients of polynomial
δx	sampling interval
Q	residual error of fitting
$\mathbf{Y}$	matrix of y_i
$\boldsymbol{F}$	matrix of $f(i)$
$\mathbf{e}$	matrix of error
$\mathbf{A}$	Vandermonde matrix
$\mathbf{a}$	matrix of a_i
$\omega_1,\ \omega_2$	normalized weights
$y^{(i)}$	ith segment of time series
$y^{(i+1)}$	$(i+1)$th segment of time series
$y^{(c)}$	overlapped region of time series
k	adaptive Pañta Criterion coefficient
k_0	initial value of k
k_w	gradient of k
R_{xx}	autocorrelation of time series
$x'(n)$	filtered data by moving window autocorrelation
M	length of time series
$Wn,\ N,\ w$	filter window size
v_0	striking velocity of penetration
e	repetition time of moving window autocorrelation

filtering effectiveness and computational complexity of the nonlinear adaptive algorithm.

2. Nonlinear adaptive algorithm [10]

2.1. Principle of the algorithm

Assume the time series $\{x_1, x_2, \ldots, x_N\}$ is partitioned into several segments with window size $w = 2n+1$, where the adjacent segments have $n+1$ overlapped points. For each segment the time series is fitted by Kth-order polynomial, and the polynomial of the ith and $(i+1)$th segments are denoted as $y^i(l_1),\ y^{i+1}(l_2),\ l_1, l_2 = 1, \ldots, 2n+1$, while the last segment may be less than $2n+1$ [11,12].

Let the corresponding curve be

$$(x_i, y_i), \quad i = 1, \ldots, w = 2n+1$$

the least square polynomial fit is $(x_i, f_i),\ i = 1, \ldots, w$, where the fitted polynomial is

$$f(x) = b_0 + b_1 x + b_2 x^2 + \cdots + b_K x^K \tag{1}$$

where K is the order of the polynomial [12]. Suppose the sampling interval is δx, then x_i can be written as [13,14]:

$$x_i = i\delta x + \alpha \tag{2}$$

We can always find α, which makes $i = -n, -n+1, \ldots, 0, 1, 2, \ldots, n-1, n$, then (1) can be written as

$$f(i) = a_0 + a_1 i + a_2 i^2 + \cdots + a_K i^K \tag{3}$$

The residual error of the fitted polynomial is

$$Q = \sum_{I=-n}^{n} [f(i) - y_i]^2$$

Coefficients $a_0, a_1, a_2, \ldots, a_K$ can be derived from polynomial regression $\mathbf{Y} = \mathbf{F} + \mathbf{e} = \mathbf{Aa} + \mathbf{e}$

Where $\underset{w\times 1}{\mathbf{Y}} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_w \end{bmatrix}$; $\underset{(K+1)\times 1}{\mathbf{a}} = \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_K \end{bmatrix}$; $\underset{K\times 1}{\mathbf{e}} = \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_K \end{bmatrix}$;

$$\underset{w\times(K+1)}{\mathbf{A}} = \begin{bmatrix} 1 & i_1 & i_1^2 & \cdots & i_1^K \\ 1 & i_2 & i_2^2 & \cdots & i_2^K \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & i_w & i_w^2 & \cdots & i_w^K \end{bmatrix} \tag{4}$$

Note that $\mathbf{A}$ is a Vandermonde matrix, $\mathbf{A}_{ij} = i^j$, $i = -n, -n+1, \ldots, 0, 1, 2, \ldots, n-1, n,\ j = 0, 1, \ldots, K$

The residual error of the fitted polynomial [15] is

$$Q = \mathbf{e}^T\mathbf{e} = (\mathbf{Y} - \mathbf{Aa})^T(\mathbf{Y} - \mathbf{Aa}) = \mathbf{Y}^\mathbf{T}\mathbf{Y} + \mathbf{a}^\mathbf{T}\mathbf{A}^\mathbf{T}\mathbf{Aa} - \mathbf{2a}^\mathbf{T}\mathbf{A}^\mathbf{T}\mathbf{Y} \Rightarrow \min \tag{5}$$

Apply the matrix differential rules from [16]:

$$\frac{\partial Q}{\partial \mathbf{a}} = \mathbf{2A}^\mathbf{T}\mathbf{Aa} - \mathbf{2A}^\mathbf{T}\mathbf{Y} = 0$$

and the solution is given by

$$\mathbf{A}^\mathbf{T}\mathbf{Aa} = \mathbf{A}^\mathbf{T}\mathbf{Y} \Rightarrow \mathbf{a} = \left(\mathbf{A}^\mathbf{T}\mathbf{A}\right)^{-1}\mathbf{A}^\mathbf{T}\mathbf{Y} \tag{6}$$

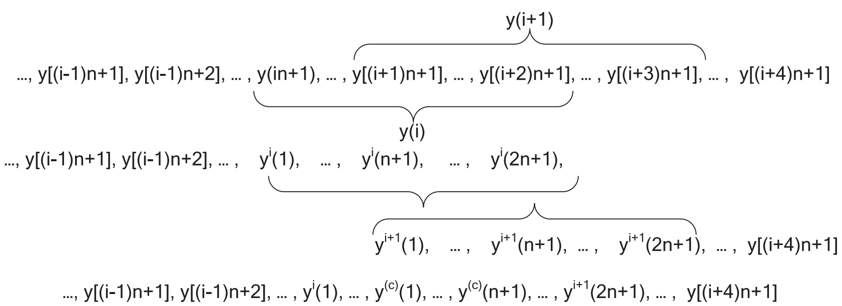

Fig. 1. Schematic diagram of the non-linear adaptive algorithm.