ABSTRACT

To satisfy the ever-increasing demand for the nonlinear system identification in various fields of engineering, as well as to tackle the system nonlinearities in the presence of non-Gaussian noise, interest has peaked in the adaptive nonlinear signal processing techniques. The nonlinear systems are conventionally modeled using the polynomial paradigms, whose output signals can be related to the input signals through the truncated Volterra series expansion. The nonlinear Volterra filter exhibits property that it depends linearly on the coefficients of the filter itself; therefore the principles of optimum linear filter theory can be naturally extended to the optimum nonlinear Volterra filter theory. These nonlinear filters are attractive because these may be able to approximate a large class of nonlinear systems with great parsimony in the use of coefficients.

The nonlinear adaptive filtering techniques for the system identification (based on the Volterra model) are widely used for the identification of nonlinearities in the domain of communication and signal processing applications. We first present the variable forgetting factor (VFF) least squares (LS) algorithm for the polynomial channel paradigm, which provides improved tracking performance under the nonstationary environment. The main focus is on updating VFF, when each time-varying fading channel is considered to be a first-order Markov process. It may be inferred from the simulation results that in addition to efficient tracking under the frequency-selective fading wireless channels, the incorporation of proposed numeric variable forgetting factor (NVFF) in LS algorithm reduces the computational complexity. Subsequently, the improved tracking capability of a numeric variable forgetting factor recursive least squares (NVFF-RLS) algorithm is presented for the first-order and second-order time-varying Volterra systems under the nonstationary environment. The nonlinear system tracking problem is converted into a state estimation problem of the time-variant system. The time-varying Volterra kernels are governed by the

first-order Gauss-Markov stochastic difference equation, upon which the state-space representation of this system is built. In comparison to the conventional fixed forgetting factor recursive least squares algorithm, the NVFF-RLS algorithm provides better channel estimation as well as channel tracking performance in terms of the minimum mean square error (MMSE) for the first-order and second-order Volterra systems. The NVFF-RLS algorithm is adapted to the time-varying signal by using the updating prediction error criterion, which accounts for the nonstationarity of the observed signal. The demonstrated simulation results manifest that the proposed method has good adaptability in the time-varying environment, and it also reduces the computational complexity.

However, an important issue in the system identification is the effect of measurement noise on the parameter estimation results. This measurement noise is usually considered to be a white Gaussian stochastic process with finite second-order statistics, which makes the mean squared error an appropriate metric for the estimation error. But, the non-Gaussian statistical signal processing plays an important role when signal and / or noise deviates from the ideal Gaussian model. The stable distributions are among the most significant non-Gaussian models. We next present the adaptive polynomial filtering using the generalized variable step-size least mean p^{th} power (GVSS-LMP) algorithm for the nonlinear Volterra system identification, under the α-stable impulsive noise environment. Due to the lack of finite second-order statistics of the impulse noise, we espouse the minimum error dispersion (MED) criterion as an appropriate metric for the estimation error, instead of the conventional minimum mean square error criterion. For the convergence of LMP algorithm, the adaptive weights are updated by adjusting $p \geq 1$ in the presence of impulsive noise characterized by $1 < \alpha < 2$.

In many practical applications, the auto-correlation matrix of input signal has the larger eigenvalue spread in the case of nonlinear Volterra filter than in the case of linear finite impulse response filter. In such cases, the time-varying step-size is an appropriate option to mitigate the adverse effects of eigenvalue spread on the convergence of LMP adaptive algorithm. Therefore, the generalized variable step-size updating criterion is proposed in combination with the LMP algorithm, to identify the slowly time-varying Volterra kernels, under the non-Gaussian α-stable impulsive noise scenario. The simulation results are presented to demonstrate that the proposed GVSS-LMP algorithm is more robust to the impulsive noise in comparison to the conventional techniques, when the input signal is correlated or uncorrelated Gaussian sequence, while keeping $1 < p < \alpha < 2$. It also exhibits flexible design to tackle the slowly time-varying nonlinear system identification problem.

The adaptive nonlinear signal processing has also found applications in the field of audio and speech signal processing. The nonlinearity of amplifiers and / or loudspeakers gives rise to the nonlinear echo in the acoustic systems, which severely deteriorates the quality of audio and speech communication systems. Further, we present a nonlinear acoustic echo cancellation algorithm, which includes two distinct modules in cascade. The first module is a polynomial Volterra filter, which is an equivalent paradigm for a loudspeaker with the nonlinear distortion. The second module in the presented cascaded structure is a linear tapped-delay-line (finite impulse response) filter, which is analogous to the impulse response of the acoustic path. In the proposed adaptive structure, the adaptive nonlinear filter in the first module tackles the nonlinear constituents of the Volterra model, which uses the conventional fixed step-size normalized least mean square (FSS-NLMS) algorithm. However, the adaptive linear filter in the second module deals with the linear constituents of the Volterra model as well as the linear impulse response of the acoustic path, in which the generalized variable step-size normalized least mean square (GVSS-NLMS) algorithm is incorporated to suppress the adverse effects of nonstationarity / distortion. Computer simulation results demonstrate that the presented GVSS-NLMS algorithm based approach outperforms the FSS-NLMS algorithm based Volterra filtering, as far as the convergence and tracking characteristics are concerned. In simulation of the real-time environment and appropriate parameter setting for the third-order polynomial model, it provides approximately 5 dB performance advantage over the conventional nonlinear filtering approach in the tracking mode, in terms of the reduction in mean squared error. Moreover, the presented adaptive technique exhibits lower computational complexity than the conventional FSS-NLMS based polynomial Volterra filtering used for the acoustic echo cancellation.

Based on the aforementioned research work, which mainly emphasis on the adaptive nonlinear system identification problem, it is apparent that the adaptive nonlinear filtering is an exciting and challenging area with a wide variety of applications; and potential breakthroughs with great impact on practical applications are expected in the near future.

LIST OF PUBLICATIONS

1. Amrita Rai and Amit Kumar Kohli, “Volterra Filtering Scheme using Generalized Variable Step-size NLMS Algorithm for Nonlinear Acoustic Echo Cancellation,” *Acta Acustica united with Acustica* , vol. 101, no. 4, pp. 821 – 828, July 2015. (SCI Indexed by Thomson Reuters; Impact Factor = 0.679).
2. A. Rai and A.K. Kohli, “Adaptive Polynomial Filtering using Generalized Variable Step-Size Least Mean p^{th} Power (LMP) Algorithm,” *Springer, Circuits, Systems, and Signal Processing*, vol. 33, no. 12, pp. 3931 – 3947, December 2014. (SCI Indexed by Thomson Reuters; Impact Factor = 1.118).
3. A. K. Kohli and A. Rai, “Numeric variable forgetting factor RLS algorithm for second-order Volterra filtering,” *Springer, Circuits, Systems, and Signal Processing,* vol. 32, no. 1, pp. 223 – 232, February 2013. (SCI Indexed by Thomson Reuters; Impact Factor = 1.118)

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TABLE OF CONTENTS

LIST OF FIGURES

ACRONYMS AND ABBREVIATIONS

AEC	:	Acoustic Echo Canceller
ANC	:	Active Noise Control
ARMA	:	Autoregressive Moving Average
AVSS-LMP	:	Aboulnasr’s Variable Step-Size LMP
BLAST	:	Bell Laboratories Layered Space-Time
BLMS	:	Block Least Mean Square
D-BLAST	:	Diagonal-BLAST
DC	:	Direct Current
DFE	:	Decision Feedback Equalizers
DFT	:	Discrete Fourier Transform
DFF	:	Dynamic Forgetting Factor
EKF	:	Extended Kalman Filtering
ERLE	:	Echo Return Loss Enhancement
FFF	:	Fixed Forgetting Factor
FFF-RLS	:	Fixed Forgetting Factor RLS
FIR	:	Finite Impulse Response
FLOM	:	Fractional Lower Order Moments
FSS-NLMS	:	Fixed Step-Size Normalized Least Mean Square
FSS-LMS	:	Fixed Step-Size LMS
FS-LMS	:	Filtered-s Least Mean Square
FX-LMS	:	Filtered-x Least Mean Square
FRLS	:	Fast Recursive Least Squares
G-LMS	:	Two-Step LMS
GSM	:	Global System for Mobile Communication

GVSS	:	Generalized Variable Step-Size
GVSS-LMP	:	Generalized Variable Step-Size LMP
GVSS-NLMS	:	Generalized Variable Step-Size NLMS
H-BLAST	:	Horizontal-BLAST
KVSS-LMP	:	Kwong's Variable Step-Size LMP
KF	:	Kalman Filtering
LS	:	Least Squares
LMP	:	Least Mean p^{th} Power
LMS	:	Least Mean Square
LMF	:	Least Mean Forth
LU	:	Lower Upper Triangular Matrix
MA	:	Moving Average
MED	:	Minimum Error Dispersion
MG-LMS	:	Modified Two-Step LMS
MIMO	:	Multi-Input Multi-Output
MSE	:	Mean Squared Error
MMSE	:	Minimum Mean Square Error
NLMS	:	Normalized LMS
NLAEC	:	Nonlinear Acoustic Echo canceller
NARMAX	:	Nonlinear Autoregressive moving average with exogenous inputs
NVFF	:	Numeric Variable Forgetting Factor
NVFF-RLS	:	Numeric Variable Forgetting Factor Recursive Least Squares
QAM	:	Quadrature Amplitude Modulation
QR-RLS	:	QR Decomposition Based RLS
RLS	:	Recursive Least Squares

SS	:	Step-Size
STBC	:	Space-Time Block-Coded
STTC	:	Space-Time Trellis-Coded
SOVFs	:	Second Order Volterra Filters
SNR	:	Signal to Noise Ratio
SVSS	:	Stochastic-Gradient Variable Step-Size
SVSS-LMS	:	Stochastic-Gradient Variable Step-Size LMS
TDNNs	:	Time Delay Neural Networks
TVVS	:	Time-Varying Volterra System
TV	:	Time-Varying
VFF-RTLS	:	Variable Forgetting Factor Recursive Total Least Squares
V-BLAST	:	Vertical-BLAST
VFF	:	Variable Forgetting Factor
VSS	:	Variable Step-Size
VSS-LMS	:	Variable Step-Size LMS
VFX-LMS	:	Volterra Filtered-x LMS