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11 A family of gain combined proportionate adaptive filtering algorithms $\frac{11}{12}$ A family of gain-combined proportionate adaptive filtering algorithms $\frac{77}{78}$ 13 for sparse system identification 79

¹⁵ 8¹
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20 ARTICLE INFO ABSTRACT 86

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₂₂ Article history: **Article history: The classical proportionate adaptive filtering (PAF) algorithms achieve a fast initial convergence for sparse** σ ₂₃ Available online xxxx **the set of the stratege of the small** coefficients receive very little gain so that the time needed to reach ₈₉ 24 **1 EXECUTE 24 EXECUTE 10** Steady-state misalignment is increased. In addition, the PAF algorithms converge much slower than the ₉₀ 25 Adaptive filter examples these problems, this paper proposes a family of gain-combined PAF (GC-PAF) algorithms. The gain-
26 Crationt decent method 26 Gradient descent method
-- Proportionate adaptive filter structure of the proposed GC-PAF algorithms is implemented by using a sigmoidal activation 27 Function to a function the summary of the proportionate matrix and identity matrix, which can retain the 93
Sigmoidal activation function ⁹⁴ advantages of both the PAF algorithms in the context of sparse impulse response and the OAF algorithms⁹⁴ 29 95 in the context of dispersive impulse response. Meanwhile, to be also applicable to the family of sign 30 96 algorithms against impulsive noise, a general framework for the update of the sigmoidal activation 31 97 function is obtained by using the gradient descent method to minimize the *L*1-norm of the system output 32 **error. Simulations in the contexts of three** different sparsity impulse responses have shown that the se 33 99 proposed GC-PAF algorithms perform much better than the OAF, PAF and improved PAF (IPAF) algorithms. 34 2017 Eisevier III. All Hguts reserved. 100 original adaptive filtering (OAF) algorithms when the impulse response is dispersive. In order to address © 2017 Elsevier Inc. All rights reserved.

1. Introduction

40 106 The PNLMS algorithm was directly extended to the affine pro-The least-mean-square (LMS) and normalized LMS (NLMS) algorithms are the most popular adaptive filtering algorithms owing to their low computational complexity and ease of implementation [\[1\].](#page--1-0) However, the LMS- and NLMS-type algorithms often fail ative transfer function (RTF) identification. The impulse responses of most of these applications are sparse in nature. Thus, sparsity property has long been investigated to improve the performance of the LMS and NLMS algorithms, such as the smoothed l_0 -norm LMS (SL0-LMS) [\[2\],](#page--1-0) non-uniform norm constraint LMS (NNCLMS) [\[3\],](#page--1-0) the PNLMS algorithm adjusts the adaptation gain in proportion to the estimated filter coefficient. But, it is difficult to *a priori* know the sparseness of the impulse response in real-world scenarios. Over the past nearly two decades, many variants of PNLMS algorithm have been proposed in the literatures [\[5–24\].](#page--1-0) A general framework for the proportionate-type NLMS algorithms is pro-

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³⁸ **1. Introduction 104 104 104 104 104 104 104 104 104 105 106** $\frac{39}{24}$ 1. The contract of the derived following this framework.

41 method of the mathematics fluctuate the contract of the contract of the contract of the contract of the distribution of the contract of the gorithms are the most popular adaptive filtering algorithms owing in ection algorithm (APA) [\[25\]](#page--1-0) and affine projection sign algorithm $\frac{108}{108}$ to their low computational complexity and ease of implementa-
⁴³ 109 tine [1] Usuring the UMS and NUMS tine algorithms often fail and many manufacture and the spatial Usuring the UMS and NUMS tine algorithms often fail ⁴⁴ in terms of the convergence rate for the wide range of applications tively. In [22] and [23], a general framework for the proportionate-⁴⁵ such as acoustic echo cancellation (AEC), network echo cancellation type APA algorithms is derived. The proportionate adaptive filtering ⁴⁶ (NEC), room impulse response (RIR) identification, as well as rel-
-- (PAF) algorithms including the PNLMS. adaptive segmented PNLMS (NEC), room impulse response (KIR) identification, as well as rel-
 47 atim turns for function (NTF) identification. The impulse assessesses ⁴⁸ arrive transier function (KIF) identification. The impulse responses (ASPNLMS) [\[22\],](#page--1-0) PAPA and RP-APSA achieve a fast initial conver-
⁴⁸ 49 or most of these applications are sparse in nature. Inus, sparsity gence rate in sparse impulse response. But the small coefficients 148 are set the small coefficients 148 property has long been investigated to improve the performance of receive very little gain so that the time needed to reach steady-
by the LMC and NLMC algorithms such a steady- $\frac{1}{10}$ and the line of the mismum state misalignment is increased. In addition, the PAF algorithms $\frac{1}{10}$ $\frac{52}{18}$ and proportionate NLMS (PNLMS) [\[4\]](#page--1-0) algorithms. Representatively, example indetirate NLMS and APSA when the impulse ⁵³ the Plubution at the Indian of the Indian and the Indian of the NEMS, APA and APSA when the impulse the intervent
⁵³ the PNLMS clearithm editors the dimension rain including to gorithms including the NLMS, APA and A 54 the erricins digital interest the dideptation in proportion to response is dispersive. Thus, the improved PAF (IPAF) algorithms 120 $\frac{1}{2}$ the symmated intervention. But, it is unit to the improved PNLMS (IPNLMS) $\frac{1}{2}$, variable parameter $\frac{1}{2}$ $\frac{56}{2}$ use spatistics of the impulse response in real-world scenarios. IPNLMS (VP-IPNLMS) [\[12\],](#page--1-0) improved PAPA (IPAPA) [\[16\]](#page--1-0) and real-
 $\frac{122}{2}$ $\frac{57}{2}$ over the past nearly two declares, many variants of 1.1 Metal and coefficient improved proportionate APSA (RIP-APSA) [\[21\]](#page--1-0) have been $\frac{123}{2}$ $\frac{58}{24}$ genuing the second in the inclusion $\frac{124}{2}$. A genuing developed to address these problems. In addition, a family of $\frac{124}{2}$ $_{59}$ maniework for the proportionate type relations algorithms is provided block-sparse proportionate algorithms has also been proposed in $_{125}$ $[27-29]$ to address these problems above, which is obtained by 12ϵ 61 **127** * Corresponding author **Contract a mixed** *L***₂** anixed *L*₂¹ norm of the weight coefficients of the 127 62 128 *E-mail addresses:* fukngaiwong@163.com (F. Huang), jszhang@home.swjtu.edu.cn 63 129 adaptive filtering to further investigate these issues. Inspired by and real-coefficient proportionate APSA (RP-APSA) [\[21\],](#page--1-0) respectively. In [\[22\]](#page--1-0) and [\[23\],](#page--1-0) a general framework for the proportionatetype APA algorithms is derived. The proportionate adaptive filtering converge much slower than the original adaptive filtering (OAF) aladaptive filter. Today, it still is one of the most active topics in

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⁽J. Zhang).

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 67 [\[30\],](#page--1-0) this paper proposes a family of gain-combined PAF (GC-PAF) 68 algorithms, which refer to the GC-PNLMS algorithm, GC-PAPA and 69 The update equations of the weight vectors of the OAF al-GC-PAPSA.

⁴ The gain-combined matrix of the proposed GC-PAF algorithms gorithms (including the NLMS algorithm, APA and APSA) can be 70 ⁵ is implemented by using a sigmoidal activation function to adap- wrote as [1,22,25,26]: 6 tively combine the proportionate matrix and identity matrix, $\frac{1}{2}$ ⁷ which can retain the advantages of both the PAF algorithms in $w(k) = w(k-1) + \frac{1}{2}A(k)\delta(k)$ (8) ⁷³ 8 the context of sparse impulse response and the OAF algorithms in $\frac{2}{1}$ 2 ⁹ the context of dispersive impulse response. Meanwhile, to obtain a where $\delta(k)$ is a Lagrange multiplier (vector), which can be derived 75 ¹⁰ general framework, the sigmoidal activation function is indirectly by substituting (8) into the constraint condition of the correspond- ⁷⁶ ⁷⁷ updated by minimizing the *L*₁-norm of the system output error, ing algorithms, and $A(k)$ is an input vector or matrix, 12 i.e., the algorithms should be robust against impulsive noise when the contract of the cont ⁷⁹ this framework is applied to the family of sign algorithms. Benefit- 21 Algorithm design 14 Ing from this combination approach, the small coefficients receive **1996** Intervalsed and the small coefficients receive ⁸¹ more gain and as a result the proposed algorithms to reach steady-
⁸¹ more gain and as a result the proposed algorithms to reach steady-¹⁶ state misalignment are faster. The performance of the proposed tioned in Sec. 1 the weight vector $w(k)$ of the adaptive filter is ⁸² 17 GC-PAF algorithms is tested in the context of three different spar-
investigated by dividing it into two parts $\mathbf{w}_1(k)$ and $\mathbf{w}_2(k)$ one 83 18 sity impulse responses. Simulation results show that the proposed part $W_i(k)$ retains the advantages of the PAF algorithms in the con-19 GC-PAF algorithms perform better than the OAF, PAF and IPAF al-
 $_{\text{next of sparse impulse response}}$ and the other part $w_2(k)$ retains The gain-combined matrix of the proposed GC-PAF algorithms gorithms.

21 The organization of this paper is as follows. The classical PNLMS impulse response Then $\mathbf{w}_i(k)$ and $\mathbf{w}_2(k)$ are combined together by 87 22 algorithm is reviewed in Sec. 2. In Sec. 3, the framework of the GC- a variable mixing factor $2(k)$ as 23 89 PAF algorithms is developed. In Sec. [4,](#page--1-0) the proposed framework is 24 applied to the NLMS algorithm, APA and APSA, respectively. The $w(k) = \lambda (k)w_1(k) + (1 - \lambda (k))w_2(k)$ (9) ⁹⁰ 25 91 simulation results and detail descriptions are presented in Sec. [5.](#page--1-0) 26 In Sec. 6, the optimal value of the key parameter ρ_{gc} of the com-
where $0 \le \lambda(k) \le 1$. When $\lambda(k) = 1$, (9) reverts to the PAF algo-2[7](#page--1-0) bined gain of the proposed algorithm is evaluated. Sec. 7 makes a strithms; when $\lambda(k) = 0$, (9) becomes the OAF algorithms. Benefit- 33 28 94 ing from this combination approach, the small coefficients receive In Sec. [6,](#page--1-0) the optimal value of the key parameter ρ_{gc} of the comconclusion.

32 We consider reference data $\{d(k)\}$ that arises from the linear the proposed algorithms, we assume that the weight vector $\mathbf{w}(k - \theta)$ We consider reference data $\{d(k)\}$ that arises from the linear model

$$
d(k) = \mathbf{u}^T(k)\mathbf{w}_{opt} + \upsilon(k),\tag{1}
$$

37 tor or matrix transpose operation, $\mathbf{u}(k) = [u(k), u(k-1), \ldots,$ $u(k-L+1)$ ^T denotes an $L \times 1$ input vector with *L* being the filter $u(k-L+1)$ ^T denotes an $L \times 1$ input vector with *L* being the filter 40 that needs to be estimated, and $v(k)$ stands for the background 2^{106} $\frac{41}{100}$ noise. Substituting (10) and (11) into (9), we can obtain the update $\frac{107}{100}$ noise.

 $\frac{43}{10}$ tions [5] $\frac{109}{109}$ tions [\[5\]:](#page--1-0)

$$
e(k) = d(k) - \mathbf{u}^{T}(k)\mathbf{w}(k-1),
$$
\n(2)

$$
\mathbf{w}(k) = \mathbf{w}(k-1) + \mu \frac{\mathbf{G}(k)\mathbf{u}(k)e(k)}{\mathbf{u}^T(k)\mathbf{G}(k)\mathbf{u}(k) + \beta},
$$
(3)

49
$$
G(k) = diag\{g_0(k), g_1(k), ..., g_{L-1}(k)\},
$$

\n(4) $+ (1 - \lambda(k))\{w(k-1) + \frac{1}{2}A(k)\delta(k)\}\$

50 where $e(k)$ is the system output error, $\mathbf{w}(k)$ is the estimate of \mathbf{w}_{opt} and the system output error, $\mathbf{w}(k)$ is the estimate of \mathbf{w}_{opt} and the system output error, $\mathbf{w}(k)$ is the estimate of \mathbf{w}_{opt ⁵¹ at iteration *k*, *μ* is a global step size, *β* is the regularization factor, $= w(k-1) + \frac{1}{2} \lambda(k) G(k)A(k) \delta(k) + \frac{1}{2} (1 - \lambda(k))A(k) \delta(k)$ $\frac{52}{2}$ and **G**(*k*) is an *L* × *L* diagonal gain distribution matrix that deter-
 $\frac{2}{3}$ ⁵³ mines the step sizes of the individual coefficients of the filter. For $-\mathbf{w}(k-1) + \frac{1}{2} \int (k) \mathbf{C}(k) + (1 - \lambda(k)) \mathbf{I}(\mathbf{A}(k) \mathbf{A}(k))$ 54 the DNUMS election the discord elements of $G(t)$ are relations $\mathbf{F}(t) = \mathbf{W}(K-1) + \frac{1}{2} \{ \lambda(K) \mathbf{G}(K) + (1 - \lambda(K)) \mathbf{I} \} \mathbf{A}(K) \mathbf{0}(K)$ the PNLMS algorithm, the diagonal elements of **G**(*k*) are calculated

⁵⁵ 2¹ 2¹ 2¹ 2¹ 2¹ 2¹ 21²¹ 21²¹ as follows:

$$
\begin{aligned}\n\mathbf{I}_{\text{max}}(k-1) &= \max\{|\omega_0(k-1)|, \dots, |\omega_{L-1}(k-1)|\}, \\
\mathbf{I}_{\text{max}}(k-1) &= \max\{|\omega_0(k-1)|, \dots, |\omega_{L-1}(k-1)|\},\n\end{aligned}
$$
\n(5)

\nwhere **I** is an $I \times I$ identity matrix and

$$
\varphi_n(k) = \max\{\rho \max[\eta, l_{\max}(k-1)], |\omega_n(k-1)|\},\tag{6}
$$

$$
\begin{array}{ll}\n\text{60} & \text{g}_n(k) = \frac{\varphi_n(k)}{\frac{1}{L} \sum_{i=0}^{L-1} \varphi_i(k)} & 0 \le n \le L-1\n\end{array}\n\tag{7}
$$
\n
$$
\begin{array}{ll}\n\text{G}_1(k) = \lambda(k) \text{G}(k) + (1 - \lambda(k)) \text{I}.\n\tag{13}
$$
\n
$$
\text{G}_2 \text{A} & \text{G}_3 \text{B} & \text{G}_4 \text{C} & \text{G}_5 \text{D} \\
\text{G}_5 & \text{G}_6 \text{C} & \text{G}_7 \text{D} & \text{G}_8 \text{D} \\
\text{G}_8 & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} \\
\text{G}_9 & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} \\
\text{G}_9 & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} \\
\text{G}_9 & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} \\
\text{G}_9 & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} \\
\text{G}_9 & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} \\
\text{G}_9 & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{D} \\
\text{G}_9 & \text{G}_8 \text{D} \\
\text{G}_9 & \text{G}_8 \text{D} & \text{G}_8 \text{D} & \text{G}_8 \text{
$$

 63 where *ρ* and *η* are positive parameters with typical values *ρ* = 129 64 5/*L* and $η = 0.01$, respectively. The parameter $η$ regularizes the Inspired by the convex combination method [31], the variable ¹³⁰ ⁶⁵ updating when all of the coefficients are zero at initialization, and mixing factor $\lambda(k)$ is defined as the output of a sigmoidal activa-
⁶⁵ ⁶⁶ the parameter *ρ* prevents the very small coefficients from stalling. tion function [32,33] with an intermediate variable α (*k*) as 132

3. The framework of the proposed GC-PAF algorithms

wrote as [\[1,22,25,26\]:](#page--1-0)

$$
\mathbf{w}(k) = \mathbf{w}(k-1) + \frac{1}{2}\mathbf{A}(k)\delta(k),
$$
\n(8)

where $\delta(k)$ is a Lagrange multiplier (vector), which can be derived by substituting (8) into the constraint condition of the corresponding algorithms, and **A***(k)* is an input vector or matrix.

3.1. Algorithm design

²⁰ gorithms. In order to overcome the drawbacks of the PAF algorithms men-tioned in Sec. [1,](#page-0-0) the weight vector $w(k)$ of the adaptive filter is investigated by dividing it into two parts $w_1(k)$ and $w_2(k)$, one part $w_1(k)$ retains the advantages of the PAF algorithms in the context of sparse impulse response, and the other part $w_2(k)$ retains impulse response. Then $w_1(k)$ and $w_2(k)$ are combined together by a variable mixing factor *λ(k)* as

$$
\mathbf{w}(k) = \lambda(k)\mathbf{w}_1(k) + (1 - \lambda(k))\mathbf{w}_2(k),\tag{9}
$$

29 95 more gain and as a result the proposed algorithms to reach steady-30 96 **2. Review of the PNLMS algorithm** rithms; when $\lambda(k) = 0$, (9) becomes the OAF algorithms. Benefitstate misalignment are faster.

31 97 In order to deduce the update equation of the weight vector of 33 99 1*)* is updated as **w**1*(k)* by using the optimization criterion in [\[22\],](#page--1-0) 34 100 \overline{T} 100 \overline{T} 100 \overline{T} and is updated as $\mathbf{w}_2(k)$ by using (8), respectively, as 100

where k stands for the time index, superscript T denotes vec-
\n
$$
\mathbf{w}_1(k) = \mathbf{w}(k-1) + \frac{1}{2} \mathbf{G}(k) \mathbf{A}(k) \delta(k),
$$
\n(10) ¹⁰²
\nfor or matrix transpose operation $\mathbf{u}(k) = [u(k) \ u(k-1)]$

$$
\mathbf{w}_2(k) = \mathbf{w}_0(k-1) + \frac{1}{2}\mathbf{A}(k)\delta(k).
$$
\n(11)

⁴² The PNLMS algorithm is summarized by the following equa- equation of the weight vector as 108 equation of the weight vector as

44 110 45 111 46 112 47 113 48 114 **w***(k)* = *λ(k)***w**1*(k)* + 1 − *λ(k)* **w**2*(k)* = *λ(k)* **w***(k* − 1*)* + 1 2 **G***(k)***A***(k)δ(k)*

$$
+\left(1-\lambda(k)\right)\left\{\mathbf{w}(k-1)+\frac{1}{2}\mathbf{A}(k)\delta(k)\right\}
$$

$$
= \mathbf{w}(k-1) + \frac{1}{2}\lambda(k)\mathbf{G}(k)\mathbf{A}(k)\delta(k) + \frac{1}{2}(1-\lambda(k))\mathbf{A}(k)\delta(k)
$$

$$
\begin{array}{ll}\n\text{54} & \text{mines the step sizes of the individual coefficients of the filter. For} \\
\text{55} & \text{the PNLMS algorithm, the diagonal elements of } \mathbf{G}(k) \text{ are calculated} \\
\text{56} & \text{as follows:} \\
\text{57} & \text{the } 4\lambda - \text{mcs}(\lambda_1, 4\lambda_2) \\
\text{58} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
$$
\n
$$
\begin{array}{ll}\n\text{58} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
$$
\n
$$
\begin{array}{ll}\n\text{59} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
$$
\n
$$
\begin{array}{ll}\n\text{50} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
$$
\n
$$
\begin{array}{ll}\n\text{51} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
$$
\n
$$
\begin{array}{ll}\n\text{51} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
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\n
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\begin{array}{ll}\n\text{52} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
$$
\n
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\begin{array}{ll}\n\text{53} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
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\begin{array}{ll}\n\text{54} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
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\begin{array}{ll}\n\text{58} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
$$
\n
$$
\begin{array}{ll}\n\text{59} & \text{the } 4\lambda_1, 4\lambda_2, 4\lambda_3\n\end{array}
$$
\n
$$
\begin{array}{ll}\n\text{50} & \text{the }
$$

58 124 where **I** is an *L* × *L* identity matrix, and

$$
\varphi_n(k) \qquad \varphi_n(k) \qquad \qquad \mathbf{G}_1(k) = \lambda(k)\mathbf{G}(k) + \left(1 - \lambda(k)\right)\mathbf{I}.\tag{13}
$$

62 128 *3.2. Variable mixing factor design*

Inspired by the convex combination method [\[31\],](#page--1-0) the variable mixing factor *λ(k)* is defined as the output of a sigmoidal activation function $[32,33]$ with an intermediate variable $\alpha(k)$ as

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