



Fig. 2. The adaptation of the filter weights.

the analog circuit, sometimes the algorithm “converged” to the saturation state of the circuit.

REFERENCES

[1] B. Widrow and S. D. Stearns, *Adaptive Signal Processing*. Englewood Cliffs, NJ: Prentice-Hall, 1985.
 [2] W. F. Gabriel, “Adaptive arrays—An introduction,” *Proc. IEEE*, vol. 64, pp. 239-272, Feb. 1976.
 [3] I. A. Mack and M. H. White, “A CCD monolithic LMS adaptive analog signal processor integrated circuit,” in *Proc. 1981 Custom Integrated Circuits Conf.*, Rochester, NY, 1981, pp. 128-131.
 [4] G. W. Donohoe, “A discrete-time analog adaptive filter,” Master thesis, Univ. New Mexico, 1982.
 [5] M. G. Larimore and C. R. Johnson, “Stationary and nonstationary learning characteristics of the LMS adaptive filter,” *Proc. IEEE*, vol. 64, pp. 1151-1162, 1976.
 [6] M. Vidyasagar, *Nonlinear Systems Analysis*. Englewood Cliffs, NJ: Prentice-Hall, 1978.
 [7] G. Zeng, “A new adaptive IIR algorithm and the convergence factors for digital and analog adaptive filters,” Ph.D. dissertation, Univ. New Mexico, May 1988.

Corrections to “Morphological Filters—Parts I and II”

PETROS MARAGOS AND RONALD W. SCHAFER

In the above papers,¹ the following should be corrected.

PART I

p. 1156: In Table I, “min $f(x)$ ” and “pin $f(x)$ ” should read “minf (x) ” and “pinf (x) ,” respectively, which are abbreviations of minus and plus infinity.

Equation (11) should read

$$[\phi(f)](x) = \sup \{t \in V: x \in \Phi[X_t(f)]\}. \quad (I.11)$$

PART II

p. 1172: For (5) it is assumed that $f(z) \geq 0 \forall z$, and hence (5) should read

$$[OS^k(f; W)](z) = \int_0^\infty \chi_{OS^k\{X_t(f); W\}}(z) dt. \quad (II.5)$$

Manuscript received August 20, 1988.

P. Maragos is with the Division of Applied Sciences, Harvard University, Cambridge, MA 02138.

R. W. Schafer is with the School of Electrical Engineering, Georgia Institute of Technology, Atlanta, GA 30332.

IEEE Log Number 8826093.

¹P. Maragos and R. W. Schafer, *IEEE Trans. Acoust., Speech, Signal Processing*, vol. ASSP-35, pp. 1153-1184, Aug. 1987.

In the proof (13th line) of Theorem 1, replace “ $T_m \neq T_1$ ” with “ $T_m, m \neq 1$.”

p. 1175: Line 16 (left column) should read

$$X_B = \dots 00000000 \dots$$

p. 1176: Equation (14) should read

$$z \in X_H \Rightarrow |H_z \cap X| \geq 4. \quad (II.14)$$

In the proof (1st line) of Theorem 8, replace “ $x \in \text{med}(X; H)$ ” with “ $z \in \text{med}(X; H)$.”

p. 1177: In line 24 (left column), replace “ $\Psi^d(X) = [\Psi(X^c)]^c \dots$ ” with “ $\Psi^d(X) = [\Psi(X^c)]^c \dots$ ”

p. 1178: In Theorem 11(b), replace “ $\dots 0 \in \{a, b\}^A$ ” with “ $\dots 0 \in \{a, b\}^A$ and $a < 0 < b$.”

p. 1179: In line 5 (right column), “Without loss . . . assume” should be replaced by “For simplicity, assume first.” Further, starting from “Let $\mathcal{L} \dots$,” lines 25-29 (right column) should be replaced by the following text:

When $g_{(1)} = p = 0, 1, 2, \dots$, (23) and (24) generalize to

$$a_2 g_{(2)} + a_3 g_{(3)} = -pa_1 \quad (23a)$$

$$\text{s.t. } p = g_{(1)} \geq g_{(2)} \geq \frac{-pa_1}{a_2 + a_3} \geq g_{(3)}. \quad (23b)$$

For each p , let \mathcal{L}_p be the finite set of basis functions defined by all tuples (g_1, g_2, g_3) corresponding to the solutions $(g_{(1)}, g_{(2)}, g_{(3)})$ of (23a) with the constraint (23b). Then the LOS filter ψ has a basis $\mathcal{B}(\psi) = \cup_{p \in \mathcal{N}} \mathcal{L}_p$ and admits a representation as in (22).

p. 1180: For (26) it is assumed that $f(z) \geq 0 \forall z$, and hence (26) should read

$$[ST_\beta(f)](z) = \int_0^\infty [\Phi_b(\chi_{X_t(f)})](z) dt. \quad (II.26)$$

In line 30 (right column) replace “form” with “from.”

p. 1182: In the table at the top (right column), the minimal true vectors of β^d are four; the missing vector is $(0, 1, 0, 1, 0)$.

Strong Consistency of the LAD (L_1) Estimator of Parameters of Stationary Autoregressive Processes with Zero Mean

STEVEN A. RUZINSKY AND ELWOOD T. OLSEN

Abstract—Strong consistency (almost sure convergence to the true parameters) of the LAD (least absolute deviations) AR parameter estimator has been proven by Gross and Steiger [1] under the condition that the i.i.d. noise driving a stationary autoregressive process has zero median. In this correspondence, we extend their proof to include the case when the driving noise has zero mean. Thus, when the noise pdf (probability density function) is asymmetric with distinct mean and median, the LAD estimator will be strongly consistent with the pdf centered with either mean or median at the origin. We also present the results of computer simulations which further indicate that under these conditions, the LAD estimator is MS consistent (mean-squared convergence to the true parameters).

The importance of these results to LAD signal processing applications is discussed in the Introduction.

Manuscript received February 11, 1988; revised July 21, 1988.

S. A. Ruzinsky is with the Department of Electrical Engineering, Illinois Institute of Technology, Chicago, IL 60616.

E. T. Olsen is with the Department of Mathematics, Illinois Institute of Technology, Chicago, IL 60616.

IEEE Log Number 8826109.