

Computational analysis of a fast algorithm for high-order sparse linear prediction

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- ▶ Linear prediction
- ▶ Solving a high-order sparse linear prediction problem
- ▶ Solving positive-definite Toeplitz systems
- ▶ Simulations and timings



- ▶ A stationary set of samples (possible speech) $x[t]$, for $t = 1, \dots, T$, are written as a linear combination of N past samples

$$x[t] = \sum_{n=1}^N \alpha_n x[t-n] + r[t], \quad (1)$$

- ▶ $\{\alpha_n\}$ are the prediction coefficients and $r[t]$ is the prediction error.
- ▶ Matrix formulation (certain boundary conditions)

$$x = X\alpha + r \quad (2)$$

- ▶ Find the prediction coefficients via

$$\underset{\alpha}{\text{minimize}} \quad \|x - X\alpha\|_p^p \quad (3)$$

- ▶ Select $p = 2$

$$\underset{\alpha}{\text{minimize}} \quad \|x - X\alpha\|_2^2 \quad (4)$$

- ▶ Solution satisfying the normal equation

$$X^T X \alpha = X^T x \quad (5)$$

- ▶ Using the autocorrelation method, $R = X^T X$, is Toeplitz and with the special right-hand side, $X^T x$ the system can be solved using the Levinson–Durbin algorithm in $\mathcal{O}(N^2)$.

Exploiting redundancies: Joint short-term and long-term prediction



- ▶ The combination of short term and long prediction filters can be seen as a sparse high order filter:

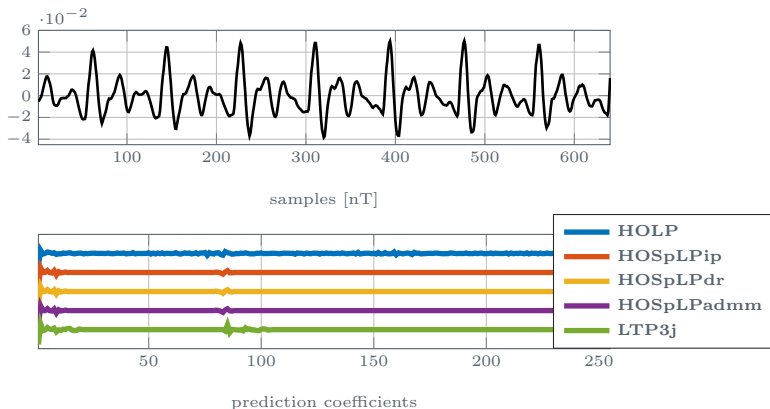


Figure : A 640 samples segment of the voiced speech (vowel /a/ uttered by a female speaker) and some predictors.

- ▶ Imposing sparsity via the 1-norm convex relaxation:

$$\underset{\alpha}{\text{minimize}} \quad \|x - X\alpha\|_2^2 + \gamma\|\alpha\|_1. \quad (6)$$

- ▶ However, when imposing sparsity on both the residual vector and high-order predictor, gains can be obtained both in terms of modeling and coding performance¹

$$\underset{\alpha}{\text{minimize}} \quad \|x - X\alpha\|_1 + \gamma\|\alpha\|_1. \quad (7)$$

- ▶ In general, see².

¹Daniele Giacobello et al. “Joint estimation of short-term and long-term predictors in speech coders”. In: *Acoustics, Speech and Signal Processing, 2009. ICASSP 2009. IEEE International Conference on*. IEEE. 2009, pp. 4109–4112.

²D. Giacobello et al. “Sparse linear prediction and its applications to speech processing”. In: *Audio, Speech, and Language Processing, IEEE Transactions on* 20.5 (2012), pp. 1644–1657.

- ▶ The objective:

$$f(\alpha) = \|x - X\alpha\|_1 + \gamma\|\alpha\|_1 \quad (8)$$

- ▶ is convex but not differentiable, neither is any of the terms
→ proximal gradient methods are not applicable³⁴⁵.

³Yu. Nesterov. *Gradient methods for minimizing composite objective function*. Université catholique de Louvain, Center for Operations Research and Econometrics (CORE). No 2007076, CORE Discussion Papers. 2007.

⁴A. Beck and M. Teboulle. “A fast iterative shrinkage-thresholding algorithm for linear inverse problems”. In: *SIAM Journal of Imaging Sciences* 2 (1 2009), pp. 183–202.

⁵S. J. Wright, R.D. Nowak, and M. A. T. Figueiredo. “Sparse reconstruction by separable approximation”. In: *Signal Processing, IEEE Transaction on* 57 (2009), pp. 2479–2493.

- ▶ The problem can be solved as a general linear programming problem using interior point (IP) methods⁶⁷.
- ▶ Work-load concentrated on solving linear systems with coefficient matrix

$$C = X^T D_1 X + D_2, \quad D_1, D_2 \text{ diagonal, change at each iteration} \quad (9)$$

- ▶ $X^T D_1 X$ is not Toeplitz and do not have low displacement rank \rightarrow resort to $\mathcal{O}(N^3)$ methods for solving linear systems.

⁶G. Alipoor and M. H. Savoji. “Wide-band speech coding based on bandwidth extension and sparse linear prediction”. In: *Telecommunications and Signal Processing (TSP), 2012 35th International Conference on*. IEEE. 2012, pp. 454–459.

⁷T.L. Jensen et al. “Real-time implementations of sparse linear prediction for speech processing”. In: *Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on*. IEEE. 2013, pp. 8184–8188.

Solving the SLP problem III



- ▶ Is it possible to exploit the structure of X and $R = X^T X$?
- ▶ Is the high accuracy of the IP methods necessary?

An ADMM algorithm



One approach, is via the following straight-out-of-the-box alternating direction method of multipliers (ADMM) algorithm

$$\alpha^{(k+1)} = (X^T X + \gamma^2 I)^{-1} [\gamma I \quad -X^T] (y^{(k)} + \begin{bmatrix} 0 \\ -x \end{bmatrix} - u^{(k)}) \quad (10)$$

$$e^{(k+1)} = x - X\alpha^{(k+1)} \quad (11)$$

$$y^{(k+1)} = S_{1/\rho} \left(\begin{bmatrix} \gamma\alpha^{(k+1)} \\ e^{(k+1)} \end{bmatrix} + u^{(k)} \right) \quad (12)$$

$$u^{(k+1)} = u^{(k)} + \begin{bmatrix} \gamma\alpha^{(k+1)} \\ e^{(k+1)} \end{bmatrix} - y^{(k+1)}. \quad (13)$$

- ▶ $S_{1/\rho}$ is the soft-threshold function.
- ▶ Operations with X is FIR filtering.

Solving positive-definite symmetric Toeplitz systems II



- ▶ Fast algorithms⁸ $\rightarrow \mathcal{O}(N^2)$.
- ▶ Superfast algorithms⁹ $\rightarrow \mathcal{O}(N \log^2 N) + \mathcal{O}(N \log N)$.
- ▶ “Intermediate”¹⁰ $\rightarrow \mathcal{O}(N^2) + \mathcal{O}(N \log N)$.
- ▶ Break-even point in the number of operations at approximately $N = 256$ for N as a radix 2 number. We will use $N = 250$, so go for the intermediate.

⁸N. Levinson. “The Weiner RMS Error Criterion in Filter Design and Prediction”. In: *Journal of Mathematics and Physics* 25 (1947), pp. 261–278.

⁹R.R. Bitmead and B.D.O Anderson. “Asymptotically fast solution of Toeplitz and related systems of linear equations”. In: *Linear Algebra and its Applications* 34 (1980), pp. 103–116; G.S. Ammar and W.B Gragg. “Superfast solution of real positive definite Toeplitz systems”. In: *SIAM Journal on Matrix Analysis and Applications* 9.1 (1988), pp. 61–76.

¹⁰J. R. Jain. “An efficient algorithm for a large Toeplitz set of linear equations”. In: *Acoustics, Speech and Signal Processing, IEEE Transaction on* 27.6 (1979).

Solving positive-definite symmetric Toeplitz systems III



The inverse of a Toeplitz matrix can be described by the Gohberg-Semencul formula

$$\delta_N T^{-1} = T_1 T_1^T - T_0^T T_0 \quad (14)$$

where

$$T_0 = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ \rho_0 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ \rho_{N-1} & \cdots & \rho_0 & 0 \end{bmatrix}, \quad T_1 = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ \rho_{N-1} & 1 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ \rho_0 & \cdots & \rho_{N-1} & 1 \end{bmatrix}. \quad (15)$$

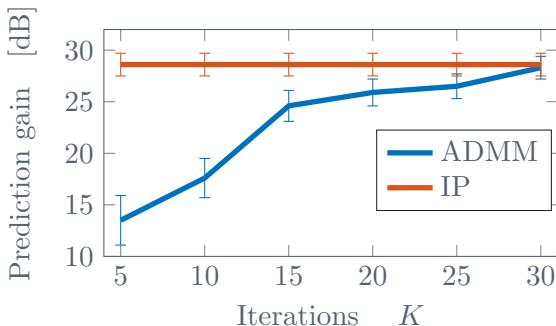
- ▶ The variables δ_N and $\rho_0, \dots, \rho_{N-1}$ can be computed using the Szegő recursions.
- ▶ Evaluation of matrix-vector products with T_0, T_0^T, T_1, T_1^T : FFTs/IFFTs.

- ▶ The LP speech model only approximates the human speech production system and the model is not noise free¹¹,
- ▶ Moreover, the convex optimization framework uses the 1-norm because of its feasibility not because it was the best choice.
- ▶ Summary: solution should only be accurate enough to capture the essence of our endeavor.
- ▶ Expectation: saturation like effect as a function of accuracy¹².

¹¹J.R. Deller, J.G. Proakis, and J.H.L. Hansen. *Discrete-time processing of speech signals*. Ieee New York, NY, USA:, 2000.

¹²B. Defraene et al. “Real-Time Perception-Based Clipping of Audio Signals Using Convex Optimization”. In: *Audio, Speech, and Language Processing, IEEE Transaction on* 20.10 (2012), pp. 2657–2671.

- ▶ Processed only the vowel and semivowel phones from the TIMIT database, 3696 sentences from 462 speakers ($\approx 40,000$ voiced speech frames).
- ▶ Regularization γ obtained via modified L-curve analysis.



- ▶ Average prediction gains for a fixed number of iterations for the ADMM solution. A 95% confidence interval is shown.

- ▶ C++/ FFTW3 library / Intel Math Kernel Library (MKL)
- ▶ Varying k and linear regression.
- ▶ ADMM: Levinson:

$$t_k \approx 7 \cdot 10^{-6} + 159 \cdot 10^{-6}k \quad [\text{s}], \quad C^2 = 0.999.$$

- ▶ ADMM: Szegö recursion + Gohberg-Semencul

$$t_k \approx 62 \cdot 10^{-6} + 55 \cdot 10^{-6}k \quad [\text{s}], \quad C^2 = 0.999.$$

- ▶ Handtailored IP method:

$$t_k \approx 1206 \cdot 10^{-6} + 2033 \cdot 10^{-6}k \quad [\text{s}], \quad C^2 = 0.999.$$

- ▶ High-order sparse linear prediction offers interesting properties for speech processing.
- ▶ Need to solve a linear program for each frame → real-time and embedded applications.
- ▶ An approach: efficient use of Toeplitz matrix structure using the alternating direction method of multipliers.
- ▶ Low accuracy is sufficient to obtain similar prediction gain as high accuracy methods.