De-noising a Group Sparse Signal in Speech Enhancement

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Abstract: Convex optimization with sparsity-promoting convex regularization is a standard approach for estimating sparse signals in noise. In order to promote sparsity more strongly than convex regularization, it is also standard practice to employ non-convex optimization. In this paper, we take a third approach. We utilize a non-convex regularization term chosen such that the total cost function (consisting of data consistency and regularization terms) is convex. Therefore, sparsity is more strongly promoted than in the standard convex formulation, but without sacrificing the attractive aspects of convex optimization (unique minimum, robust algorithms, etc.). We use this idea to improve the recently developed ‘overlapping group shrinkage’ (OGS) algorithm for the denoising of group-sparse signals. The algorithm is applied to the problem of speech enhancement with favorable results in terms of both SNR and perceptual quality.

Keywords: Convex Optimization, Denoising, Group Sparse Model, Non-Convex Optimization, Sparse Optimization, Speech Enhancement, Translation-Invariant Denoising.

1. INTRODUCTION

By group-sparse, we mean that large magnitude values of tend not to be isolated. Rather, large magnitude values tend to form clusters (groups). Furthermore, we do not assume that the group locations are known, nor that the group boundaries are known. In fact, we do not assume that the groups have well defined boundaries. An example of such a vector (in 2D) is the spectrogram of a speech waveform. The spectrogram of a speech waveform exhibits areas and ridges of large magnitude, but not isolated large values. The method proposed in this work will be demonstrated on the problem of speech filtering. Convex and non-convex optimizations are both common practice for the estimation of sparse vectors from noisy data. Convex formulations are advantageous in that a wealth of convex optimization theory can be leveraged and robust algorithms with guaranteed convergence are available. On the other hand, non-convex approaches are advantageous in that they usually yield sparser solutions for a given residual energy. However, non-convex formulations are generally more difficult to solve (due to suboptimal local minima, initialization issues, etc.). Also, solutions produced by non-convex formulations are generally discontinuous functions of input data (e.g., the discontinuity of the hard-threshold function).

In this work, we take a different approach, proposed by Blake and Zimmerman and by Nikolova. Namely, the use of a non-convex non-smooth penalty function chosen such that the total cost function (consisting of data consistency and regularization terms) is strictly convex. This is possible “by balancing the positive second derivatives in the [data consistency term] against the negative second derivatives in the [penalty] terms”. The contribution of this work relates to the formulation of the group-sparse denoising problem as a convex optimization problem albeit defined in terms of a non-convex penalty function, and the derivation of a computationally efficient iterative algorithm that monototonically reduces the cost function value. We utilize non-convex penalty functions (in fact, concave on the positive real line) with parametric forms; and we identify an interval for the parameter that ensures the strict convexity of the total cost function. As the total cost function is strictly convex, the minimizer is unique and can be obtained reliably using convex optimization techniques. The algorithm we present is derived according to the principle of majorization minimization (MM). The proposed approach:

- does not underestimate large amplitude components of sparse solutions to the extent that convex penalties do,
- is translation invariant (due to groups in the proposed method being fully overlapping),
- is computationally efficient (per iteration) with
- monotonically decreasing cost function, and
- requires no algorithmic parameters (step-size, Lagrange, etc.).

We demonstrate below that the proposed approach substantially improves upon our earlier work that considered only convex regularization.

A. Related Work

The estimation and reconstruction of signals with group sparsity properties has been addressed by numerous authors. We make a distinction between two cases: non-overlapping groups and overlapping groups, The non-overlapping case is the easier case: when the groups are non-overlapping, there is a decoupling of variables, which simplifies the optimization problem. When the groups are overlapping, the variables are coupled. In this case, it is common to define auxiliary variables (e.g., through the variable splitting technique) and apply methods such as the alternating direction method of multipliers (ADMM). This approach
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increases the number of variables (proportional to the group size) and hence increases memory usage and data indexing. In previous work we describe the 'overlapping group shrinkage' (OGS) algorithm for the overlapping-group case that does not use auxiliary variables. The OGS algorithm exhibits favorable asymptotic convergence in comparison with algorithms that use auxiliary variables. It was applied to total variation denoising in. In comparison with previous work on convex optimization for overlapping group sparsity, including, the approach we propose here promotes sparsity more strongly. In this paper, we extend the OGS algorithm to the case of non-convex regularization, yet the approach remains within the convex optimization framework.

II. PROPOSED SYSTEM

The process of estimating regression parameters subject to a penalty on the one-norm of the parameters times a, known as the lasso, has become ubiquitous in modern statistical applications. In particular, in settings of low to moderate multi-collinearity where the solution is believed to be sparse, the application of the lasso is almost de rigueur. Outside of the sparse and low to moderate multi-collinearity setting the performance of the lasso is suboptimal. In this vein, many of the theoretical and algorithmic developments for the lasso assume and/or cater to a sparse estimator in the presence of low to moderate multi collinearity. A prime example of this phenomenon is coordinate wise algorithms, which have become the most common means of computing the lasso solution. The performance of coordinate wise algorithms, while ideal for sparse and low to moderate correlation settings, degrades as sparsity decreases and multi-collinearity increases. However, the model selection capabilities of the lasso can still be essential even in the presence of high multi-collinearity or in the absence of sparsity. The limitations of coordinate wise algorithms in such settings motivate us to propose in this paper the novel Deterministic GSS algorithm for computing the lasso solution. The performance of this proposed algorithm improves as sparsity decreases and multi-collinearity increases, and hence our approach offers substantial advantages over coordinate wise techniques in such settings.

The popularity of the lasso comes despite the inability to express the lasso estimator in any convenient closed form. Hence, there is keen interest in algorithms capable of efficiently computing the lasso solution. Arguably, the two most well known algorithms for computing the lasso solution are least angle regression and the even faster path wise coordinate optimization. Least angle regression (LARS) can be viewed as a form of stage wise regression. By exploiting the geometry of the lasso problem, LARS is able to efficiently compute the entire sequence of lasso solutions. Path wise coordinate optimization is based on the idea of cycling through the coefficients and minimizing the objective function 'one coefficient at a time', while holding the other coefficients fixed. Since it has been shown to be considerably faster than competing methods, including LARS, path wise coordinate optimization is today the most commonly utilized algorithm for computing lasso solutions.

While path wise coordinate optimization is generally a fast and efficient algorithm for computing the lasso solution, the algorithm is not without limitations. In particular, the computational speed of path wise coordinate optimization degrades as sparsity decreases and multi-collinearity increases.

III. SIMULATION RESULT

This example compares the proposed non-convex regularized OGS algorithm with the earlier (convex regularized) version of OGS and with scalar thresholding. Figure shows a synthetic group-sparse signal (same as in). The noisy signal, shown in Figure was obtained by adding white Gaussian noise (AWGN) with SNR of 10 dB. For each of soft and hard thresholding, we used the threshold, T that maximizes the SNR. The result obtained using the prior version of OGS is shown in Figure. This is equivalent to setting to the absolute value function; i.e., we use \( \phi(x) = |x| \). So, we denote this as OGS[abs]. The result using the proposed non-convex regularized OGS is shown in Figure. We use the arctangent penalty function with a set to the maximum value of \( 1/(K \lambda) \) that preserves convexity of F; i.e., we use \( \phi(. ) = \phi_{atan} (1/(K \lambda)) \). We denote this as OGS [atan]. We also used the logarithmic penalty (not shown in the figure). For each version of OGS, we used a group size of K=5, and we set to maximize the SNR. As a second experiment, we selected T and λ for each method, so as to reduce the noise standard deviation, σ, down to 0.01σ, as described. The resulting SNRs, given in the second row of Table IV, are much lower. (This method does not maximize SNR, but it does ensure residual noise is reduced to the specified level.) The low SNR in these cases is due to the attenuation (bias) of large magnitude values. However, it can be observed that OGS, especially with non-convex regularization, significantly outperforms scalar thresholding.

Fig.1. Example1: Group-sparse signal denoising. (a) Signal; (b) Signal+noise(SNR=10.00dB); (c) OGS[abs] (SNR = 12.30dB); (d) OGS[atan] (SNR=15.37 dB).
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Fig. 2. Example 1. Comparison of OGS [abs] and OGS [atan] in Fig. 2. (a) Output versus input; (b) sorted error.

Fig. 3. Spectrograms before and after denoising (male speaker). (a) Noisy signal. (b) OGS [abs] with group size K=(8,2). Gray scale represents decibels.

Fig. 4. SNR comparison of speech enhancement algorithms.

IV. CONCLUSION

This paper formulates group-sparse signal denoising as a convex optimization problem with a non-convex regularization term. This regularizer is based on the overlapping groups so as to promote group-sparsity. The regularizer, being a concave on the positive real line, promotes the sparsity more strongly than any convex regularizer can. For several non-convex penalty functions, parameterized by a variable, a, it has been shown how to constrain to ensure the optimization problem is strictly convex. Then develop a group suboptimal shrinkage algorithm for the proposed approach. This algorithm gives the effectiveness of the proposed method for speech enhancement.

V. REFERENCES
