Superiorization and Perturbation Resilience of Algorithms: A Continuously Updated Bibliography

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Abstract

This document presents a, chronologically ordered, bibliography of scientific publications on the superiorization methodology and perturbation resilience of algorithms which is compiled and continuously updated by us at: http://math.haifa.ac.il/yair/bib-superiorization-censor.html.

Since the topic is relatively new it is possible to trace the work that has been published about it since its inception. To the best of our knowledge this bibliography represents all available publications on this topic to date, and while the URL is continuously updated we will revise this document and bring it up to date on arXiv approximately once a year. Abstracts of the cited works, and some links and downloadable files of preprints or reprints are available on the above mentioned Internet page. If you know of a related scientific work in any form that should be included here kindly write to me on: yair@math.haifa.ac.il with full bibliographic details, a DOI if available, and a PDF copy of the work if possible. The Internet page was

initiated on March 7, 2015, and has been last updated on March 7, 2018.

1 Trailer

We replace the text that appeared in this section in the previous versions of the report with a quotation from the preface to the special issue Y. Censor, G.T. Herman and M. Jiang (Guest Editors), "*Superiorization: Theory and Applications*", Special Issue of the journal *Inverse Problems*, Volume **33**, Number 4, April 2017 [50][1], followed by some additional notes.

> "The superiorization methodology is used for improving the efficacy of iterative algorithms whose convergence is resilient to certain kinds of perturbations. Such perturbations are designed to 'force' the perturbed algorithm to produce more useful results for the intended application than the ones that are produced by the original iterative algorithm. The perturbed algorithm is called the 'superiorized version' of the original unperturbed algorithm. If the original algorithm is computationally efficient and useful in terms of the application at hand and if the perturbations are simple and not expensive to calculate, then the advantage of this method is that, for essentially the computational cost of the original algorithm, we are able to get something more desirable by steering its iterates according to the designed perturbations.
>
> This is a very general principle that has been used successfully in some important practical applications, especially for inverse problems such as image reconstruction from projections, intensity-modulated radiation therapy and nondestructive testing, and awaits to be implemented and tested in additional fields.
>
> An important case is when the original algorithm is 'feasibility-seeking' (in the sense that it strives to find some point that is compatible with a family of constraints) and the perturbations that are introduced into the original iterative algorithm aim at reducing (not necessarily minimizing) a given merit function. In this case superiorization has a unique place in optimization theory and practice.

[1] All references refer to the bibliography in the next section of this report.

> Many constrained optimization methods are based on methods for unconstrained optimization that are adapted to deal with constraints. Such is, for example, the class of projected gradient methods wherein the unconstrained minimization inner step 'leads' the process and a projection onto the whole constraints set (the feasible set) is performed after each minimization step in order to regain feasibility. This projection onto the constraints set is in itself a non-trivial optimization problem and the need to solve it in every iteration hinders projected gradient methods and limits their efficiency to only feasible sets that are 'simple to project onto.' Barrier or penalty methods likewise are based on unconstrained optimization combined with various 'add-on's that guarantee that the constraints are preserved. Regularization methods embed the constraints into a 'regularized' objective function and proceed with unconstrained solution methods for the new regularized objective function.
>
> In contrast to these approaches, the superiorization methodology can be viewed as an antipodal way of thinking. Instead of adapting unconstrained minimization algorithms to handling constraints, it adapts feasibility-seeking algorithms to reduce merit function values. This is done while retaining the feasibility-seeking nature of the algorithm and without paying a high computational price. Furthermore, general-purpose approaches have been developed for automatically superiorizing iterative algorithms for large classes of constraints sets and merit functions; these provide algorithms for many application tasks."

To a novice on the superiorization methodology and perturbation resilience of algorithms we recommend to read first the recent reviews in [16, 25, 39]. For a recent description of previous work that is related to superiorization but is not included here, such as the works of Sidky and Pan, e.g., [6], we direct the reader to [24, section 3]. The SNARK14 software package [42], with its in-built capability to superiorize iterative algorithms to improve their performance, can be helpful to practitioners. Naturally there is variability among the bibliography items below in their degree of relevance to the superiorization methodology and perturbation resilience of algorithms. In some, such as in, e.g., [23] below, superiorization does not appear in the title, abstract or introduction but only inside the work, e.g., [23, Subsection

6.2.1: Optimization vs. Superiorization].

A word about the history. The terms and notions "superiorization" and "perturbation resilience" first appeared in the 2009 paper of Davidi, Herman and Censor [7] which followed its 2007 forerunner by Butnariu, Davidi, Herman and Kazantsev [3]. The ideas have some of their roots in the 2006 and 2008 papers of Butnariu, Reich and Zaslavski [2, 4]. All these culminated in Ran Davidi's 2010 Ph.D. dissertation [13].

2 The Bibliography

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