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PG Sharing Session: Proposal Writing Tips

Dr. Tarmizi bin Adam

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Innovating Solutions

Typical Outline of Research Proposal

a. Introduction
   i. Topic area/ Background
   ii. Research question/ Problem statement
   iii. Research objectives
   iv. Research scope
   v. Significance to knowledge/ Contribution
b. Literature review
   i. Previous research
   ii. Other & your previous works
   iii. Findings and Unanswered questions
   iv. Your preliminary work on the topic
   v. The remaining questions
   vi. Reprise/repeat of your research question(s) in this context
c. Methodology
   i. Approach
   ii. Data needs
   iii. Analytic techniques
   iv. Plan for interpreting results
   v. Gantt chart
d. Expected results & preliminary results
e. Bibliography (or References)

Outline of Talk

- **Title**
- **Executive Summary/Abstract**
- **Research Background**
- **Objectives**
- **Methodology**

Proposal Title

- Specific in nature reflecting fundamental issues to be resolved/novelty
- Brief and reflects the content of the proposal

Example

A(ii). Title of Proposed Research Project	A New Alternating Minimization Algorithm for Nonconvex Optimization Problems Based on Proximal Re-Weighted l1-norm Method

- Reflects the novelty of a method
- Specific (the underlying methods) and reflects the contents

Example

Check for updates

A combined higher order non-convex total variation with overlapping group sparsity for Poisson noise removal

Tarmizi Adam[1] · Raveendran Paramesran[2] · Kuru Ratnavelu[3]

Received: 8 July 2021 / Revised: 26 January 2022 / Accepted: 8 March 2022 /
Published online: 6 April 2022

- Reflects the novelty of a method
- Specific (the underlying methods) and reflects the contents

Example

- Avoid titles being too general:

Color Cast Removal Algorithm for Image Restoration under Varying Illumination Conditions

A Better Suggestion:
A New Adaptive Color Cast Removal Algorithm for Varying Illumination Conditions Based on Convolutional Neural Network Method.

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Executive Summary

- Problem statement
- Objectives
- Methodology
- Expected output/outcome/implication
- Significance of output

Example

C(xi). Executive Summary of Research Proposal

(Please include the problem statement, objectives, research methodology, expected output/outcomes/implication, and significance of output from the research project)

Nonconvex composite optimization problems serve as one of the fundamental problems in the mathematical optimization literature. This is partly due to the wide range of practical problems which naturally arise as minimizing a nonconvex objective function. In a convex setting such as the l1-norm minimization problem, Tseng's alternating minimization algorithm (AMA) serves as an efficient method to minimize convex composite optimization problems. However, in various practical problems, nonconvex composite optimization such as the nonconvex lp-norm, $0<p<1$ minimization problem has been shown to give better results. Therefore, it is crucial to extend Tseng's AMA to the nonconvex setting which is almost non-existent in the optimization literature. When minimizing convex composite optimization problems involving l1-norm, the operator-splitting nature of the AMA gives rise to individual sub-minimization problems. In this case, one of the main and crucial sub-minimization problems is to solve an l1-norm minimization problem. Due to the convexity of the l1-norm, this sub-minimization problem could be solved in a closed form via the soft thresholding operator. However, when the composite optimization problem involves the nonconvex lp-norm, $0<p<1$, the sub-minimization problem involved in the AMA is no longer convex and the soft thresholding can no longer be used.

To tackle this problem, this research proposes to solve this nonconvex lp-norm sub-minimization problem of AMA by formulating a proximal linearization of the sub-minimization problem by re-casting it into a proximal re-weighted l1-norm minimization problem. Hence, this research aims to propose and formulate a new nonconvex proximal re-weighted l1-norm AMA by utilizing proximal linearization and also to mathematically establish its convergence to a critical point. The outcome of this research is expected to contribute to the theoretical knowledge of nonconvex optimization theory. On the practical side, the theories and methods can be used in digital image restoration and signal/data recovery problems.

Example

- Intro and motivation
- Technical details leading to the problem.

- The problem
- Method to address the problem.

C(xi). Executive Summary of Research Proposal

(Please include the problem statement, objectives, research methodology, expected output/outcomes/implication, and significance of output from the research project)

Nonconvex composite optimization problems serve as one of the fundamental problems in the mathematical optimization literature. This is partly due to the wide range of practical problems which naturally arise as minimizing a nonconvex objective function. In a convex setting such as the l1-norm minimization problem, Tseng's alternating minimization algorithm (AMA) serves as an efficient method to minimize convex composite optimization problems. However, in various practical problems, nonconvex composite optimization such as the nonconvex lp-norm, 0<p<1 minimization problem has been shown to give better results. Therefore, it is crucial to extend Tseng's AMA to the nonconvex setting which is almost non-existent in the optimization literature. When minimizing convex composite optimization problems involving l1-norm, the operator-splitting nature of the AMA gives rise to individual sub-minimization problems. In this case, one of the main and crucial sub-minimization problems is to solve an l1-norm minimization problem. Due to the convexity of the l1-norm, this sub-minimization problem could be solved in a closed form via the soft thresholding operator. However, when the composite optimization problem involves the nonconvex lp-norm, 0<p<1, the sub-minimization problem involved in the AMA is no longer convex and the soft thresholding can no longer be used. To tackle this problem, this research proposes to solve this nonconvex lp-norm sub-minimization problem of AMA by formulating a proximal linearization of the sub-minimization problem by re-casting it into a proximal re-weighted l1-norm minimization problem. Hence, this research aims to propose and formulate a new nonconvex proximal re-weighted l1-norm AMA by utilizing proximal linearization and also to mathematically establish its convergence to a critical point. The outcome of this research is expected to contribute to the theoretical knowledge of nonconvex optimization theory. On the practical side, the theories and methods can be used in digital image restoration and signal/data recovery problems.

- Aims of the research.
- Expected outcome & significance to the body of knowledge.

Abstract

- General Introduction
- Problem statement
- Proposed method (methodology)
- Motivation of the proposed method
- Experiments
- Results

Example

Abstract

Poisson noise removal is a fundamental image restoration task in imaging science due to the Poisson statistics of the noise. The total variation (TV) image restoration has been promising for Poisson noise removal. However, TV-based denoising methods suffer from the staircase artifacts which makes the restored image blocky. Apart from that, the ℓ_1-norm penalization in TV restoration tends to over-penalize signal entries. To address these shortcomings, in this paper, we propose a combined regularization method that uses two regularization functions. Specifically, a combination of a non-convex ℓ_p-norm, $0 < p < 1$ higher order TV, and an overlapping group sparse TV (OGSTV) is proposed as a regularizer. The combination of a higher order non-convex TV and an overlapping group sparse (OGS) regularization serves as a means to preserve natural-looking images with sharp edges and eliminate the staircase artifacts. Meanwhile, to effectively denoise Poisson noise, a Kullback–Leibler (KL) divergence data fidelity is used for the data fidelity which better captures the Poisson noise statistic. To solve the resulting non-convex minimization problem of the proposed method, an alternating direction method of multipliers (ADMM)-based iterative re-weighted ℓ_1 (IRℓ_1) based algorithm is formulated. Comparative analysis against KL-TV, KL-TGV and, KL-OGS TV for restoring blurred images contaminated with Poisson noise attests to the good performance of the proposed method in terms of peak signal-to-noise ratio (PSNR) and structure similarity index measure (SSIM).

Research Background

- Elaboration of title
- Clarity of problem statement and research question/hypothesis/theoretical framework (if applicable)

Research Background

1. Problems Statement

- Must refer to previous literature to motivate the problem
- Why the problem is important/interesting
- What will the research contribute to the field

Example

1. Problem Statement

Convex optimization has been the standard choice for the past decades for data processing and analysis due to the myriad of efficient algorithms and provable convergence rate. However, in many instances, the objective function to be minimized are nonconvex functions [1, 2, 3]. Nonconvex optimization has also been shown to be better than convex optimization in many applications [2, 3].

Motivate with literature.

Unlike the minimization of convex functions where numerous fast and efficient algorithms exist, nonconvex minimization requires special attention to the problem structure [4]. Furthermore, nonconvex optimization problems are not guaranteed to converge to a global minimum which is the main attraction in convex optimization problems. Indeed, nonconvex optimization is generally not guaranteed to converge. Hence, being unable to converge or only converge to a local minimum is a challenge pertaining to nonconvex optimization.

Apart from convergence issues, nonconvex optimization is made more complex and challenging in the high dimensional data regimes which are indispensable in today's big data era [5]. Consequently, developing tractable and provable computationally fast

The success of ADMM in both convex and nonconvex settings has somehow overshadowed other equally efficient algorithms. Another relatively more recent convex optimization algorithm compared to the ADMM is Tseng's alternating minimization algorithm (AMA) [9]. This algorithm which bears some similarities with the ADMM has also been used extensively in the convex setting [10, 11, 12]. Unfortunately, unlike ADMM, its extension, and analysis in the nonconvex case is relatively missing in the literature.

Formulating and extending the AMA for nonconvex optimization will contribute directly to the field of optimization in terms of nonconvex optimization algorithm analysis. As mentioned earlier, this is particularly due to the missing gap between studies of convex AMA and nonconvex AMA in the literature. Therefore, to narrow this gap, it is interesting to formulate AMA for nonconvex optimization problems. Hence, this research proposes to formulate and extend AMA for nonconvex composite optimization problems.

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Research Background

2. Hypothesis

- Expected outcome of the research
  - Specificity
  - Clarity
  - Testability

Example

2. Hypothesis

1. The alternating minimization algorithm (AMA) can be re-formulated for minimizing nonconvex optimization problems by utilizing proximal linearization.

2. The iterates generated by the proposed nonconvex proximal AMA will converge to a critical point of the nonconvex objective function being minimized.

3. The generated iterates of the nonconvex proximal AMA will converge with a suboptimal complexity rate of $O(1/k)$ where k being the kth iteration of the nonconvex proximal AMA.

Research Background

3. Research Questions

- Address the
  - Hows
  - Whys

Example

3. Research Questions

To study the fundamental and theoretical aspects of the proposed nonconvex proximal alternating minimization algorithm (np-AMA) the following research questions are central to this research

1. How can the original alternating minimization algorithm (AMA) for convex optimization problems be formulated to nonconvex optimization problems utilizing nonconvex proximal linearization?

2. What are the required mathematical assumptions on the nonconvex optimization objective function to guarantee convergence of the nonconvex proximal AMA to a critical point?

3. How does the formulated nonconvex AMA compare with other nonconvex algorithms such as the nonconvex ADMM in terms of convergence speed and computational complexity?

Research Background

4. Literature Review

- Address the relevance, motivation, problems, and research gap through previous work
- Address the literature on the methods in your title
- Cite the latest paper/literature in the field

Blend them in a coherent flow

Example

the nonconvex functions to be minimized inherits the KL property, nonconvex optimization algorithms can be shown to converge to a critical point [19].

Due to the missing literature on AMA in the nonconvex optimization case, it is interesting to formulate a combination of AMA with a nonconvex proximal linearization i.e., proximal IRL1 and derive its convergence analysis under the KL property. Therefore, this research aims to focus on formulating a nonconvex AMA. Consequently, this research will contribute to the fundamental knowledge of mathematical optimization theory which is the core driving force in many real-world applications.

Objectives

- Specific, Measurable, Achievable, Realistic and within Time-frame (SMART)
- Relate to problem statement/research question/hypothesis

Example

(c) Objective(s) of the Research

1. To propose a nonconvex proximal alternating minimization algorithm (np-AMA) for nonconvex composite optimization problems.

2. To mathematically prove the convergence to a critical point of the proposed np-AMA along with its convergence rate.

3. To conduct numerical simulations to empirically validate the theoretical convergence and convergence rate in objective 2.

Research Questions:

1. How can the original alternating minimization algorithm (AMA) for convex optimization problems be formulated to nonconvex optimization problems utilizing nonconvex proximal linearization?

2. What are the required mathematical assumptions on the nonconvex optimization objective function to guarantee convergence of the nonconvex proximal AMA to a critical point?

3. How does the formulated nonconvex AMA compare with other nonconvex algorithms such as the nonconvex ADMM in terms of convergence speed and computational complexity?

Example

(c) Objective(s) of the Research

1. To propose a nonconvex proximal alternating minimization algorithm (np-AMA) for nonconvex composite optimization problems.
2. To mathematically prove the convergence to a critical point of the proposed np-AMA along with its convergence rate.
3. To conduct numerical simulations to empirically validate the theoretical convergence and convergence rate in objective 2.

Research hypothesis

1. The alternating minimization algorithm (AMA) can be re-formulated for minimizing nonconvex optimization problems by utilizing proximal linearization.
2. The iterates generated by the proposed nonconvex proximal AMA will converge to a critical point of the nonconvex objective function being minimized.
3. The generated iterates of the nonconvex proximal AMA will converge with a suboptimal complexity rate of O(1/k) where k being the kth iteration of the nonconvex proximal AMA.

Methodology

- Clear and detailed description of methodology (may consist of field work, sampling techniques, interview session, analysis, lab work of different phases, experimental protocol, statistical analysis)
- Able to achieve research objectives
- Include research design, flow chart, Gantt chart, activities and milestones
- Relate to objectives, research question, and hypothesis

Methodology

Phases in the **methodology**:

1. Literature review and problem definition
2. Formulation of the problem
3. Analysis of the algorithm
4. Validation of the algorithm

Example

which will result in the following nonconvex optimization problem for solving v

$$v_{k+1} = \underset{v \in R^n}{\arg\min} ||\boldsymbol{v}||_p^p + \langle \rho_k, v - \nabla u \rangle + \frac{\beta}{2} ||v - \nabla u_{k+1}||_2^2. \quad (7)$$

To solve (7) the IRL1 and its proximal version [22, 23] can be integrated and formulated. This will result in a novel combination of IRL1 and AMA for solving nonconvex optimization problems. However, the mathematical equivalence between (7) and the ones in [22, 23] needs to be established and derived. As a consequence, the AMA needs to be re-formulated and new theoretical analysis for its convergence must be analyzed. Thus the crux of this phase is to develop the nonconvex AMA for solving problems of the form (1) when the function g is nonconvex. This phase is related to objective 1 of the research. By the end of this phase, objective 1 is completed and research question 2 will be answered.

Example

1.3. Analysis of the algorithm

The main body of work in this phase is to theoretically analyze the developed nonconvex AMA algorithm. In this phase, detailed mathematical assumptions on both functions f(.) and g(.) need to be precisely established. Once these assumptions are established, the mathematical proof for the nonconvex AMA can be derived. An important step in this phase is to prove that the nonconvex function in problem (7) satisfies the KL property.

Once this is proven, the convergence of the sequence of iterates of the nonconvex AMA to a critical point can be shown along with its convergence rate analysis. This phase completes objective 2 of the research and answers research question 2.

Methodology: Flow Chart

Must-haves:

1. Research activities to be conducted
2. Relation of each activity to the objectives/hypothesis /research questions

Quality of Proposal

- Meticulous
- Proper use of language (grammar, spelling, sentence construction)
- Good formatting and presentation

THANK YOU

Questions?

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Kerana Tuhan untuk Manusia