

## A Convex and Exact Approach to Discrete Constrained TV-L1 Image Approximation

Jing Yuan<sup>\*,1</sup>, Juan Shi<sup>2</sup> and Xue-Cheng Tai<sup>2,3</sup>

<sup>1</sup> *Computer Science Department, Middlesex College, University of Western Ontario, London, Ontario, N6A 5B7, UK.*

<sup>2</sup> *Division of Mathematical Sciences, School of Physical and Mathematical Sciences, Nanyang Technological University, Singapore.*

<sup>3</sup> *Department of Mathematics, University of Bergen, Norway.*

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**Abstract.** We study the TV-L1 image approximation model from primal and dual perspective, based on a proposed equivalent convex formulations. More specifically, we apply a convex TV-L1 based approach to globally solve the discrete constrained optimization problem of image approximation, where the unknown image function  $u(x) \in \{f_1, \dots, f_n\}$ ,  $\forall x \in \Omega$ . We show that the TV-L1 formulation does provide an exact convex relaxation model to the non-convex optimization problem considered. This result greatly extends recent studies of Chan et al., from the simplest binary constrained case to the general gray-value constrained case, through the proposed rounding scheme. In addition, we construct a fast multiplier-based algorithm based on the proposed primal-dual model, which properly avoids variability of the concerning TV-L1 energy function. Numerical experiments validate the theoretical results and show that the proposed algorithm is reliable and effective.

**Key words:** Convex optimization, primal-dual approach, total-variation regularization, image processing.

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### 1. Introduction

Many tasks of image processing can be formulated and solved successfully by convex optimization models – e.g. image denoising [21, 24], image segmentation [5], image labeling [4, 22] etc. The reduced convex formulations can be studied in a mathematically sound way and usually tackled by a tractable numerical scheme. Minimizing the total-variation function for such convex image processing formulations is of great importance [5, 6, 17–20, 24, 27], as it preserves edges and sharp features.

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\*Corresponding author. *Email addresses:* cn.yuanjing@gmail.com (J. Yuan), shij0004@e.ntu.edu.sg (J. Shi), tai@mi.uib.no (X.-C. Tai)

In their pioneer works [8,9], Chan et al. proposed the TV-L1 regularized image approximation model

$$\min_u \{P(u) := \alpha \int_{\Omega} |f - u| dx + \int_{\Omega} |\nabla u(x)| dx\}, \tag{1.1}$$

which was first introduced and studied by Alliney [1,2] for discrete one-dimensional signals' denoising. Chan et al. [8,9] demonstrated an interesting property of the TV-L1 model (1.1) – viz. that for the input binary image  $f(x) \in \{0, 1\}$ , there exists at least one global optimum  $u(x) \in \{0, 1\}$ . It follows that the convex TV-L1 formulation (1.1) actually solves the nonconvex optimization problem

$$\min_{u(x) \in \{0,1\}} \alpha \int_{\Omega} |f - u| dx + \int_{\Omega} |\nabla u(x)| dx, \tag{1.2}$$

globally and exactly! Hence (1.1) provides an exact convex relaxation of the binary constrained optimization problem (1.2). Chan et al. [8, 9] also proved that rounding the computed result of (1.1) may give a series of global optima of the binary constrained optimization model (1.2).

**Previous work and motivation**

With the help of co-area formula, Chan et al. [8,9] proved that the energy functional  $P(u)$  of (1.1) can be represented in terms of the upper level-set sequence of the image functions  $u(x)$  and  $f(x)$  – i.e.

$$P(u) = \int_{-\infty}^{+\infty} \{|\partial U^\gamma| + \alpha |U^\gamma \Delta F^\gamma|\} d\gamma, \tag{1.3}$$

where  $U^\gamma$  and  $F^\gamma$  denote the  $\gamma$ -upper level set of the unknown  $u(x)$  and the input  $f(x)$  for each  $\gamma$  respectively, such that

$$U^\gamma(x) = \begin{cases} 1, & \text{when } u(x) > \gamma \\ 0, & \text{when } u(x) \leq \gamma \end{cases}, \quad x \in \Omega, \quad i = 1, \dots, n; \tag{1.4}$$

and  $|\partial U^\gamma|$  denotes the perimeter of  $U^\gamma$  and  $|U^\gamma \Delta F^\gamma|$  the area of the symmetric difference of the two level sets, respectively.

Yin et al. [30] pointed out that minimizing such a layer-wise energy function (1.3) actually amounts to properly stacking the optimal  $U^\gamma$ s, which corresponds to solving (1.2) for each given binary indicator function of  $F^\gamma$ . In other words, solving (1.1) can be reduced to optimizing a sequence of binary constrained problems as (1.2). Since  $U^{\gamma_1} \subset U^{\gamma_2}$  when  $\gamma_1 \geq \gamma_2$ , the process recovers the optimum  $u^*(x)$  of (1.1) by properly arranging all the associated level sets  $U^\gamma$ ,  $\gamma \in (-\infty, +\infty)$ . The same result was also discovered by Darbon et al. [10,11] in an image graph setting, where the anisotropic total-variation term was considered and a fast graph-cut based algorithm introduced. Goldfarb and Yin also developed an efficient pre-flow based graph-cut approach to such L1 image approximation regularized by discretized total-variation.