DEVELOPMENT OF FILTERING INCLUDING STATIC AND DYNAMIC ALGORITHMS

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Abstract: Regularizing images under a guidance signal has been used in various tasks in computer vision and computational photography, particularly for noise reduction and joint upsampling. The aim is to transfer fine structures of guidance signals to input images, restoring noisy or altered structures. One of main drawbacks in such a data-dependent framework is that it does not handle differences in structure between guidance and input images. We address this problem by jointly leveraging structural information of guidance and input images. Image filtering is formulated as a nonconvex optimization problem, which is solved by the majorization-minimization algorithm. The proposed algorithm converges quickly while guaranteeing a local minimum. It effectively controls image structures at different scales and can handle a variety of types of data from different sensors. We demonstrate the flexibility and effectiveness of our model in several applications including depth superresolution, scale-space filtering, texture removal, flash/nonflash denoising, and RGB/NIR denoising.

Key words: Regularization, ETP, EDM, Filtering, Mesh Denoising, Image

Introduction: Many tasks in computer vision and computational photography can be formulated as ill-posed inverse problems, and thus theoretically and practically, require regularization. In the classical setting, this is used to obtain a smoothly varying solution and/or ensure stability. Recent work on joint regularization (or joint filtering) provides a new perspective on the regularization process, with a great variety of applications including stereo correspondence, optical flow, joint upsampling, dehazing, noise reduction, and texture remova. The basic idea of joint regularization is that the structure of a guidance image is transferred to an input image, e.g., for preserving sharp structure transitions while smoothing the input image. It assumes that the guidance image has enough structural information to restore noisy or altered structures in the input image. Joint regularization has been used with either static or ⇤WILLOW project-team, Departement d'Informatique de l'Ecole Nor- ´ male Superieure, ENS/Inria/CNRS UMR 8548. ´ dynamic guidance images. Static guidance regularization provides an output image by modulating the input image with an affinity function that depends on the similarity of features in the guidance signal. This static guidance is fixed during the optimization. It can reflect internal properties of the input image itself, e.g., its gradient or be another signal aligned with the input image, e.g., a near infrared (NIR) image. This framework determines the structure of the output image by referring to that of the guidance image only, and does not consider structural (or statistical) dependencies and inconsistencies between input and guidance images. This is problematic, especially in the case of data from different sensors, e.g., depth and color images. Dynamic guidance regularization uses an affinity function obtained from the regularized input image. It is assumed that the affinity between neighboring pixels can be determined more accurately from already regularized images, than from the input image itself. This method is inherently iterative, and dynamic guidance (the regularized input image, i.e., a potential output image) is updated at every step. In contrast to static guidance regularization, dynamic guidance regularization does not use static guidance and takes into account of the properties of the input image. Data-dependent static guidance is needed to impose structures on the input image, especially when the input image is not enough in itself to pull out reliable information, e.g., joint upsampling. We present a unified framework for image filtering taking advantage of both static and dynamic guidances. We address the aforementioned problems by fusing appropriate structures of static and dynamic guidance images, rather than unilaterally transferring structures of guidance images to the input image. To encourage comparison and future work, our source code is available at our project webpage1.

Materials:. This implicit regularization is simple and easy to implement, but the filtering formalization prevents its wide applicability. For example, it is hard to handle input images where information is sparse, e.g., in image colorization. The local nature of this approach might introduce artifacts, e.g., halos and gradient reversal. Accordingly, implicit regularization has been applied in a highly controlled condition, and usually employed as a pre- and/or post-processing for further applications. An alternative approach is to explicitly encode the regularization process into an objective functional, while taking advantage of a guidance signal. The objective functional typically consists of two parts: A fidelity term describes the consistency between input and output images, and a regularization term encourages the output image to have a similar structure to the guidance image. The weighted least-squares (WLS) framework is the most popular explicit regularization method that has been used in static guidance regularization.

Methods: The regularization term is modeled as a weighted l2 norm. Anisotropic diffusion (AD) is an explicit regularization framework using dynamic guidance. In contrast to INM and the RGF, AD updates both input and guidance images at every step; The regularization is performed iteratively with regularized input and updated guidance images. This explicit regularization enables formulating a task-specific model, with more flexibility than using implicit regularization. Furthermore, this type of regularization overcomes several limitations of implicit regularization, such as halos and gradient reversal, at the cost of global intensity shifting. Existing regularization methods typically apply to a limited range of applications and suffer from various artifacts: For example, the RGF is applicable to scale-space filtering only, and suffers from poor edge localization. In contrast, our approach provides a unified model for many applications, gracefully handles most of these artifacts, and outperforms the state of the art in all the cases considered in the paper. Although the proposed model may look similar to WLS and the RGF, our nonconvex objective function needs a different solver. Contrary to iteratively reweighted least-squares (IRLS), we do not split a nonconvex regularizer but approximate the objective function by a surrogate (upper-bound) function.

Results: Due to the introduction of the WCNs, the filtering problems for NSs have encountered some notable problems. The most important one is the limited network bandwidth which will inevitably lead to packet dropouts and transmission delays. To improve the utilization efficiency of the limited network bandwidth and alleviate the network-induced phenomena, some communication protocols have been introduced in the NSs such as the Round-Robin protocol the random access protocol the Weighted Try-Once-Discard protocol, and the event-triggered protocol (ETP). Under the communication protocols, the transmission is executed according to certain principles to relieve network bandwidth pressure. In this case, the network load is largely reduced since the transmission is now sparse under the communication protocols. Nevertheless, it is of vital importance to develop filtering algorithm which can still ensure the desired filtering performance under the sparse measurements. Until now, considerable excellent achievements have been made in the research of the filtering problems for the NSs under communication protocols.

Under the ETP, the data transmission is executed only when a certain triggering condition is satisfied. Generally speaking, the ETP can be divided into the static ETP, and the dynamic ETP. As the name implies, the main difference between these two protocols is that the triggering threshold is constant in the static ETP and is dynamically adjusted in the dynamic ETP. Compared to the static ETP, the dynamic ETP is able to further reduce the triggering times by adjusting the triggering threshold according to the system information, which further improves the energy efficiency of the communication networks. In recent, some representative results have been obtained on the filtering problems under the dynamic ETP. For example, a distributed RF algorithm has been proposed for a class of discrete nonlinear time-varying systems based on the dynamic ETP. The state estimation problem has been studied by Ma et al. for the singularly perturbed systems, where the dynamic ETP has been introduced to schedule communication data.

On the other hand, compared to the traditional analog transmission method, the digital communication strategy has outstanding superiority in terms of anti-jamming ability, data encryption, and bandwidth saving. In general, the analog-to-digital conversion consists of four steps: sampling, retention, quantization and encoding. The encoding process is introduced to protect the transmitted data from being attacked or stolen by the enemy. Specifically, in the encoding process, the original data is compiled into special codeword and then transmitted. After being received, the codeword is restored to the original data as accurately as possible. Owing to the advantages such as safety and energy-saving, the encoding-decoding mechanism (EDM) has attracted a surge of attention from researchers and the control problems under the EDM have received ever-increasing interest. Unfortunately, the filtering problems under the EDM has received inadequate attentions due to the difficulties in constructing relationship between the decoded measurement output and the real measurement output. Therefore, this paper is dedicated to solving such a challenging problem by studying the RF problem under the EDM.

In conclusion, we are committed to designing a RF algorithm for a class of NSs with the dynamic ETP and the dynamic-quantization-based EDM. The main challenges are identified as: 1) how to design a reasonable EDM to encrypt the transmitted data and 2) how to establish the relationship between the decoded measurement output and the real measurement output. The main contributions of this paper are highlighted in the following aspects: 1) a dynamic-quantization-based EDM is introduced to encrypt the transmitted measurement to improve the security of WCNs; 2) a bounded uncertainty is introduced to describe the difference between the decoded measurement output and the real measurement output; and 3) an effective dynamic event-based RF method is designed for the NSs under the EDM.

Conclusion: We consider the problem of estimating neural activity from measurements of the magnetic fields recorded by magnetoencephalography. We exploit the temporal structure of the problem and model the neural current as a collection of evolving current dipoles, which appear and disappear, but whose locations are constant throughout their lifetime. This fully reflects the physiological interpretation of the model. In order to conduct inference under this proposed model, it was necessary to develop an algorithm based around state-of-the-art sequential Monte Carlo methods employing carefully designed importance distributions. Previous work employed a bootstrap filter and an artificial dynamic structure where dipoles performed a random walk in space, yielding nonphysical artefacts in the reconstructions; such artefacts are not observed when using the proposed model. The algorithm is validated with simulated data, in which it provided an average localisation error which is approximately half that of the bootstrap filter. An application to complex real data derived from a somatosensory experiment is presented.

Assessment of model fit via marginal likelihood showed a clear preference for the proposed model and the associated reconstructions show better localisation.

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