

Image Processing Procedures Based on Multi-Quadratic Dynamic Programming

Pham Cong Thang
 The University of Da Nang - University of Science and Technology
 54 Nguyen Luong Bang, Da Nang, Viet Nam
 Email: pcthang@dut.udn.vn

Thesis summary

Keywords: dynamic programming, Bayesian framework, Markov random fields (MRFs), edges-preserving smoothing, Gibbs energy, pair-wise potential functions

Received: January 29, 2017

This paper summarizes the doctoral dissertation [1] of the author. The main subject of this thesis is the study and development of a method for edge preserving in image smoothing, which is developed based on multi-quadratic dynamic programming procedure for maximum a posteriori probability estimation. Additionally, a new non-convex type regularization is proposed, with ability to flexibly set a priori preferences, using different penalties for various ranges of differences between the values of adjacent image elements. Procedures of image processing, as presented here, consider heterogeneities and discontinuities in the source data, while retaining high computational efficiency of the dynamic programming procedure and Kalman filter-interpolator. Comparative study shows, that proposed algorithms has high accuracy to speed ratio, especially in the case of high-resolution images.

Povzetek: Predstavljena je doktorska disertacija, ki se ukvarja z glajenjem robov pri procesiranju slik.

Image denoising is a necessary stage in almost every computer vision system. It plays an important role in improving the quality of further analysis and interpretation. One of the main problems encountered in image pre-processing and reconstruction is the preservation or restoration of the original structure of the local edges and sudden changes in brightness. Many edge-preserving image denoising methods have been proposed in the literature. Nevertheless, the monitoring of dynamic processes needs to improve the performance of the low-level processing stage in both speed and accuracy.

One of the most popular approaches for image processing is Bayesian framework. In this approach, the problem of image analysis can be expressed as the problem of estimation of a hidden component of two-component random field, where the analyzed image plays the role of the observed component. An equivalent representation of Markov random fields in the form of Gibbs random fields can be used to define prior probability properties of a hidden Markov field by means of so called Gibbs potentials on cliques. In the case of a singular loss function, the Bayesian estimation of the hidden component can be found as a maximum a posteriori probability (MAP) estimation, which leads us to the problem of minimization of the objective function, often called the Gibbs energy function [2]. The structure of the objective function reflects the ordering property of analyzed data and is determined by means of an undirected neighborhood graph. In image analysis, objective function can often be represented as the sum of the two types of potential functions on cliques, called node functions and

edge functions. In image smoothing node functions play the role of a penalty on the difference between the values of input data and the sought for function, and are usually chosen in quadratic form. Each edge function imposes penalty upon the difference of values in the corresponding pair of adjacent elements of the edge of neighborhood graph, and can have various forms. In a Bayesian framework, the edge functions are usually called pair-wise potential functions.

Different types of prior assumptions result in several types of pair-wise potential functions [3]. However, corresponding optimization techniques are rather time consuming and they require high computational power. The quadratic form of the Gibbs potentials corresponds to the assumption of a normal priori distribution. In such a case, there exists a highly computationally effective parametric dynamic programming procedure [3] based on recurrent decomposition of the initial problem of minimizing function of many variables into a succession of partial problems, each of which consists in minimizing a function of only one variable. The corresponding intermediate objective functions of one variable are called Bellman functions. Unfortunately, the assumption of a normal priori distribution does not possess any edge-preserving properties.

In this thesis, we proposed a new non-convex type of pair-wise potential functions that allows more flexibility to set a priori preferences, using different coefficients of penalty for various ranges of differences between the values of adjacent image elements [4].

Moreover, a more specific case of signal processing has been considered [5]. In this case, pair-wise Gibbs potentials are selected as a minimum of a finite set of quadratic functions and an efficient optimization procedure is proposed for the Blake and Zisserman function, which is often used in edge-preserving procedures.

To apply the similar procedure for image processing, image processing technique based on tree-like approximation of the pixel lattice has been used. We use a separate pixel neighborhood tree for each stem column, which is defined, nevertheless, on the whole pixel grid and has the same horizontal branches as the others. The resulting image processing procedure is aimed at finding optimal values only for the hidden variables at the stem nodes of each tree. For this combination of partial pixel neighborhood trees, the algorithm of finding the optimal values of the stem-node variables boils down to a combination of two usual dynamic programming procedures, each deal with single, respectively, horizontal and vertical image rows considered as signals on the one-dimensional argument axis. First, such a one-dimensional procedure is applied to the horizontal rows independently. The result, in the form of so called marginal functions, should be stored in the memory. Then, the procedure is applied to the vertical rows independently for each row with the only alteration: the respective marginal node functions, obtained at the first step, are taken instead of the image-dependent node functions [6].

It can be proven that if the pair-wise Gibbs potentials are selected as a minimum of a finite set of quadratic functions, and node functions are in quadratic form, the Bellman function at each step of the dynamic programming procedure is also represented as a minimum of a finite set of quadratic functions.

In the case of signal processing the number of quadratic functions that are required for representation of a Bellman function, generally, does not increase by more than one at each step [5]. It can be noted that not all the quadratic function will participate in forming of the final function, because their values are not minimum for any point. Such functions can be dropped using enough simple procedure that considers the position of the minimum point and the points of intersection of quadratic functions with each other.

Nevertheless, then we apply this approach for processing two-dimensional data based on the tree approximation of lattice-like neighborhood graph, the number of quadratic functions in the representation of the Bellman functions may be too large. It leads to a lack of effective implementation of the proposed procedures. For effective implementation of the proposed procedures, a set of quadratic functions in the representation of the Bellman functions has been approximated with a quadratic function. However, it allows to keep only one quadratic function with the lowest value at the minimum among all quadratic functions in the representation of the Bellman function. It can lead to the loss of accuracy when the Bellman function has a few of minimums with similar values. Therefore, to save several minimums we divide the quadratic functions into the groups that close to each other.

The number of groups is determined by the number of retained minimums. For the separation of functions into the group, one of the most popular clustering algorithms - k-means is used. This algorithm contains the benefits of speed and ease of implementation. To implement this method, it is necessary either to determine the set of features of a quadratic function, or to determine the distance between them. In this work, a variant without features with clustering set based on the distances between quadratic functions has been used [7].

Application of the proposed approximation methods allow to receive some parametric dynamic programming procedures, that allow us to consider the existence of irregularities and discontinuities in the source data, while retaining high computing efficiency of the dynamic programming procedure. Furthermore, a comparison between the proposed dynamic programming procedures and related methods was performed. The results show that the proposed dynamic programming procedures obtain the high computational efficiency of dynamic programming for image processing.

References

- [1] Pham Cong Thang (2016). Parametric Image Processing Procedures Based on Multi-Quadratic Dynamic Programming. Ph.D. dissertation, Tula State University, Russia, 140 pages.
- [2] Mottl V., et al. (1998). Optimization techniques on pixel neighborhood graphs for image processing. Graph-Based Representations in Pattern Recognition. Computing, Supplement 12. Springer-Verlag/Wien, pp. 135-145.
- [3] Nikolova M., Michael K., and Tam C.P. (2010). Fast Nonconvex Nonsmooth Minimization Methods for Image Restoration and Reconstruction. IEEE Transactions on Image Processing, Vol. 19 (12), pp. 3073-3088.
- [4] Pham C. T. and Kopylov A. V. (2015). Multi-Quadratic Dynamic Programming Procedure of Edge-Preserving Denoising for Medical Images. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XL-5/W6, pp. 101-06.
- [5] Kopylov A., et al. (2010). A Signal Processing Algorithm Based on Parametric Dynamic Programming. Lecture Notes in Computer Science, Vol. 6134, pp. 280-86.
- [6] Kopylov A.V. (2005). Parametric dynamic programming procedures for edge preserving in smoothing of signals and images. Pattern recognition and image analysis, Vol. 15, pp. 227-229.
- [7] Dvoenko S. D. (2009). Clustering Sets Based on Distances and Proximities between Its Elements. Sib. Zh. Ind. Mat., Vol. 12 (1), pp. 61–73.