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Accurate Belief Propagation with parametric and non-parametric measure for stereo matching

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ABSTRACT

Stereo matching is one of the most active research areas in computer vision. Recently, Belief Propagation algorithm based on global optimization has great advances. However, traditional data term of Belief Propagation algorithm mainly lies on pixels-based intensity measure, and its effect is not very well. In this paper, a novel stereo matching is proposed that utilizes Census measure and pixels-based intensity measure into data term of Belief Propagation algorithm. But only simply adding Census measure is not enough to improve the accuracy of Belief Propagation, therefore the post procession for the algorithm is very essential. We combine intensity measure with Census algorithm into data term of Belief Propagation algorithm and acquire more accurate results by using the post procession. This proposed method may be more exacter than traditional Belief Propagation algorithm. The experimental results demonstrate the superior performance of our proposed method.

1. Introduction

In recent years, stereo vision has made significant process in computer vision [19]. Stereo matching is basically a problem of correspondence of the image pairs and aims to obtain the correct correspondence between images captured from different point of views or at different times. Recently, there are great advances based on global optimization, which minimizes a global energy function through finding the disparity map [11]. Two of the more exciting recent results have been the fast development for approximate inference in Markov Random Field (MRF): Belief Propagation (BP) [3,4,20,21] and Graph Cuts [1,9].

Belief Propagation algorithm works by passing messages around the graph using Markov Random Field models [2,3]. This method can be less sensitive to occlusion region and textureless region. However, traditional data term lie mainly on pixels-based intensity measure, which is not very sensitive to illumination as well as noise, and its effect is not enough well. Census measure based on non-parametric measure is more robust and especially more benefitful for judgment in outliers, radiometric changes, image noise, camera gain and textureless region. Therefore, combining Census measure and pixels-based intensity measure in data term of Belief Propagation algorithm is more accurate, because accurate of Belief Propagation algorithm lie on the precision of correspondence of the image pairs. Moreover, in order to improve the accuracy of Belief Propagation, another contribution for our algorithm is the post procession for the above algorithm.

The main contribution of this paper is combining Census measure and pixels-based intensity measure into data term of Belief Propagation algorithm, simultaneously improving the accuracy of Belief Propagation by using post procession technology. This algorithm produces excellent results on the Middlebury test set, especially near the occluded areas, and more exacter than traditional Belief Propagation algorithm.

The paper is organized as follows: in Section 1.1, we survey the related work. In Section 2, after reviewing previous work, we give an overview of the BP algorithm and then present our algorithm combining Census measure and pixels-based intensity measure into data term of Belief Propagation algorithm by using post procession technology. The results of our comparison are presented in Section 3, and results shows the efficacy of our optimization framework on the Middlebury data set. Section 4 concludes.

1.1. Background

In this section, we briefly review related Belief Propagation algorithm for stereo algorithms and Census measure.

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Recently, Belief Propagation algorithms have attracted more attention due to their well performance. Sun had formulated stereo matching problem as a Markov network [14]. Li [4] introduced the principle of geometric consistency to stereo matching based on Belief Propagation. Yang defined a hierarchical Belief Propagation to refine the disparity in the occluded and low texture areas [6,10]. Sun has devised a symmetric framework and used the conventional Belief Propagation to minimize the energy field [15]. But traditional data term of Belief Propagation algorithm only lie on intensity measure, the effect of stereo matching is not very well.

Census measure is more robust in non-parametric one which relies on relative ordering of pixel values, so they are invariant under radiometric changes, such as radiometric changes and image noise, camera gain, textureless region. Woodfill [12] has proposed Census algorithm, which preserves the spatial distribution by encoding them in a bit string. For image regions with similar local structures, the census transform over a window is more robust than pixel-based intensity difference. Hirschmüller and Scharstein evaluate census algorithm which shows the better results in local and global stereo matching methods [13].

Therefore, we show that the method combining pixel-based intensity and census measure algorithm is an effective regularizer to improve effect of stereo matching.

2. Belief Propagation-Census algorithm

We now start by briefly reviewing the Belief Propagation algorithm, and then describe combining Census measure and pixels-based intensity measure model. Lastly, we add the post-processing procedure in progress.

2.1. Belief Propagation

Belief Propagation algorithm is an iterative inference algorithm based on Markov Random Fields [4,5,17]. We model stereo matching by Markov Random Fields (MRF) and introduce the max-product algorithm to find the approximate minimum cost value of energy functions. Let P be the set of pixels in an image and Γ be a finite set of labels. D denotes the smooth disparity of the reference view and I denotes the reference view (the left view). A labeling f assigns a label $f_p \in \Gamma$ to each pixel $p \in P$. With the compatibility functions defined, the joint posterior probability of the MRF can be written as [16]:

$$P(D|I) = \prod_{(p,q)\in N} \Psi(f_p, f_q) \prod_{p\in P} \Phi(p, f_P), \tag{1}$$

where (p, q) represents a pair of neighboring nodes. $\Phi(p, f_P)$ relates how compatible a disparity value is with the intensity measure observed in the image and $\Psi(f_p, f_q)$ relates two intensity measures.

Then, taking the log of Eq. (1), we find that the MAP estimate is equivalent to minimizing a function of the above form. Therefore, the max-product method becomes the min-sum one, which is more helpful for calculation and simultaneously less sensitive to numerical artifacts:

$$E(P(D|I)) = \sum_{(p,q)\in N} -\log \Psi(f_p, f_q) + \sum_{p\in P} -\log \Phi(p, f_p). \tag{2}$$

We simplify $E(P(D|I))$ by using $E(D|I)$. This equation may become expressed as:

$$E(D|I) = \sum_{(p,q)\in N} V(f_p, f_q) + \sum_{p\in P} D(p, f_p). \tag{3}$$

The functions $V(\cdot)$ and $D(\cdot)$ are energy functions. Our aims are to finding a labeling that minimizes this energy corresponds to the maximum a posteriori (MAP) estimation problem [18] for an appropriately defined MRF.

2.2. Choice and propagation of Belief Propagation algorithm

The typical Belief Propagation algorithm works by passing messages around the graph defined by the four-connected image grid. Let $m^i_{p\to q}(f_p, f_q)$ be the message vector passed from node f_p sends to one of its neighbors f_q at time i, and Belief Propagation algorithm is given as follows:

$$m^{i+1}_{p\to q}(f_q) = \max_{f_p} \left[\psi_{pq}(f_p, f_q) m^i_p(f_p) \prod_{s\in N(p)\backslash p} m^i_{s\to p}(f_p) \right] \tag{4}$$

After i iterations, a belief vector is computed for each node:

$$b_p(f_p) = m_p(f_p) \prod_{p\in N(f_p)} m_{p\to q}(f_p) \tag{5}$$

Finally, the label f^*_p that minimizes $b_p(f_p)$ individually at each node f_p is selected as:

$$x^{\max}_p = arg \max_p \ b_p(f_p) \tag{6}$$

2.3. AD-Census algorithm

Generally, Belief Propagation algorithm based on global methods includes data term and smoothness term. Data term often depends on intensity differences measure, but there are a large amount of errors in these measures.

Census algorithm is a non-parametric measure [15], which is based on the local order of intensities. This measure may increase robustness of windows-based methods to outliers including radiometric changes, image noise, camera gain and textureless region [12]. In our approach, we use an improved self-adapting dissimilarity measure that combines sum of absolute intensity differences and Census-based measure. Note that the algorithm above may be more robust in camera gain, bias and textureless region.

$D_{AD}(p, f_p)$ can be defined as follows:

$$D_{AD}(p, f_p) = \frac{1}{3} \sum \left| I^{Left}_i(p) - I^{Right}_i(p) \right| \tag{7}$$

$D_{CENSUS}(p, f_p)$ encodes images with relative orderings of pixel intensities other than the intensity values.

For $D_{CENSUS}(p, f_p)$, we use a local window to encode each pixel's local structure in a 64-bit string and $D_{CENSUS}(p, f_p)$ is defined as Hamming distance of the two bit strings. Therefore, the AD-Census cost value $D(p, f_p)$ is then defined as follows:

$$D(p, f_p) = \rho(D_{CENSUS}(p, f_p), \lambda_{CENSUS}) + \rho(D_{AD}(p, f_p), \lambda_{SAD}) \tag{8}$$

where $\rho(D, \lambda)$ is a robust function on variable [7]:

$$\rho(D, \lambda) = 1 - \exp\left(-\frac{D}{\lambda}\right) \tag{9}$$

so, data term of Belief Propagation algorithm is simply changed as:

$$D(p, f_p) = D_{AD}(p, f_p) + D_{CENSUS}(p, f_p) \tag{10}$$

Combining Eqs. (3) and (10), we can obtain:

$$E(D|I) = \sum V(f_p, f_q) + \sum (D_{AD}(p, f_p) + D_{CENSUS}(p, f_p)) \tag{11}$$

Fig. 1 shows that more details through Census measure in Middlebury data set, which is different from only intensity map, can be helpful for acquiring more rich information, i.e. edge and texture, and so on. Our "Tsukuba", "Venus", "Teddy", "Cones" images