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EFFICIENT BELIEF PROPAGATION WITH CENSUS AND INTENSITY MEASURE

XIAOFENG WANG, HONGKE WANG
College of Mathematical and Physical Sciences, Chongqing University of Science and Technology,
Chongqing 401331, China

ABSTRACT

Stereo matching is one of the most active research areas in computer vision. 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. Traditional data term of Belief Propagation lies on pixels-based intensity measure, and its effect is not very well. We combine intensity and Census algorithm into data term, run through Belief Propagation algorithm and acquire more accurate results. This proposed method may be more exacter than traditional BP algorithm. The experimental results demonstrate the superior performance of our proposed method.

Keywords: *Stereo Matching, Belief Propagation, Markov Network, Census Measure, Intensity*

1 INTRODUCTION

Over the past few years, stereo matching has been many advances in the development of different algorithm. The stereo matching is basically a problem of correspondence of the image pairs. The methods solving the stereo matching problem may be classified into categories: global methods and local methods. Global methods minimize a global energy function to find the disparity map. Many effective global methods have been reported in literature, including Belief Propagation, Graph Cuts, etc [1, 9].

Belief Propagation (BP) algorithm works by passing messages around the graph using Markov Random Field (MRF) models [2, 3]. This method can be less sensitive to occlusion region and textureless region. However, traditional data term lie on pixels-based intensity measure, and its effect is not very well. Census measure based on non-parametric measure is more robust in outliers, radiometric changes, image noise, camera gain and textureless region. So combining Census measure and pixels-based intensity measure in data term of Belief Propagation algorithm is more accurate, because accurate of BP algorithm lie on the precision of correspondence of the image pairs.

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

The paper is organized as follows. In Section 2, after reviewing previous work, we give overview of the approach. 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.

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

Census is more robust in non-parametric measure 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. Hirschmuller and Scharstein evaluate census algorithm which shows

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the better results in local and global stereo matching methods [13].

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

2 OVERVIEW OF THE PROPOSED ALGORITHM

We start by briefly reviewing the improved BP algorithm. Our algorithm review consists of two steps:

2.1 Belief Propagation

Belief Propagation algorithm (BP) is an iterative inference algorithm inferring on Markov random fields [4, 5]. We use the max-product algorithm to find the approximate minimum cost value of energy functions.

The typical BP algorithm works by passing messages around the graph defined by the four-connected image grid. Let $m_{st}^{i}(x_s, x_t)$ be the message vector passed from node x_s sends to one of its neighbors x_t at time i, and BP algorithm is given as follows:

$$m_{st}^{i+1}(x_t) = \max_{x_i}\left[\psi_{st}(x_s, x_t) m_s^i(x_s) \prod_{x_k \in N(x_k)\setminus x_k} m_{ks}^i(x_s)\right] \tag{1}$$

We define the belief at the node x_s at iteration t as:

$$b_s(x_s) = m_s(x_s) \prod_{x_k \in N(X_S)} m_{ks}(x_s) \tag{2}$$

The belief at node x_s at last is computed as:

$$x_s^{\max} = \arg\max_{x_k} b_s(x_k) \tag{3}$$

2.2 Ad-Census Algorithm Data Term

BP 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. The algorithm above is more robust in camera gain, bias and textureless region.

$C_{CENSUS}(p,d)$ encodes images with relative orderings of pixel intensities other than the intensity values, and $C_{AD}(p,d)$ is then defined as follows:

$$C_{AD}(p,d) = \frac{1}{3}\sum \left| I_i^{Left}(p) - I_i^{Right}(p) \right| \tag{4}$$

The AD-Census cost value $C(p,d)$ is then defined as follows:

$$C(p,d) = \rho(C_{CENSUS}(p,d), \lambda_{CENSUS}) + \rho(C_{AD}(p,d), \lambda_{AD}) \tag{5}$$

For $C_{CENSUS}(p,d)$, we use a 9×7 window to encode each pixel's local structure in a 64-bit string. $C_{CENSUS}(p,d)$ is defined as Hamming distance of the two bit strings; while $C_{AD}(p,d)$ is defined as the average intensity difference. Where $\rho(c,\lambda)$ is a robust function on variable [7]:

$$\rho(c,\lambda) = 1 - \exp(-\frac{c}{\lambda}) \tag{6}$$

So, data term of BP algorithm is changed as:

$$D(x,y,d) = D_{SAD}(x,y,d) + \varpi D_{CENSUS}(x,y,d) \tag{7}$$

Our Census images in data Teddy set are shown in Fig 1. Fig 1 shows that more details in Teddy which is different from only intensity map. So, combining Census and intensity measure is more beneficial to acquire accurate results.

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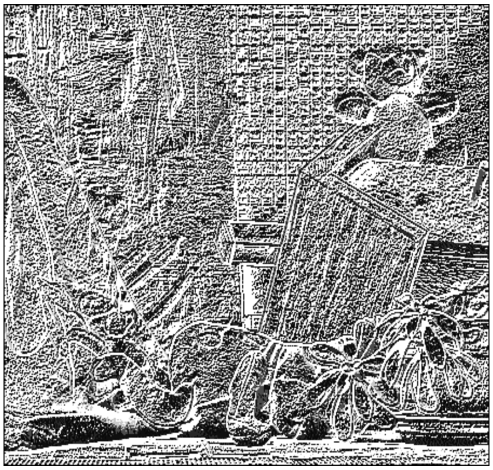

Figure 1: Census Measure Map On The Data Teddy Set

3 EXPERIMENTS

The proposed method was using the Middlebury data set [1]. In order to compare the BP without Census and the BP with Census in data term, we show results and pictures in Table 1 and Fig 2 with error threshold 1 on the Middlebury data set by measuring the percentage of pixels "Venus". From Table 1 and Fig 2, we see that BP with Census is better than BP without Census in all pixels, pixels in non-occluded areas, in the textureless areas. Because only pixel-based measure, such as absolute differences, is not enough accurate, especially in occluded areas and the textureless areas. However, non-parametric measure relies on relative ordering of pixels and is robust in radiometric changes. So combining non-parametric matching and pixel-based matching performs better than only pixel-based matching measure[8].

We often evaluate the performance using percentages of 'bad' pixels among: all pixels, pixels in non-occluded areas, pixels near disparity discontinuities. Where the subset of non-occluded pixels, denoted as "nonoccl"; the subset of the pixels near the occluded areas, denoted as "disc."; the subset of the pixels being either non-occluded or half-occluded, denoted as "all." The data show that our algorithm works pretty well. These results demonstrate the effectiveness of our Belief Propagation based on absolute intensity differences and Census measure for stereo matching.

Table I : Contrast In Bp With Census And Without
Census On The Venus Data Set

	With Census	Without Census
all	0.031421	0.047091
nonocc	0.021022	0.035312
discont	0.012060	0.011640

Figure 2: Results On Middlebury Data Sets In "Venus". From Left To Right Order: Left Reference Images, Right Reference Images Extracted Disparity Maps With Gradient Census, Extracted Disparity Maps Without Census.

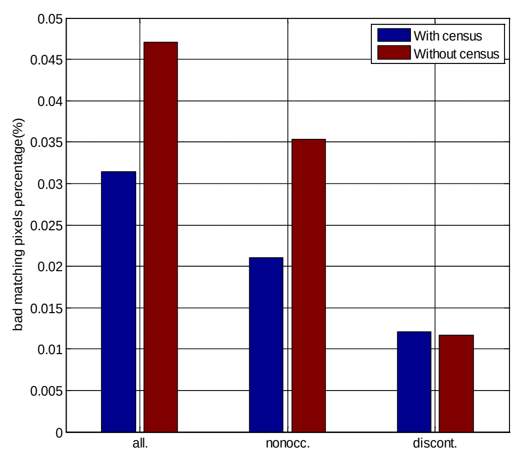

Figure 3: Histograms Of Bad Matching Pixels Percentage Result About BP With Census And Without Census In All Pixels ,In Non-Occluded Areas, In Textureless Areas On The Venus Data Set .

Error statistics of bad matching pixels in the following picture at seven different thresholds

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ranging from 0.5 to 2, including all pixels ,pixels in non-occluded areas, pixels in occluded areas, pixels in textured areas, pixels in textureless areas. Fig 4 shows that Belief Propagation based on absolute intensity differences and Census measure for stereo matching performs better at seven different thresholds.

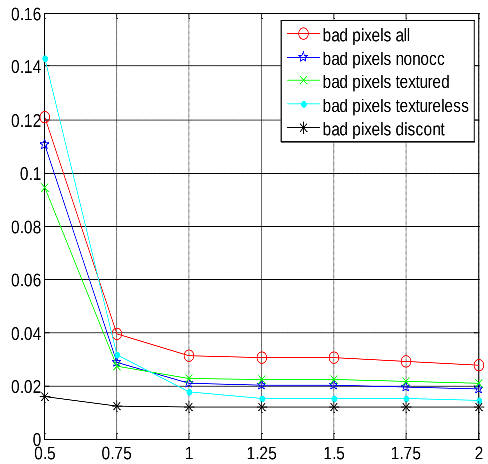

Figure 4: Error Statistics For The Percentage Of Bad Matching Pixels At Seven Different Thresholds Ranging From 0.50 To 2.0 Pixels On The Venus Data Set ,Including All Pixels ,Pixels In Non-Occluded Areas, Pixels In Occluded Areas, Pixels In Textured Areas, Pixels In Textureless Areas.

4 CONCLUSION

BP algorithm only based on absolute intensity differences in data term is far from accurate. In this paper, we present new algorithm to improve preciseness of stereo matching. We combine absolute intensity differences and Census measure of non-parametric measure into data term, run through BP algorithm and acquire more accurate results. Experimental results are evaluated on Middlebury data sets, showing the superior performance of the proposed method. Future work should be aimed at improving the accuracy of disparities in occluded areas, textureless areas using BP algorithm.

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