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Procedia Technology 6 (2012) 223 – 230
Procedia Technology

2nd International Conference on Communication, Computing & Security [ICCCS-2012]

Entropy Based Log Chromaticity Projection for Real-time Stereo Matching

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Abstract

Most of the existing stereo matching algorithms will assume a similar corresponding color values between stereo images. In the real scenario, these color values are effected by several radiometric factors such as illumination direction, illumination color, camera parameters, etc, which results in different color values between the corresponding points. Hence, applying the stereo algorithm directly on the raw color values is not appropriate for the real-time environment. This paper proposes an entropy minimization based log chromaticity projection for stereo image, thereby extracting the invariant image, which is independent of illumination and color. The developed invariant image is the perfect measure for finding the similarity between the corresponding points. Normalized cross correlation based similarity measure is applied on the generated invariant image and the obtained disparity outperforms some of the local and global stereo algorithms.

Keywords: Stereo matching; invariant image; radiometric difference

1. Introduction

Stereo matching has been one of the most active research topic in computer vision (Scharstein & Szeliski 2001). The process of stereo matching is to analyze the images taken from a stereo camera and to estimate the displacement of corresponding points in the stereo image. This displacement in terms of pixels is referred as Disparity, which is one of the essential requirement for depth estimation and robot navigation.

In a real-time scenario, various factors will prevent corresponding pixels from having same color values. The major preventing factor is the radiometric difference. The radiometric difference is the pixels that correspond to same scene point which will have different intensity (or color) values. This may be caused by the camera(s) due to slightly different settings, exposure variation, vignetting, image noise, non Lambertian surface, etc. Under this variation, there exist a nonlinear relationship between the corresponding pixels that leads to poor disparity for most of the stereo

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doi:10.1016/j.protcy.2012.10.027

matching algorithms. In practice, most of the existing stereo matching algorithms do not take this color constancy process into consideration. There is a need to include color constancy process in stereo matching, thereby developing a robust algorithm for radiometric variations.

The rest of the paper is organized as follows. Section 2 gives the related work. Section 3 presents invariant image using log chromaticity projection. NCC based matching cost computation is given in Section 4. Experimental results and discussions are given in section 5. Conclusion of the paper is in Section 6.

2. Related work

Heiko Hirschmuller and Daniel Scharstein (Hirschmüller & Scharstein 2009) have carried out evaluation of various cost functions for stereo matching on radiometrically different images caused by various factors such as light configuration, change in exposure, gamma correction variations, noise, etc. In their study, they have compared Birchfield Tomashi data cost (BT) (Birchfield & Tomasi 1998), BT with Laplacian of Gaussian (LOG) (Hirschmüller, Innocent & Garibaldi 2002), BT with mean filtering, BT with rank Transform (Zabih & Woodfill 1994), Normalized cross correlation (NCC) and also some of the local, global and semi global methods. BT cost is very popular data cost in stereo algorithms and it is insensitive to radiometric variations as it employs linearly interpolated function of intensity values. LOG filter is also insensitive to outliers due to usage of the second order derivatives. BT with Rank transform (Zabih & Woodfill 1994) shows the robustness to global radiometric variations due to the principle of rank ordering based on pixel intensities and it is insensitive to local radiometric variations. NCC is a very popular similarity measure for stereo matching and suitable only for matching affine-transformed intensity or color values. It suffers from fattening effect across object boundaries. Yong Seok Heo et. al (Heo, Lee & Lee 2011) proposed an algorithm, which is computationally expensive and weak at global variations. Ogale (Ogale & Aloimonos 2004) presented an algorithm for variation in contrast for local matching, which can compensate only for global variations.

It is observed in the literature that, most of the stereo algorithm uses raw intensity (or color) information for stereo matching. This information is sensitive to radiometric variations due to the fact that, raw intensity depends only on the direction of the light and the surface normal. It will not consider the color of the surface, lighting and camera parameters. However, the intensity information can be used for compensating some global variation, but it still remains insensitive to local variation. This research work proposes a log chromaticity based invariant image generation for real-time stereo matching.

3. Invariant Image using Log Chromaticity Projection

Consider a calibrated stereo camera, where the target object is composed of colored patches and it is imaged under different illumination. The response of the image is in terms of three sensor outputs, namely red, green and blue. The basic process is to transform each pixel from RGB triplets into a 2D band ratio chromaticity color space such as G/R and B/R. Taking logarithm over band ratios will eliminate the effect of non linear transformation occurred during color image formation (Heo, Lee & Lee 2011). This transformation will result in the values across the different illuminants, which tends to fall on straight lines in a 2D scatter plot. All such lines are parallel to each other for a given camera. The change in illumination will result in the movements only in the direction of scan lines. It is possible to generate an invariant image by projecting the 2D chromaticity points into a direction orthogonal to all such lines. The projection is based on the minimum entropy direction. The projected image will be in the form of grayscale. The generated grayscale image is independent of lighting and illuminant color. Figure shows the functional block diagram of the proposed invariant image construction using log chromaticity projection.

The color image formation equation is given by (Finlayson, Drew & Lu 2009),

$$h_k = \sigma \int E(\lambda)S(\lambda)Q_k(\lambda)d\lambda,\ k = R,G,B \tag{1}$$

where h_k is the kth sensor response, σ is the Lambertian shading and λ is the wavelength. The spectral power distribution of the incident illumination is given by $E(\lambda)$. The surface reflectance of the scene is given by $S(\lambda)$ and $Q_k(\lambda)$ is the spectral response of the kth sensor. If the camera sensor $Q_k(\lambda)$ is exactly a Dirac delta function

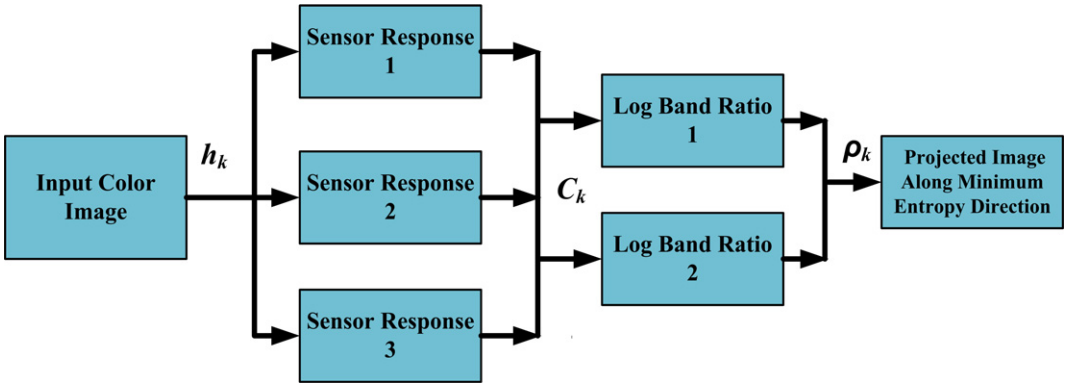

Fig. 1. Functional Block Diagram of Proposed Log Chromaticity Based Invariant Image Construction

(Finlayson, Drew & Funt 1994), then $Q_k(\lambda) = q_k\delta(\lambda - \lambda_k)$. Then equation (1) can be written as,

$$h_k = \sigma E(\lambda_k)S(\lambda_k)q_k \tag{2}$$

Using Planks law in Wien's approximation (Wyszecki & Stiles 2000), it is possible to approximate the lighting (Hirschmüller & Scharstein 2009) and it is given by,

$$E(\lambda, T) \cong Ik_1\lambda^{-5}e^{-k_2/T\lambda} \tag{3}$$

Where k_1 and k_2 are the normalizing constants. Temperature T characterizes the lighting color and I gives the lighting intensity. Using this approximation the RGB color h_k can be rewritten as,

$$h_k = \sigma Ik_1\lambda_k^{-5}e^{-k_2/T\lambda_k}S(\lambda_k)q_k \tag{4}$$

The band ratio 2-vector chromaticity C can be formed as

$$C_k = h_k/h_p \tag{5}$$

where p is one of the channel. For example, if $p = 1$ (divided by red) it is possible to calculate $C_1 = G/R$ and $C_2 = B/R$. From equation 5, it is observed that the chromaticity will effectively removes the intensity and shading information. Let $s_k = k_1\lambda_k^{-5}S(\lambda_k)q_k$ and $e_k = -k_2/\lambda_k$. By taking logarithm of equation (5). we get

$$\rho_k = \log(C_k) = \log(s_k/s_p) + (e_k - e_p)/T \tag{6}$$

Equation (6) is a straight line parameterized by T. The 2-vector direction $(e_k - e_p)$ is independent of the surface, although the line for a particular surface has offset that depends on s_k. Every such lines are parallel with a slope given by $(e_k - e_p)$.

It is possible to generate an invariant image by projecting these 2D logs of band ratio chromaticity into the direction orthogonal to the vector $\mathbf{e} = (e_k - e_p)$. The projected output will be a single scalar grayscale image. The more emphasis needs to be given to identify the angle for projecting 2D chromaticity space. This work will consider the entropy minimization based invariant direction technique proposed by (Finlayson, Drew & Lu 2009) for identifying the projection angle, where the variance with minimum entropy will be the perfect projection angle. Shannon's entropy measure has been used for identifying the minimum entropy and it is given by.

$$n = -\sum_i P_i(I)\ log(P_i(I)) \tag{7}$$

where n is the entropy of the projected angle and P is the probability function. The generated invariant image is independent of lighting and it will be a better cost function for matching the stereo images. In this work, there are two images named I_L (left) and I_R (right), which are transferred to log chromaticity color space in the initial stage. The invariant images are extracted from these stereo pair using log chromaticity projection as shown in Figure 1. The minimum entropy for the projected left and right Aloe stereo images have been identified using the equation 7 at 80° and 73° respectively as shown in Figure 2. The generated invariant images are I_L^i and I_R^i as shown in Figure 3.

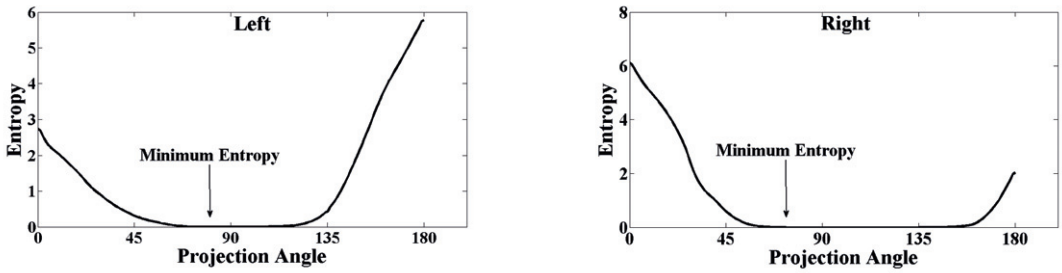

Fig. 2. Minimum entropy measurement of Aloe stereo image for different projection angles.

Fig. 3. Invariant image of (from left to right) left and right Aloe stereo pair.

4. Stereo Matching using Normalized Cross Correlation

In this section, the generated invariant left and right images have been applied to stereo matching process. let $I_L^i(p)$ and $I_R^i(p+d)$ are the corresponding pixel, where $I_L^i(p)$ is a value in the left image at a pixel p and $I_R^i(p+d)$ is a value in the right image at a pixel $(p+d)$. NCC (Scharstein & Szeliski 2001) is a well-known traditional similarity measure that can compensate for camera gain and bias. It is denoted by,

$$NCC = \frac{\sum_{i=1}^{N}((I_L^i(p))).(I_R^i(p+d))}{\sqrt[2]{\sum_{i=1}^{N}(I_L^i(p))^2 \cdot \sum_{i=1}^{N}(I_R^i(p+d))^2}} \tag{8}$$

where N is the number of pixels in the neighbors and d is the disparity range. This similarity measure is applied to the invariant image of left and right stereo pair to generate disparity image.

5. Experimental Results and Discussions

The developed algorithm is applied to the Middlebury stereo images (Scharstein 2002) and the results are evaluated. Initially a gaussian smoothing operator has been applied on the invariant stereo image to reduce the effect of noise and all the parameters such as correlation window and environmental conditions are kept constant for each and every experiments. Aloe stereo image with different illumination and the exposure conditions are used to test the robustness of the algorithm. To compare the results, three different local stereo matching algorithms namely sum of absolute difference (SAD), sum of squared difference (SSD), NCC are used with raw matching cost (Scharstein & Szeliski 2001). The proposed method is also compared with a global algorithm proposed by Ogale-Aloimonos (Ogale & Aloimonos 2005). Testing is performed in three different stages. In the first stage, algorithms are applied to the Aloe stereo image with different illumination index. In the second stage, algorithms are evaluated based on the different exposure index. In the third stage, algorithms are compared against some color constancy algorithms and the robustness of the proposed method is evaluated.

5.1. Change in Light Source

To test the effect of light source (illumination), exposure index of the stereo image is fixed to 1 and the illumination index is varied from 1 to 3. Figure 4 shows the Aloe stereo image taken under extremely different illumination condition and it also shows the disparities of the different algorithm for different illumination conditions.

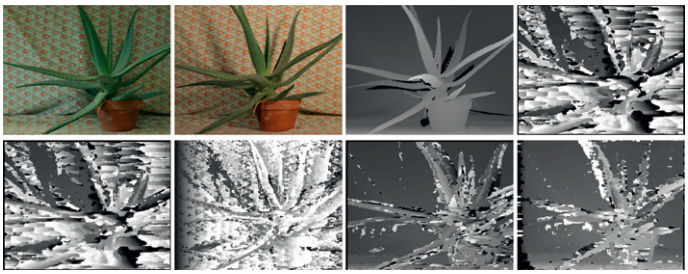

Fig. 4. Results of tested stereo algorithms on Aloe stereo image with varying illumination. First row (from left to right): Left image with illumination(1)-exposure(0), Right image with illumination(3)-exposure(0),the ground truth disparity map and Output disparity of SAD. Second row (from left to right): Disparity of SSD, Ogale-Aloimonos algorithm, NCC and proposed method.

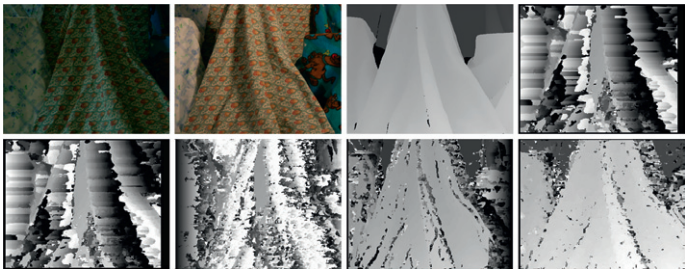

Fig. 5. Results of tested stereo algorithms on Cloth stereo image with varying illumination. First row (from left to right): Left image with illumination(1)-exposure(0), Right image with illumination(3)-exposure(0),the ground truth disparity map and Output disparity of SAD. Second row (from left to right): Disparity of SSD, Ogale-Aloimonos algorithm, NCC and proposed method.

Change in light source will result in various local radiometric variations and it is one of the most difficult factors among radiometric effects. Figure 4 and 5 shows the qualitative results of the stereo algorithms for Aloe and Cloth stereo image respectively. SAD and SSD algorithms are very sensitive to this local variation and produces poor disparity. Ogale-Aloimonos algorithm is also sensitive but produces better result than SAD and SSD. NCC algorithm with raw matching cost is not strong at the local variation because it assumes only the global affine transformed difference. The proposed method can preserves the image features against this local variation due to the log chromaticity representation and is robust among the other methods tested during the experiments. Table 1 gives the quantitative evaluation of stereo algorithms. It is observed that the proposed algorithm has maintained minimum error as compared to other algorithms.

Table 1. Quantitative evaluation of stereo algorithms for Aloe stereo image with change in light source

Algorithms	R.M.S Error (%)	Amount of Bad Pixel (%)
SAD	30.54	83.75
SSD	29.81	78.56
Ogale	38.38	90.96
NCC	16.15	51.81
Proposed method	**15.81**	**51.19**

5.2. Change in Exposure

To test the effect of change in exposure, illumination index is fixed to 1 and the exposure index is varied from 0 to 2. Figure 6 and 7 shows the qualitative results of the stereo algorithms for Aloe and Cloth stereo image respectively. Change in exposure will create a global intensity variation between stereo images. As a result, SAD, SSD and Ogale-Aloiminos algorithms are too sensitive to these global variation and produces very poor result. These algorithms will make the disparity as very dark or bright. NCC shows good performance against this global variation and produces better result. The proposed method is still robust against these global changes as compared to other methods. Table 2 gives the quantitative evaluation of stereo algorithms for change in exposure condition. It is observed that the proposed algorithm is efficient among the set of popular stereo algorithms.

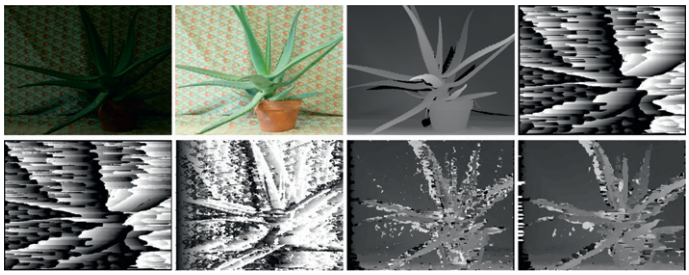

Fig. 6. Results of test stereo algorithms on Aloe stereo image with varying exposure. First row (from left to right): Left image with exposure(0)-illumination(1), Right image with exposure(2)-illumination(1),the ground truth disparity map, Output disparity of SAD. Second row (from left to right): Disparity of SSD, Ogale-Aloimonos algorithm, NCC and proposed method.

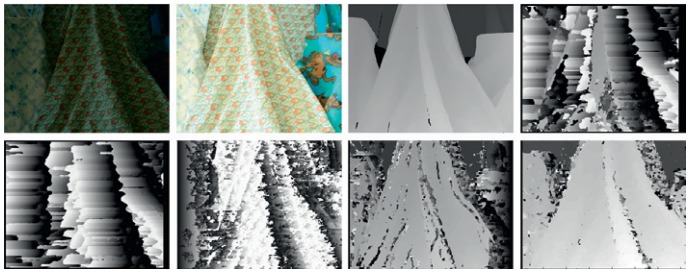

Fig. 7. Results of test stereo algorithms on Cloth stereo image with varying exposure. First row (from left to right): Left image with exposure(0)-illumination(1), Right image with exposure(2)-illumination(1),the ground truth disparity map, Output disparity of SAD. Second row (from left to right): Disparity of SSD, Ogale-Aloimonos algorithm, NCC and proposed method.

Table 2. Quantitative evaluation of stereo algorithms for change in exposure condition

Algorithms	R.M.S Error (%)	Amount of Bad Pixel (%)
SAD	30.07	96.95
SSD	30.19	91.08
Ogale	40.00	97.41
NCC	14.08	48.75
Proposed method	**13.95**	**50.50**

5.3. Comparison with Different Color Constancy Methods

In this section, different color constancy techniques are used as a preprocessing technique for the Ogale-Aloimonos algorithm to test the robustness of the proposed algorithm. The popular color constancy algorithms such as Retinex algorithm (D.J. Jobson 1997) and a Human Vision System (HVS) inspired algorithm proposed by Vonikakis (Vonikakis,

Andreadis & Gasteratos 2008) are used for color normalization process on the Ogale-Aloimonos algorithm and the results are compared with the proposed method in Figure 8.

Figure 8 shows the output disparities of the proposed method and the Ogale-Aloimonos algorithm with different color constancy techniques. In the first set, Retinex algorithm is applied on the stereo images with local illumination variation and the matching process is carriedout using the Ogale-Aloimonos algorithm. In the second set, Vonikakis color normalization is applied with Ogale-Aloimonos stereo algorithm. Ogale-Aloimonos algorithm is still weak at local variations. It is observed that the proposed method still maintains the robustness as compared to Ogale-Aloimonos algorithm even with the different color normalization applied to it.

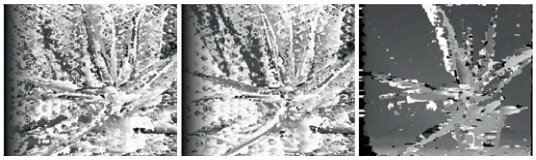

Fig. 8. Output disparities of Ogale-Aloimonos proposed algorithm with different color constancy techniques. From left to right: Retinex with Ogale-Aloimonos algorithm, Vonikakis with Ogale-Aloimonos algorithm, Proposed method.

Table 3. Quantitative evaluation of Ogale-Aloimonos and the proposed algorithm with different color constancy techniques

Algorithms	R.M.S Error (%)	Amount of Bad Pixel (%)
Ogale-Aloimonos with Retinex Algorithm	73.15	80.06
Ogale-Aloimonos with Vonikakis Algorithm	67.55	71.67
Proposed method	**15.81**	**51.19**

Table 3 gives the quantitative evaluation of proposed method and Ogale-Aloimonos algorithm for different color constancy methods. It is observed that the proposed method is insensitive to change in illumination and maintained less percentage of error as compared to Ogale-Aloimonos algorithm. It is also observed that the color constancy methods compensate only for small change in the brightness and they are sensitive to local variations.

6. Conclusion

This paper proposes a log chromaticity based invariant image developed for real-time stereo matching. The input stereo image will be transferred to log chromaticity color space in the initial stage and the invariant image extraction will be done in the second stage. The developed invariant image is independent of illumination and the color, which is a better cost for stereo matching application. The comparison results show the robustness of the proposed algorithm against different illumination and exposure conditions. The proposed algorithm will be a better choice for real- time application.

Acknowledgements

This research work is carried out under the scheme of Manipal University PhD with scholarship.

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