

An adaptive contrast enhancement method for stereo endoscopic images combining binocular just noticeable difference model and depth information

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Abstract

Endoscopic image enhancement has become a very popular research field due to the success of minimally invasive interventions and the innovation of new technological treatment and diagnosis tools such as stereoscopic laparoscopes and the wireless capsule endoscopy. In spite of the important advances achieved in terms of image processing and enhancement, only a few techniques can be adapted to stereo endoscopic images. This can be explained by the specificities of the stereo endoscopic video acquisition process, the surgical tasks artifacts and the endoscopic domain characteristics (e.g., organ textures, edges, color distribution). In this paper we present a contrast enhancement method for stereo endoscopic images taking into consideration some of these specificities, namely those of the acquired stereo images i.e. the depth information, the binocular vision and the organs boundaries/textures. The idea is to enhance the image quality by a contrast enhancement process that exploits the local image activity, the depth information and the binocular just noticeable difference (BJND) model. The results of the conducted subjective experiment show that the proposed method produces stereo endoscopic images with sharper details of the underlying tissues and organs, without introducing any halo effect or overshooting. The observers reported as well a more depth feeling and less visual fatigue when perceiving the enhanced stereo endoscopic images.

Introduction

During the last three decades, minimally invasive surgery (MIS) has become a popular diagnostic and treatment tool widely used in the clinical routine. While conventional open surgery relies on making large incisions in the skin and separating the underlying tissues to get a direct access to the surgical target, MIS is performed through small incisions (usually between 0.5 and 1.5 cm) to reduce the surgical trauma and morbidity. The abdomen is insufflated with a specific dose of gas in order to create a working volume through which surgical instruments can be inserted via ports. Since direct viewing of the surgical scene is not possible, an endoscopic camera assists the surgeon's navigation by providing views of the anatomical structures and the surgical instruments.

One of the main challenges facing the surgeons during the laparoscopic chirurgical training is to adapt their tasks to a two dimensional (2D) flat view of the surgical field. This lack of depth perception in addition to the loss of tactile feedback, implies a significant sensory loss for the surgeons and can affect their performance. Therefore 3D laparoscopic visual systems such as the

Da Vinci Surgical System [17], the *EndoSite 3Di Digital Vision System* [18] and stereoscopic laparoscopes have been recently developed to address this need.

The convergence to 3D visual endoscopic systems introduced, however, new issues related to image quality. Additionally, applying conventional 2D enhancement techniques on stereo endoscopic images does not give necessarily the best results as it does not account for the inherent dependencies between the perceived stereo image quality and the two views. This difficulty to adapt conventional 2D enhancement methods for stereo images may be explained by two main reasons. First, the human visual system (HVS) does not perceive the left and right images independently. The slightly different views captured by each eye are monocularly processed than fused by the visual cortex taking into account many complex binocular vision features such as the binocular rivalry and suppression depending on how much different the images are. Therefore, a depth sensitive enhancement approach exploiting a cross view processing could be a more appropriate approach to enhancing stereo 3D images. Second, most of the image enhancement methods are not adapted to the particular characteristics of the endoscopic domain (moist homogenous tissues, dynamic illumination conditions, non-rigid deformation due to the patient and surgeon motion, specular reflections), the specificities of the endoscopic video acquisition process and the surgical task artifacts (smoke, lens fogging and blood pools).

Endoscopic image enhancement aims either to improve the visual video quality for the surgeons or to ameliorate the input of subsequent post processing tasks such as feature extraction for 3D organ reconstruction and registration. One of the main challenges for MIS is to determine the intra-operative morphology of the surgical field. Such information is prerequisite to the registration of the patient-specific data and to the navigation capacity providing the surgeon an efficient control of robotic-assisted surgical systems. The characteristics of the endoscopic environment including dark areas (up to 40% of the special image resolution in some cases) and different acquisition and surgical artifacts makes feature extraction from stereo endoscopic images a very challenging task, which can influence the accuracy of 3D organ reconstruction and registration tasks.

Among the image processing methods that can address this problem, a proper contrast enhancement technique can improve the endoscopic image quality and the depth feeling. Indeed, it has been demonstrated in [13] that performing a sharpness enhancement on the stereo image views increases the depth perception.

Based on the subjective experiment results, the authors proposed an adaptive sharpness enhancement algorithm taking into account the depth perception of the HVS. In [4], *Walid et al.* improve the stereo image contrast with an algorithm combining the local edge information and the depth level of each object of the scene obtained by segmenting the disparity map. An unsharp masking technique is used in [8] to enhance images containing depth information by darkening the background objects. The aforementioned methods, however, neglect the inter-view differences between right and left luminance components, which can produce visual fatigue and eyestrain for the observer. This question has been addressed by [6], in which the authors propose a sharpness enhancement technique for stereo images using the binocular just noticeable difference model (BJND) [16].

In this paper, we propose an adaptive contrast enhancement method for stereo endoscopic images combining depth information and BJND visibility thresholds. The contrast is improved combining edginess information, depth data and the local image activity to adapt the enhancement in each region (homogenous or boundary region). The BJND is then used to control the overall inter-view enhancement and avoid any noticeable difference that can trigger eyestrain or visual fatigue.

The remainder of this paper is organized as follows. Section 2 describes the contrast enhancement method based on local edge detection [1]. Section 3 presents an overview of the BJND model as derived in [16]. The proposed contrast method for stereo endoscopic images is introduced in Section 4. Section 5 describes the experimental settings and discusses the results. Finally, Section 6 conclude the paper.

Edge-based contrast enhancement (EBCE)

In this section we present an overview of the contrast enhancement based on local edge detection technique [1], which accounts for contour detection perceptual features of the HVS by combining *Gordon's* method [3] and the theory of contour detection [9]. Given a pixel P at spatial coordinates (i, j) and its gray-level intensity $I_{i,j}$, the local contrast is defined as follows:

$$C_{i,j} = \frac{|I_{i,j} - E_{i,j}|}{I_{i,j} + E_{i,j}} \quad (1)$$

where $E_{i,j}$ is an estimate of the mean edge gray-level computed by averaging the weighted gray-level intensities within a window $w_{i,j}$ centered at (i, j) and computed as follows:

$$E_{i,j} = \frac{\sum_{(m,n) \in w_{i,j}} I_{m,n} \cdot \Phi(\delta_{m,n})}{\sum_{(m,n) \in w_{i,j}} \Phi(\delta_{m,n})} \quad (2)$$

where $\delta_{m,n}$ represents the edge value and Φ is an increasing function. The improved contrast $C'_{i,j}$ can be generated by simply applying a function f to the local contrast $C_{i,j}$, satisfying the following conditions:

$$\begin{cases} f : [0, 1] \rightarrow [0, 1] \\ C_{i,j} \mapsto f(C_{i,j}) = C'_{i,j} \geq C_{i,j} \end{cases} \quad (3)$$

The output intensity is computed as follows:

$$I'_{i,j} = \begin{cases} E_{i,j} \cdot \frac{1 - C'_{i,j}}{1 + C'_{i,j}} & \text{if } I_{i,j} \leq E_{i,j} \\ E_{i,j} \cdot \frac{1 + C'_{i,j}}{1 - C'_{i,j}} & \text{otherwise} \end{cases} \quad (4)$$

In [1], the authors demonstrated the efficiency and noise-robustness of this low complexity algorithm in sharpening the edges and the micro-edges (e.g., the veins) of 2D images and discriminating objects according to their boundaries. This well-known method improves also the gray-level distribution [20] and facilitates the detection and the extraction of relevant information such as feature points. Such data is crucial in performing a 3D organ reconstruction for the navigation and the surgery planning.

Overview of the BJND

The BJND model measures the minimal noise/distortion in one stereoscopic view evoking noticeable perceptual difference when combined with the other view in the binocular vision process. Based on psychophysical experiments, the authors [16] investigated the visual sensitivity to contrast masking effect, the binocular combination of noise and the luminance masking effect for stereo images. In this section, we give an overview of the BJND model and the derivation of its formula as described in [16]. Given the left and the right images, the BJND map of the left view, (i.e., $BJND_l$) is defined as follows:

$$\begin{aligned} BJND_l(i, j, d) &= f(bg_r(i+d, j), eh_r(i+d, j), na_r(i+d, j)) \\ &= A_C(bg_r(i+d, j), eh_r(i+d, j)) \\ &\quad \times \left(1 - \left(\frac{na_r(i+d, j)}{A_C(bg_r(i+d, j), eh_r(i+d, j))}\right)^\lambda\right)^{\frac{1}{\lambda}} \end{aligned} \quad (5)$$

where i and j refers to the spatial pixel coordinates, d is the disparity value corresponding to the point (i, j) and na is the noise amplitude $0 \leq na_r \leq A_C$. The parameter λ controls the impact of the right-view noise and it is set experimentally to 1.25. We can notice that the BJND left is dependent on the background luminance intensity (bg), the edge high (eh) and the noise amplitude (na) of the right image. The inter-view pixel correspondence data is crucial for processing stereo content and generating the BNJD map. Such data can be provided by the ground-truth disparity information, which is not often available for real time constraints such as in our 3D endoscopic application domain. Therefore, performing a correspondence matching step (i.e., stereo matching) is important to obtain the disparity map. Stereo matching has become a very active research field in the last decade because of the difficulty and the complexity of this task for both image processing and computer vision. Since the aim of this paper is not to study nor address the stereo matching problematic, we adopt a recently proposed disparity map estimation algorithm of [7]. A more detailed review and taxonomy of stereo-matching techniques is given by [12] and a ranking of the top performing algorithms in terms of complexity and accuracy is provided by the *Middlebury* website [11]. Note that if the right view is noise-free, the $BJND_l$ is reduced to the expression of A_C , which is defined by

$$A_C(bg, eh) = A_{C,limi}(bg_r(i+d, j)) + K(bg_r(i+d, j)) \cdot eh_r(i+d, j) \quad (6)$$

The background luminance component (bg) can be obtained by computing the average of a 5×5 sliding window centered in the spatial active-pixel location (i, j) , and the edge high (eh) is given by:

$$eh(i, j) = \sqrt{E_H^2(i, j) + E_V^2(i, j)} \quad (7)$$

where

$$E_k(i, j) = \frac{1}{24} \sum_{h=1}^5 \sum_{v=1}^5 l(i-3+h, j-3+h) \cdot G_k(h, v) \quad (8)$$

$$k = H, V$$

$$G_H = \begin{pmatrix} -1 & -2 & 0 & 2 & 1 \\ -2 & -3 & 0 & 3 & 2 \\ -3 & -5 & 0 & 5 & 3 \\ -2 & -3 & 0 & 3 & 2 \\ -1 & -2 & 0 & 2 & 1 \end{pmatrix}$$

$$G_V = \begin{pmatrix} 1 & 2 & 3 & 2 & 1 \\ 2 & 3 & 5 & 3 & 2 \\ 0 & 0 & 0 & 0 & 0 \\ -2 & -3 & -5 & -3 & -2 \\ -1 & -2 & -3 & -2 & -1 \end{pmatrix}$$

where $l(i, j)$ refers to the luminance value related to pixel (i, j) . The terms $A_{C,limit}(bg)$ and $K(bg)$, which have been determined empirically, are defined as follows:

$$A_{C,limit}(bg) = \begin{cases} 0.0027 \cdot (bg^2 - 96 \cdot bg) + 8 & \text{if } 0 \leq bg \leq 48 \\ 0.0001 \cdot (bg^2 - 32 \cdot bg) + 1.7 & \text{if } 48 \leq bg \leq 255 \end{cases} \quad (9)$$

$$K(bg) = -10^{-6} \cdot (0.7 \cdot bg^2 + 32 \cdot bg) + 0.07 \quad (10)$$

The BJND of the right stereo view (i.e., $BJND_r$) can be generated similarly by substituting l for r and estimating the disparity map corresponding to the right image.

Proposed adaptive edge-based contrast enhancement method (AEBCE)

This work aims to exploit both monocular cues (i.e., contrast, edges) and binocular cues (i.e., disparity map, BJND) in enhancing the contrast of stereo endoscopic images and exhibiting the inner vessels/organs boundaries. The motivation behind using the edge-based method can be explained by two main reasons. First, the local contrast depends strongly on the contour sharpness which is related to the mean-edge value [19]. Second, the edge high (eh) of the BJND contrast masking component is also based on the gradient magnitude, which means that both approaches rely on the edginess information. Adapting the local edges detection based algorithm and combining it with depth and binocular information should yield more depth feeling for the surgeons and can facilitate the extraction of feature points. The contrast is adjusted locally for each object of the endoscopic scene based on its depth information available via the computed disparity map.

Our proposed method is composed of 5 steps as illustrated by Figure 1. The first step consists in estimating the right and left disparity maps based on the stereoscopic views. Since stereoscopic images are captured using two cameras having slightly different horizontal perspectives, a disparity map is an estimation of the distance between two corresponding pixels in the left and right views.

In order to estimate the disparity map, we used the stereo matching algorithm proposed by [7], which is based on the adaptive random walk with restart (RWR) method. The choice of this technique is justified by two main advantages that are important for this endoscopic image processing context. First, it takes into

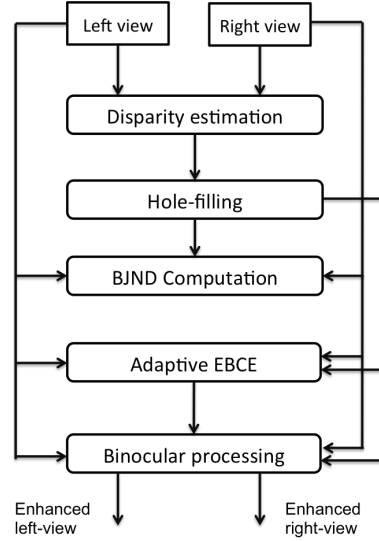


Figure 1: Work-flow diagram of the proposed endoscopic stereo image enhancement.

consideration occlusions and depth discontinuities and operates well on images with varying exposures and illumination, which implies estimated disparity maps with high accuracy. Second, its implementation in a real-time environment revealed minimal processing time requirements with low computational costs.

One of the major concerns related to stereo matching is the occluded regions of the scene, which are represented by holes (i.e., pixel disparity value equal to zero) in the estimated disparity maps. Although this problem is addressed in the used disparity estimation method, we apply a hole-filling algorithm on the generated disparity maps to ensure that each pixel is assigned to a valid disparity value.

Many approaches have been proposed to fill the disparity holes such as the Gaussian filter based method used in depth image based rendering [14, 15] or the hole-filling based memory controller for multiview 3D videos [2]. These methods can, however, involve disparity information loss and blur in the disparity map specially if the hole-size is large. In our work we simply replace each pixel hole by the mean of its surrounding pixels in a window sized 15×15 .

The following step consists in incorporating the estimated disparity information in the edge-based contrast enhancement process. Inspired from experimental perceptual studies proving that the HVS is more sensitive to closer objects of the scene [13], the objects having low depth information are more highlighted in the contrast enhancement. Therefore, we integrate the disparity in the computation of the improved contrast $C'_{i,j}$ to make the latter proportional to the depth level. The enhanced contrast expression is defined as follows:

$$C'_{i,j} = \tanh \left(\left(\frac{d_{i,j}}{d_{max}} + \lambda \right) \times C_{i,j} \right) \quad (11)$$

where $d_{i,j}$ refers to the disparity of the current pixel at coordinates (i, j) , d_{max} is the closest perceived depth level indicated by the maximum disparity value and $\lambda \in [0, 1]$ controls the contrast increase. In order to take into consideration the local image activity and avoid any halo effect or overshooting that may occurs

when applying the classical edge-based contrast enhancement [1], we propose an adaptive edge-based contrast enhancement (AE-BCE) treatment to compute the final intensity $I'_{i,j}$. The resulting pixel intensity $I'_{i,j}$ of the Equation 4 is replaced by the following expression:

$$I_{i,j}^{AEBC E} = (1 - \varphi_{i,j}) \times I'_{i,j} + \varphi_{i,j} \times I_{i,j} \quad (12)$$

where $\varphi_{i,j}$ indicates the local image activity and it is computed using the gradient $\nabla_{i,j}$ as follows:

$$\varphi_{i,j} = \frac{1}{1 + \nabla_{i,j}} \quad (13)$$

Note that when the pixel region is homogeneous, the gradient $\nabla_{i,j}$ tends to zero and we keep the original pixel intensity value $I_{i,j}$ since $\varphi_{i,j} \simeq 1$. However, when the gradient is strong, our adaptive approach gives more weight to the enhanced new intensity value $I'_{i,j}$. Taking into account the binocular combination property of the HVS, the following step consists in perceptually controlling the stereo enhancement using the binocular visibility thresholds provided by the BJND maps. Figure 2 shows the $BJND_{left}$ profiles (2c,2d) of two endoscopic images (2a, 2b) respectively. The BJND thresholds are mapped linearly to $[0, 255]$ for better visualization. The corresponding histograms (2e,2f) show that the BJND values are usually comprised between 4 and 14, which gives an idea about the minimum and maximum visually non noticeable inter-view difference levels. We can notice that the BJND is dependent on the local background information that affects the BJND sensitivity to edges as the luminance increases. Furthermore, in regions not containing specular reflexions, the BJND is proportional to the edginess information of the corresponding area of the other view, which is correlated with the noise-free case represented by Equation 6. Each inter-view pixel difference, defined as follows

$$IVDiff_{i,j} = |I'_{i,j, left} - I'_{i,j, right}|, \quad (14)$$

is compared to the corresponding $BJND_{i,j}$ visibility threshold. If $IVDiff_{i,j} \leq BJND_{i,j}$, then there is no detectable visible difference for the observer and we keep the enhanced intensity values. In the other case (i.e., $IVDiff_{i,j} > BJND_{i,j}$), we define what we will call “visual conflict” as the inter-view difference exceeding the binocular visibility threshold, defined by the following expression:

$$VC_{i,j} = IVDiff_{i,j} - BJND_{i,j} \quad (15)$$

Figure 3 shows binary maps illustrating the inter-view difference of an endoscopic stereo image before (Figure 3a) and after our adaptive edge-based contrast enhancement (Figure 3b). Figure 3c highlights the corresponding noticeable visual conflict and Figure 3d shows the visual-conflict binary map superimposed on the left gray-scale component. One can think that the inter-view difference should be negligible before the enhancement, this depends however on the accuracy of the stereo matching algorithm that can results in differences depending on the disparity map values accuracy. We can notice that the inter-view difference increases after the enhancement process and that the noticeable difference lies especially on the enhanced edges and some homogeneous regions. Moreover, we can notice that some noticeable boundaries

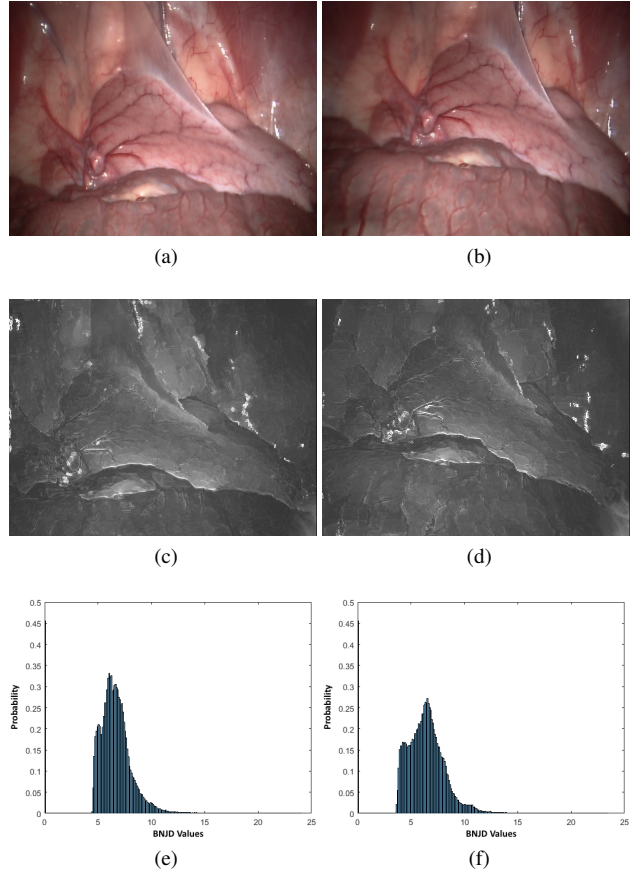


Figure 2: BJND profiles. Two original endoscopic left views (a) and (b). The corresponding scaled BJND maps (c,d), and histograms (e,f), respectively.

are shifted from the corresponding scene objects. This can be explained by the fact that the visual conflict component is generated from a binocular processing that depends on both left and right views, which implies that it cannot correspond exactly on none of the stereo views object boundaries. Once computed, we remove the visual conflict $VC_{i,j}$ from the left or the right view to suppress any noticeable perceptual difference without affecting the luminance distribution. The new intensity values are obtained as follows:

$$\begin{cases} I_{i,j, left}^{AEBC E} = I_{i,j, left}^{AEBC E} - VC_{i,j} & \text{if } I_{i,j, left}^{AEBC E} \geq bg_{i,j, left} \\ I_{i,j, right}^{AEBC E} = I_{i,j, right}^{AEBC E} - VC_{i,j} & \text{if } I_{i,j, right}^{AEBC E} \geq bg_{i,j, right} \end{cases} \quad (16)$$

where $bg_{i,j}$ is the average background luminance, computed the same way as for of the BJND model.

Experimental setup, results and discussions

The aim of the experiment is to emphasize the impact of the proposed adaptive depth-based contrast enhancement and the binocular enhancement control process. The subjective test is performed considering the double-stimulus continuous quality scale method (DSCQS), recommended in ITU-R BT.500 [5]. We consider the stereo enhancement method based on local edge detection and depth information [4] as a baseline for comparison. 10

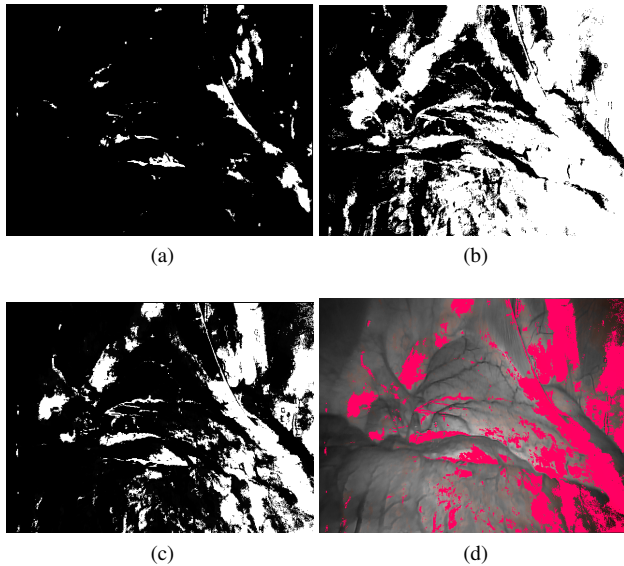


Figure 3: Inter-view difference and binocular visual-conflict. (a) Inter-view difference before applying the AEBCE, (b) Inter-view difference after applying the AEBCE, (c) the correspondig noticeable visual stereo conflict, (d) visual conflict binary map superimposed on the left gray-scale image.

endoscopic stereo images from *Hamlyn Centre* laparoscopic /endoscopic dataset [10] having the same resolution (480×640) are used to conduct the experiment. The images are first converted to Lab color-space where only the luminance component L is processed then displayed on an 23-in LG FLATRON W2363D monitor with NVIDIA wireless polarized glasses, after being reconverted to RGB color-space. 17 expert observers, mostly males (11 males and 6 females) having an average age of 30 and with normal or corrected-to-normal visual acuity are invited to evaluate the subjective quality of the stereo endoscopic images. Prior to each test session, each observer is screened and briefly informed about the experiment. Then a training session is performed based on “dummy presentations” to stabilize the observer opinion and allow to ask questions. Each original endoscopic stereo image is displayed randomly with two enhanced versions using our proposed AEBCE method and the technique proposed in [4], separated by a uniform grayscale image. The observer is then invited to evaluate the visual quality by attributing a score to each stereo image using the grading scale illustrated by Figure 4.

Figure 5 illustrates the enhancement of two endoscopic left views (5a,5b) using the proposed method (5c,3d) and the technique proposed in [4] (5e,5f). We can notice that the contrast of the images enhanced using our adaptive depth-based technique is well adjusted without introducing any halo effect and the tissues/veins edges are more exhibited. The images processed using the method of [4] presents, however, an over-enhancement illustrated by a graying effect in the homogeneous regions and a halo effect visible specially surrounding the specular reflection regions. This can be explained by the used enhancement function (generating $C'_{i,j}$) that over-amplify the contrast and does not take into account the local image activity, unlike our proposed adaptive enhancement method. These artifacts are visible especially with a stereo vision when both the left and right views are binocularly



Figure 4: Rating scales used for assessing the stereo image quality

fused.

Figure 6 shows the results of the subjective test described above. Figure 6b illustrates the standard box-plot of the obtained scores related to the three sets of images where the black bars indicate the corresponding maximum (top bar) and minimum (bottom bar) score and the red line indicates the median. We can notice that the proposed adaptive depth-based method outperforms the technique proposed by [4]. The proposed method produces better stereo image quality then both the original images and the stereo pairs enhanced by [4], with a more comfortable 3D visualization for the observers. We performed also a Paired t-test on the experimental data to compute the statistical difference between the different groups of images regarding the visual quality (Figure 6a). The paired t-test serves to compare the mean score before and after the enhancement using both the conventional [4] and the proposed method. This process serves to indicate whether the enhancement process affects really the perceived quality, i.e. whether there is a noticeable difference in the observer’s scores after applying each enhancement technique. The obtained significance level ($p < 0.00005$) indicates a less than 0.005% risk of concluding that a visible image quality difference exists when there is no actual perceived difference, which proves statistically the effectiveness of the proposed enhancement technique.

Conclusion

In this work, we propose an adaptive depth-based contrast enhancement technique for stereo endoscopic images. The stereo views processed using the adaptive edge-based contrast enhancement are binocularly treated using the BJND model to control the noticeable inter-view differences. The conducted subjective experiment shows the efficiency of the proposed method combining local image features, namely the edginess and the depth information. The experimental results show that the proposed adaptive enhancement method produces stereo endoscopic images with sharper details and better depth perception, without introducing any overshooting or halo effect. Studying the impact of the stereo matching accuracy on the enhancement process and the introduction of visual saliency map will be considered in a future work.

References

- [1] Azeddine Beghdadi and Alain Le Negrate, Contrast Enhancement Technique Based on Local Detection of Edges, Proc. CVGIP, pg. 162–174. (1989).
- [2] Yu-Cheng Fan, Jung-Ching Chiou, and Yan-Hong Jiang. Hole-filling Based Memory Controller of Disparity Modification System for Multiview Three-Dimensional Video, J. Magnetics, 47, 679 (2011).

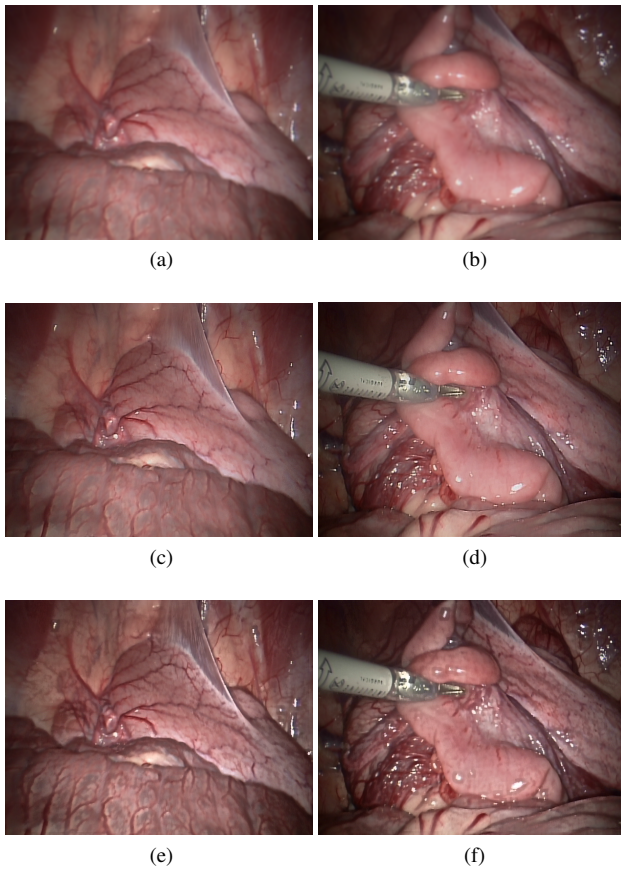


Figure 5: Enhancement of two endoscopic stereo views (a,b) using the proposed method (c,d) and the technique proposed in [4] (e,f).

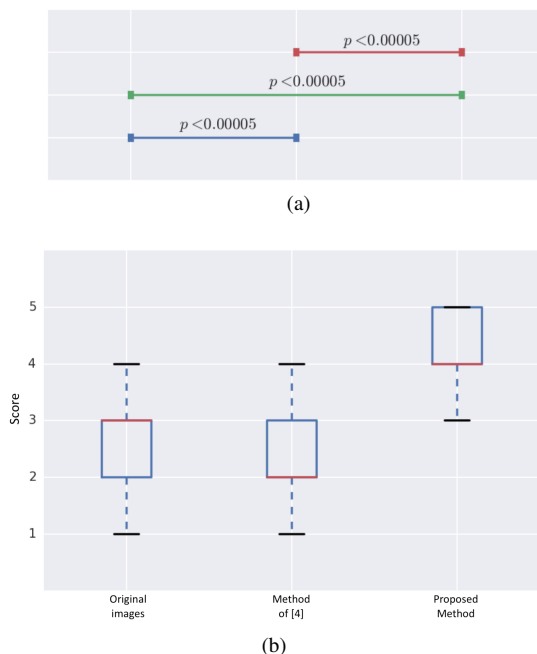


Figure 6: Subjective assessment results grouped by method (b) and the Paired T-test results (a)

- [3] Richard Gordon and Rangaraj M Rangayyan. Feature Enhancement of Film Mammograms Using Fixed and Adaptive Neighborhoods, *J. Applied Optics*, 23, 560 (1984).
- [4] Walid Hachicha, Azeddine Beghdadi, and Faouzi Alaya Cheikh, Combining Depth Information and Local Edge Detection for Stereo Image Enhancement, *Proc.SP EUSIPCO*, pg. 250. (2012).
- [5] ITU Geneva Switzerland., Methodology for the Subjective Assessment of the Quality of Television Pictures , Recommendation ITU-R BT.500-11, 2002.
- [6] Seung-Won Jung, Jae-Yun Jeong, and Sung-Jea Ko, Sharpness Enhancement of Stereo Images Using Binocular Just-Noticeable Difference, *J. Image Processing*, 21, 1191 (2012).
- [7] Sehyung Lee, Jin Han Lee, Jongwoo Lim, and Il Hong Suh, Robust Stereo Matching Using Adaptive Random Walk with Restart Algorithm, *J. Image and Vision Computing*, 37, 1 (2015).
- [8] Thomas Luft, Carsten Colditz, and Oliver Deussen, Image Enhancement by Unsharp Masking the Depth Buffer, *J. ACM Graphics*, 25, 3 (2006).
- [9] David Marr and Ellen Hildreth, Theory of Edge Detection, *Proc. Royal Society of London, Series B, Biological Sciences*, 207, 187 (1980).
- [10] Peter Mountney, Danail Stoyanov, and Guang-Zhong Yang, Three-dimensional Tissue Deformation Recovery and Tracking: Introducing Techniques Based on Laparoscopic or Endoscopic Images, *J. Signal Processing Magazine*, 27, 14 (2010).
- [11] Daniel Scharstein and Richard Szeliski, Middlebury Stereo Vision Website, <http://vision.middlebury.edu/stereo/>.
- [12] Daniel Scharstein and Richard Szeliski, A Taxonomy and Evaluation of Dense Two-frame Stereo Correspondence Algorithms, *J. Computer Vision*, 47, 7 (2002).
- [13] Mahesh M Subedar and Lina J Karam, Increased Depth Perception With Sharpness Enhancement for Stereo Video, *Proc. IS&T SPIE*, pg. 75241. (2010).
- [14] Liang Zhang and Wa James Tam, Stereoscopic Image Generation Based on Depth Images for 3D TV, *J. Broadcasting*, 51, 191 (2005).
- [15] Liang Zhang, Wa James Tam, and Demin Wang, Stereoscopic Image Generation Based on Depth Images. *Proc. Image Processing ICIP*, pg. 2993. (2004).
- [16] Yin Zhao, Zhenzhong Chen, Ce Zhu, Yap-Peng Tan, and Lu Yu, Binocular Just-Noticeable-Difference Model for Stereoscopic Images, *Proc. Signal Processing*, pg.19. (2011).
- [17] Garth Ballantyne and Fred Moll, The da Vinci Telerobotic Surgical System: The Virtual Operative Field and Telepresence Surgery, *J. Surgical Clinics of North America*, 6, 1293 (2003).
- [18] Anne Staylor, *Trends in MIS: Part 2, Medtech Insight*, 2012, pg. 246.
- [19] Azeddine Beghdadi and M-C Larabi, and Abdesselam Bouzerdoum Khan M Iftekharuddin, A Survey of Perceptual Image Processing Methods, *J. Signal Processing Image Communication*, 28, 811 (2013).
- [20] Alain Le Négrate, Azeddine Beghdadi, and Henri Dupoisot, An Image Enhancement Technique and its Evaluation Through Bimodality Analysis, *J. Computer Vision Graphics and Image Processing : Graphical Models and Image Processing*, 54, 13-22 (1991).

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