SDI Review Form 1.6

Journal Name:	**Journal of Advances in Mathematics and Computer Science**
Manuscript Number:	**Ms_JAMCS_57935**
Title of the Manuscript:	**Fast and Effective Region-based Depth Map Upsampling with Application to Location Map-Free Reversible Data Hiding**
Type of the Article	**Type of Article**

General guideline for Peer Review process:

This journal's peer review policy states that **NO** manuscript should be rejected only on the basis of '**lack of Novelty'**, provided the manuscript is scientifically robust and technically sound.
To know the complete guideline for Peer Review process, reviewers are requested to visit this link:

(http://www.sciencedomain.org/journal/10/editorial-policy)

SDI Review Form 1.6

PART 1: **Review Comments**

	Reviewer's comment	**Author's comment** *(if agreed with reviewer, correct the manuscript and highlight that part in the manuscript. It is mandatory that authors should write his/her feedback here)*
Compulsory REVISION comments	**This paper proposed a region based depth map upsampling scheme. It also proposed a joint upsampling and location map-free reversible data hiding method. The proposed upsampling approach partitioned missing depth pixels into three disjoint regions: the homogeneous, semi-homogeneous, and non-homogeneous regions. Further, the proposed JUR method integrates depth copying, mean value, and bicubic interpolation approaches to reconstruct the three kinds of missing depth pixels.** **The authors improve the manuscript and address the following comments:** **1) The authors claim that the proposed approach addresses common weakness of existing methods for depth map upsampling which lack of taking the region classification of missing depth pixels into account.** **The authors should clarify how proposed approach differs from following existing methods. All these methods are based on depth upsampling and region classification.** **[a] Kim et al., Fast Depth Map Upsampling Based on Region Classification, International Conference on 3D Systems and Applications, pp. 243-247.** **[b] O. Choi and S. Jung, "A Consensus-Driven Approach for Structure and Texture Aware Depth Map Upsampling," in IEEE Transactions on Image Processing, vol. 23, no. 8, pp. 3321-3335, Aug. 2014, doi: 10.1109/TIP.2014.2329766.** **[c] Konno et al., "Depth Map Upsampling by Self-Guided Residual Interpolation", 23rd International Conference on Pattern Recognition (ICPR) Cancún Center, Cancún, México, December 4-8, 2016.** **[d] Miguel Tallón, "Upsampling and Denoising of Depth Maps via Joint-Segmentation", : EUSIPCO 2012 (20th European Signal Processing Conference 2012)**	***Compulsory comment 1:*** The authors claim that the proposed approach addresses common weakness of existing methods for depth map upsampling which lack of taking the region classification of missing depth pixels into account. The authors should clarify how proposed approach differs from following existing methods. All these methods are based on depth upsampling and region classification. [a] Kim *et al*., Fast Depth Map Upsampling Based on Region Classification, International Conference on 3D Systems and Applications, pp. 243-247. [b] O. Choi and S. Jung, "A Consensus-Driven Approach for Structure and Texture Aware Depth Map Upsampling," in IEEE Transactions on Image Processing, vol. 23, no. 8, pp. 3321-3335, Aug. 2014, doi: 10.1109/TIP.2014.2329766. [c] Konno *et al*., "Depth Map Upsampling by Self-Guided Residual Interpolation", 23rd International Conference on Pattern Recognition (ICPR) Cancún Center, Cancún, México, December 4-8, 2016. [d] Miguel Tallón, "Upsampling and Denoising of Depth Maps via JointSegmentation", : EUSIPCO 2012 (20th European Signal Processing Conference 2012) ***Response:*** Since the whole paper of the suggested reference [a] cannot be accessed from International Conference on 3D Systems and Applications (June 2011) via Google, the reference [a] is not included in the related work. The suggested reference [c] proposed by Konno *et al*. has already been introduced in the related work of our paper, as shown at the end of third paragraph of Subsection 1.1.1; Konno *et al.*'s method has been included in the comparative methods and the related experimental results have been listed in Table 2, Table 3, and Table 5. Therefore, the other two suggested references [b] and [d] are included in the related work. The main difference between our approach and theirs is that their region classification approaches are based on the high-resolution color image, while our region classification approach is only based on the low-resolution depth map and the D-NOSE concept. The second paragraph of Subsection 1.1.1 has been modified to cover the two suggested methods in [b] and [d]. The second paragraph of Subsection 1.1.1 has been modified as follows. (see the second paragraph of Subsection 1.1.1) Ham *et al*. [B. Ham (2015)] proposed the majorization-minimization (MM) method by considering the structure relation between the guided color image and the depth map. Based on the Middlebury dataset, the MM method outperforms the guided-filtering (GF) [K. He (2013)] and the method in [D. Ferstl (2013)]. Based on the color image and the tentative estimated depth map as the guidance, Li *et al*. [Y. Li (2016)] proposed a hierarchical optimization framework by progressively performing a cascaded and guided global interpolation (CGI). Based on the ToFMark test dataset, the CGI method outperforms the methods in [J. Kopf (2007)], [K. He (2013)], [D. Ferstl (2013)]. Considering the correlation between the objects in the color image and the depth map via joint segmentation, Miguel *et al*. [M. Tallon (2012)] proposed a robust upsampling and noise removal method for depth maps. Choi *et al*. [O. Choi (2014)] first segmented the depth map into regions of

smooth surfaces, and then these regions are used to segment the color image to continuous regions and discontinuous regions. Corresponding to the discontinuous color regions, the depth upsampling is done by the depth-histogram-based method; otherwise, it is done by interpolating from the low-resolution depth map.

Minor comment 1:
Incorporating location map-free reversible data hiding method for depth upsampling is new and interesting. Comparative analysis has been done with state-of-the-art methods. However, I have not seen any reference beyond 2016. Despite several algorithms for depth upsampling are presented recently.
The authors should make a comparative analysis with very recent algorithms. Some reference are given below:
[e] Y. Chang, S. Kim and Y. Ho, "Depth upsampling methods for high resolution depth map," 2018 International Conference on Electronics, Information, and Communication (ICEIC), Honolulu, HI, 2018, pp. 1-4, doi: 10.23919/ELINFOCOM.2018.8330567.
[f] Beomjun Kim, Jean Ponce, Bumsub Ham, "Deformable kernel networks for guided depth map upsampling", arXiv:1903.11286, 2019
[g] Yi Guo, Ji Liu, Depth Edge Guided CNNs for Sparse Depth Upsampling, arXiv:2003.10138, 2020
Response:
Many thanks for your commit. The third paragraph and the fourth paragraph in Subsection 1.1.1 have been modified as follows.

(see the third paragraph in Subsection1.1.1 on pages 1-2)
Xie *et al*. [R. Feris (2016)] proposed an edge-guided upsampling (EGU) method. Their EGU method first integrated the Markov random field technique and the training-based patch synthesis technique to generate a temporary upsampled depth map. Then, with the help of the modified version of the joint bilateral filtering, EGU can effectively remedy the jagged artifact and has better quality and edge-preserving effect. Based on the Middlebury dataset, EGU has shown better quality when compared with the related methods [R. Zeyde (2010)], [B. Zhang (2008)], [C. Chou (2014)]. Because of involving the Markov random field and training-based patch synthesis techniques, EGU is time-consuming. Konno *et al*. [Y. Konno (2016)] proposed a self-guided residual interpolation (SRI) method. The techniques used in SRI include the displacement field-guided filtering technique [L. Wang (2014)], the GF technique [K. He (2013)], and the bicubic interpolation (BIC). Based on the Middlebury dataset, SRI has better quality relative to the methods in [K. He (2013)], [D. Ferstl (2013)], [L. Wang (2014)], [J. Yang (2010)], [O. Aodha (2012)]. Chang *et al.* [Y. Chang (2018)] compared and analyzed the advantages and disadvantages among the five depth map upsampling methods, namely the bilinear, joint bilateral [J. Kopf (2007)], noise-aware filter [D. Chan (2008)], guided image filter [K. He (2013)], discontinuity adaptive [S. B. Lee (2013)] depth upsampling methods. Furthermore, they applied depth refinement processes to achieve the quality improvement of the upsampled depth map.

(see the fourth paragraph in Subsection1.1.1 on page 2)
Recently, under the deep learning supporting environment, Hui *et al*. [T. Hui (2016)] proposed a multi-scale guided convolutional end-to-end network (MSG-Net) for depth map upsampling. In MSG- Net, a convolutional neural networks-based (CNN-based) multi-scale fusion strategy was

		presented to complement the low-resolution depth features with the high-resolution luma features. Unlike some super-resolution networks that require pre-upsampling of input image by BIC in advance, MSG- net learns upsampling kernels inside the CNN. Based on the Middlebury dataset, the MSG-Net outperforms several traditional upsampling methods and Dong *et al*.'s super-resolution CNN (FSRCNN) method [C. Dong (2016)]. Kim *et al.* [B. Kim (2019)] learned sparse and spatially-variant kernels for determining the weighted averaging process to transfer structural details to low-resolution depth maps. Then, they propose a fast deformable kernel network to output sparse sets of neighbors and the corresponding weights adaptively for each pixel, leading to depth map upsampling. Based on the normalized convolution operation, Guo and Liu [Y. Guo (2020)] proposed a guided convolutional layer to recover a dense depth map using a sparse and irregular depth map with a depth edge map as guidance. Further, they proposed a convolution network by combining different related methods, achieving better performance.
Minor REVISION comments	2) Incorporating location map-free reversible data hiding method for depth upsampling is new and interesting. Comparative analysis has been done with state-of-the-art methods. However, I have not seen any reference beyond 2016. Despite several algorithms for depth upsampling are presented recently. The authors should make a comparative analysis with very recent algorithms. Some reference are given below: [e] Y. Chang, S. Kim and Y. Ho, "Depth upsampling methods for high resolution depth map," 2018 International Conference on Electronics, Information, and Communication (ICEIC), Honolulu, HI, 2018, pp. 1-4, doi: 10.23919/ELINFOCOM.2018.8330567. [f] Beomjun Kim, Jean Ponce, Bumsub Ham, "Deformable kernel networks for guided depth map upsampling", arXiv:1903.11286, 2019 [g] Yi Guo, Ji Liu, Depth Edge Guided CNNs for Sparse Depth Upsampling, arXiv:2003.10138, 2020	
Optional/General comments	Add missing references mentioned above	

PART 2:

	Reviewer's comment	**Author's comment** *(if agreed with reviewer, correct the manuscript and highlight that part in the manuscript. It is mandatory that authors should write his/her feedback here)*
Are there ethical issues in this manuscript?	*(If yes, Kindly please write down the ethical issues here in details)*	