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EMF- MHCRF: Enhanced Median Filter (EMF) Based Noise Removal and Multilayer Hidden Conditional Random Field (MHCRF) Model for Dense Depth Map Reconstruction

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Abstract
Depth map reconstruction also named as disparity estimation and it becomes very difficult task in computer vision three dimensional (3D) tasks which has been studied used for more than three decades. Present high quality depth sensors proficient of creating dense depth maps are costly, noise and bulky, at the same time as dense low-cost sensors be able to simply consistently generate sparse depth measurements. In this work, propose an Enhanced Median Filter (EMF) for noise removal of images. Since the preprocessing stage is an important and initial step in the depth map construction step, it retaining the important information of patches or frames. And the major issue in processing stereophotogrammetry images is the presence of noise which presents as bright dots or dust particles more than the image. So EMF is proposed to remove impulse noise from stereo images. EMF is proposed to remove the noisy pixel from the original pixel; here the noise is removed depending on the threshold value computed from genetic operations. Secondly propose a novel Multilayer Hidden Conditional Random Field (MHCRF) model to restructure a dense depth map of a target scene known the sparse depth measurements and related to photographic measurements computed from stereo photogrammetric systems. This MHCRF model assured global optimum in the modeling of the temporal action dependencies following the Hidden Markov Model (HMM) stage. In MHCRF model, dense depth map is estimated by formulating the as a Maximum A Posteriori (MAP) inference problem wherever efficiency previous is assumed. The any middle representation, depth is computed directly from the Middlebury stereo vision data for ground truth, it has been also deal with any number of cameras. Shows potential experimental results demonstrate the ability of this EMF- MHCRF model and compared to MCRF, CRF models.
Index terms: Depth estimation, light fields, sparse linear systems, Enhanced Median Filter (EMF), noise removal, Hidden Conditional Random Field (HCRF), Maximum A Posteriori (MAP) inference and stereophotogrammetry.

Introduction

Depth map reconstruction also named as disparity estimation and it becomes very difficult task in computer vision three dimensional (3D) tasks which has been studied used for more than three decades. Present high quality depth sensors proficient of creating dense depth maps are costly, noise and bulky, at the same time as dense low-cost sensors be able to simply consistently generate sparse depth measurements. Reconstructing 3-D depth from images is a general issue in computer vision, and has significant applications in robotics, scene thoughtful and 3-D restoration. Many of the work on visual 3-D restoration has paying attention on stereopsis [1] and on conventional algorithms with the purpose of need multiple images, for instance formation from motion [2] and depth from defocus [3]. These conventional algorithms focus only the triangulation variation.

Further than stereo/triangulation cues, there are moreover many monocular cues for instance texture difference and gradients, defocus, color, etc. with the purpose of includes helpful and significant depth data. A color in the depth map represents the estimated distances between camera stereo and monocular cues, many of the work related to depth estimation majorly focuses on stereovision. The traditional manner to obtain depth values from stereo images. Scharstein and Szeliski review a details analysis related to this topic [1]. Many of the work have overcome this problem by optimization of energy value, which generally includes of information term and a smoothness term. Present high value depth sensors for instance time-of-flight cameras or high motion controlled light scanners are costly and large. At the same time as current improvement for example the Kinect (Microsoft Corp.) have decreased the cost of depth sensors, there is currently a push in the direction of have depth sensors in a dense and convenient standard. A possible application consists of 3D scanning by means of mobile phones, follow the map usual environments by means of robots, or object detection with surveillance drones. Presently, there are new low-cost depth sensors are obtainable in a little form factor.

Some of the solutions are stereophotogrammetric systems for example Leap Motion Controller (Leap Motion Inc. [4]) and DUO (Code Laboratories Inc. [5]) with the purpose of use two or more cameras to perform stereophotogrammetry and obtain depth information of the scene. However, the limitations of these systems are the small stereo baseline and low quality camera sensors; these limitations make stereo correspondence difficult and results in many non-existent or erroneous matches. Hence, these sensors are capable of only obtaining sparse depth measurements. For applications for instance 3D scanning, dense depth maps are needed and sparse depth measurements are inadequate designed for generating high quality models. Consequently in the direction of have a system with the purpose is low-cost, dense, and able of creating correct dense depth maps are extremely popular.

The two mainly well-liked models designed for the energy functions are the Markov Random Fields model [6] (MRFs) and variational approaches [7], at the same time as the model of the information term and the smoothness term be able to be varied. For stereo matching, a many of recent work shows with the purpose of energy functions by means of non-convex terms model the issues improved, though in fact simply an estimated optimization be able to be found. In this case, the recovered depth values are not constant however distinct in the depth value. A major issue of the discrete methods is with the purpose of the time and memory cost of the algorithm is regarding in the direction of the number of quantized levels. When the level is not high sufficient "stair" property are frequently obvious in the recovered depth maps. Depth estimation from a single still image is a challenge task, because depth normally remains confusing known simply local image features. Consequently, proposed work should take into account the global features of the image, in addition to make use of prior information regarding the scene. They moreover view depth evaluation as a small however difficult step in the direction of the superior goal of image kind, in with the purpose of it determination facilitate in tasks for instance considerate the spatial layout of a scene, discovery walkable areas in a scene, identify objects, etc.

The main contribution of this paper is to propose a new Multilayer Hidden Conditional Random Field (MHCRF) model for creating dense depth maps with lesser cost compressed stereophotogrammetric systems. The method follows a MHCRF model for labelling the intense depth map known the interpretation including of photographic dimensions and dense depth measurements. The MHCRF is extended from MCRF model by considering the dense depth evaluation depending as an extra observation layer by means of missing observations appropriate toward sparsity. Additionally, the MHCRF model makes use of multivariate feature functions depending on the photographic and depth evaluation in the direction of describe unary and pairwise relationships among the results and labels. Using the MHCRF model, the sparse depth map reconstruction issue is solved and modeled as MAP inference problem. Additionally consider how monocular cues beginning a single image are able to be integrated into a stereo system. The proposed MHCRF model has many advantages with the purpose of added examination layers and feature functions, for instance with multi-spectral capacity, be able to straightforwardly be integrated into the model. While the proposed MHCRF model is developed approximately stereophotogrammetric systems, it be able to be useful in the direction of some depth sensor with the purpose of gives depth and photographic measurements.

Literature Review

Kim et al [8] developed a new algorithm with the purpose of leverages consistency in huge light fields by means of breaking among a number of well-known practices in image-based restoration. This method initially calculates consistent intensity estimates particularly approximately object boundaries as a substitute of interior regions, with operating on single light rays rather than image patches. Further consistent interior regions are then developed in a well-to-common process before the conventional coarse-to-fine approaches. On no position in proposed in image-based restoration is any form of large-scale optimization is performed for depth map reconstruction. These permits algorithms in the direction of maintain precise object contours at the same time as still guarantee smooth reconstructions in less in depth areas. Additional enhance effectiveness by means of transmit dependable depth estimates during the whole light field by means of a novel sparse information structure, such with the purpose of the algorithm successfully calculates depth maps designed for each and every one input images concurrently.

Tao et al [9] developed a new easy algorithm with the purpose of calculates dense depth estimation by means of merging equally defocus and association depth cues. Investigate the x-u 2D epipolar image (EPI), wherever by means of principle presume the spatial x coordinate is parallel and the angular u coordinate is perpendicular. The results demonstrated with the purpose of defocus depth cues are attained by means of calculating the horizontal variance following vertical integration, and association depth cues by means of calculating the vertical variance.

Kim et al [10] developed a new depth map estimation method designed for light field cameras by exploiting association and center cues. Total costs between each and every one the sub-aperture images on cost volume in the direction of improve noise effects. By means of effectiveness of the cost amount, cost-aware depth estimation is rapidly attained via discrete-continuous optimization. Additionally, evaluate each property of association and focus cues to make use of them to choose consistent anchor points. Well reconstructed first depth map beginnings the anchors are shown in the direction of improve convergence. The results demonstrated that the proposed depth map estimation method performs better when compared to other traditional methods by measuring it on real datasets acquired through a Lytro camera. Defocus is one more clue with the intention is able to be used for depth. As alternative of the colour variance, researchers try in the direction of discover by how much angle the EPIs require to be sheared in the direction of make the interest point in focus. Defocus and colour variance are used simultaneously in the direction of discover the depth in [9] and [10].

Wanner and Goldluecke [11] proposed a new depth map reconstruction algorithm to detect 4D light fields in a variational framework. By considering the individual structure of light field information, reformulate the problem of stereo matching in the direction of a constrained labeling problem taking place epipolar plane images, which are able to be consideration of as perpendicular and parallel 2D cuts during the area. This another formulation permit approximation perfect depth values constant designed for specular surfaces, at the same time as concurrently taking into account global visibility constraints sequentially in the direction of attain consistent depth maps designed for each and every one views. In this work, make use of the estimation from the structure tensor as an initial point, followed by means of a fine-tuning step by means of investigative the colour association next to the distinguished line from the structure tensor.

Hoiem et al [12] proposed an appearance-based model to approximate the coarse statistical properties of a scene by means of knowledge of geometric classes, constant in cluttered normal scenes. A geometric class defines the 3D direction of an image region regarding the camera. Present a multiple-hypothesis framework designed for strongly approximation scene structure from a particular image and attaining confidences designed for every geometric label. These confidences are able to then be used in the direction of increase the performance of several applications. Present a detail evaluation of the appearance-based model with a set of outdoor images and results are measured with two applications: object detection and automatic single-view restoration.

Hoiem et al [13] design a new “pop-up” type 3-d model from an image by categorizing them into ground, vertical and sky. This type 3-d model presumes an easy “ground vertical” formation of the world; fails on several environments with the purpose of shouldn’t assure this assumption and also shouldn’t provide precise metric depth-maps.

Hoiem et al [14] develop a new model for introduction local object discovery in the framework of the overall 3D scene by means of formulating the interdependence of objects, face orientations, and camera position. Many object detection methods regard as each and every one scales and locations in the image as regularly possible. Results demonstrate with the purpose of probabilistic estimates of 3D geometry, together in terms of surfaces and world coordinates, place objects addicted to viewpoint and form the scale and location variance in the image. The object detection approach reproduces the repeated scenery of the problem by means of considering probabilistic object hypotheses in the direction of improve geometry and vice-versa. This framework permits painless replacement of approximately several object detectors and is straightforwardly absolute in the direction of comprise other aspects of image perceptive.

Sudderth et al [15] proposed new learning object detection for 3-d scene reconstruction. This method follows a probabilistic model designed for the exterior and three-dimensional geometry of cluttered scenes. Object classifies are formulated via distributions over the 3D position and form of visual features. Improbability in the number of object instances represented in a specific image is then obtained by means of a transformed Dirichlet process. In distinguish by means of image-based approaches in the direction of object detection, form scale variations as the angle ridge of objects in varied 3D poses. In the direction of calibrate the fundamental geometry, consist of binocular stereo images addicted to the training process. A robust likelihood model is designed for outliers in matched stereo features, permitting effective learning of 3D object formation from partial 2D segmentations. Functional in the direction of a dataset of office scenes, model identifies objects on multiple scales by means of a coarse reconstruction of the related 3D geometry.

Yang et al [16] developed a new depth map reconstruction and refinement designed for the asymmetric coding scheme in the direction of avoid the blurring effect by means of using coding parameters in bit-streams. In the initialize step, make use of an edge-oriented interpolation algorithm in the direction of increase the accuracy approximately edge-related regions designed for the up-sampled depth map. A weight model is formulated by edge and structural variation, where edge variation is a computation among depth maps and their related texture images for many depth maps. Based on the weight model, the up-sampling coefficients are able to be chosen adaptively related to the edge orientation. Subsequently, a block-based histogram refinement method is developed in the direction of remove blurring artifacts caused by means of loop filter in decoder and up-sampling. A mapping function is constructing designed for the growing histogram of the up-sampled depth map and its new depth map in the direction of accurate the error pixels in the up-sampled depth map. The block data of the histogram modification algorithm is extracted beginning the bit-stream at the decoder. The experimentation results concludes with the purpose of proposed depth map reconstruction is able to increase on together subjective and objective performances when compared with conventional methods.

Li et al [17] examine how the lately appeared photography technology - the light field - is able to advantage depth map evaluation, a difficult computer vision problem. A new method is proposed in the direction of restructure continuous depth maps beginning light field information. Different various conventional methods designed for the stereo matching difficulty, the proposed method shouldn't need in the direction of quantize the depth range. By making use of the formation information between the densely data views in light field information is able to obtain dense and comparatively consistent local estimations. Beginning from first estimations, go on to introduce an optimization algorithm depending on solving a sparse linear system iteratively by means of a conjugate gradient method. Two different affinity matrices designed for the linear system are proposed in the direction of balancing the effectiveness and value of the optimization. Then, a depth-assisted segmentation is proposed with the purpose of varied segments be able to make use of varied affinity matrices. The results demonstrated that the proposed work is performed on both synthetic and real light fields; it concludes that the continuous results are more correct, well-organized, and capable in the direction of maintain more details when compared with discrete approaches.

Li et al [18] developed a new Multilayer Conditional Random Field (MCRF) approach in the direction of reconstruct a dense depth map of a target scene known the sparse depth computation and related photographic evaluation gathered from stereo photogrammetric systems. Measuring the sparse depth map and it is modeled as MAP problem in which the smoothness information is also measured in this work. MCRF model make use of the sparse depth measurement as a further examination layer and defines the association among nodes by means of multivariate feature functions depending on the depth and photographic measurements. The MCRF model is first qualitatively measured on information collected by means of a compressed stereo camera, and subsequently quantitative performance is calculated by means of the Middlebury stereo vision data designed for view truth.

Proposed Methodology

The main contribution of this paper is to propose a new Multilayer Hidden Conditional Random Field (MHCRF) model for creating dense depth maps with lesser cost compressed stereophotogrammetric systems. The method follows a MHCRF model for labelling the intense depth map known the interpretation including of photographic dimensions and dense depth measurements. The MHCRF is extended from MCRF model by considering the dense depth evaluation depending as an extra observation layer by means of missing observations appropriate toward sparsity. Additionally, the MHCRF model makes use of multivariate feature functions depending on the photographic and depth evaluation in the direction of describe unary and pairwise relationships among the results and labels. Using the MHCRF model, the sparse depth map reconstruction issue is solved and modeled as MAP inference problem. Additionally consider how monocular cues beginning a single image are able to be integrated into a stereo system. The proposed MHCRF model has many advantages with the purpose of added examination layers and feature functions, for instance with multi-spectral capacity, be able to straightforwardly be integrated into the model. While the proposed MHCRF model is developed approximately stereophotogrammetric systems, it be able to be useful in the direction of some depth sensor with the purpose of gives depth and photographic measurements. The proposed EMF- MHCRF model is illustrated in Figure 1 and discussed as follows. The depth sensor creates photographic and sparse depth measurements. These measurements are the outcomes and input to the proposed EMF- MHCRF model based depth reconstruction method, which creates and outputs a dense depth map. The dense depth map has been used for instance as a viewpoint in 3D reconstruction.

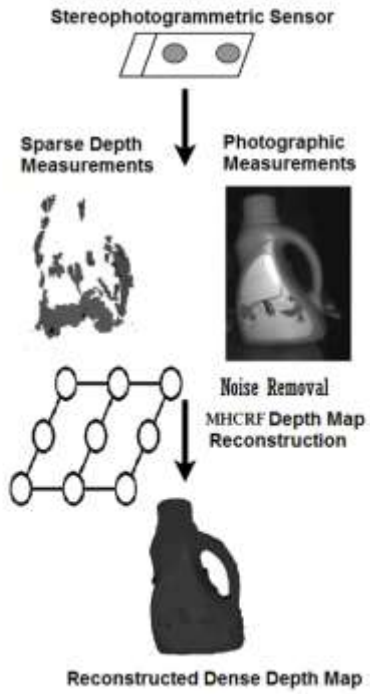

Figure 1. Proposed EMF- MHCRF model

1.1.Enhanced Median Filter (EMF) algorithm

The major idea of the proposed Enhanced Median Filter (EMF) algorithm is developing a filter in such a manner with the purpose of the individuality operator acts on the noise-free samples and noisy pixels are simulated by the filter process. In order to present a trade-off among the individuality filter and the median filter, the proposed method EMF algorithm is combined with a novel considerably easy noise detecting algorithm, known as EMF algorithm. The original input image is considered as the feature vector; consider the rows of the image. In the feature vector scheme, the followed pixels in the similar row still becomes a challenging task with followed pixels and the pixel earlier than the last pixel of the row is the tag along pixel of the subsequent pixel of the next row. Note with the purpose of the first row, the last row, the first column, and the last column are missed in the vector scheme. Consequently, the image $I_{n\times m}$ will be VN×1 in the vector scheme, where N = (n-2) × (m-2). A window $W_i(p)$ is a two-dimensional with many of pixels by means of the size i×i, where i is an odd integer and p is the center pixel of the window.

For finding the noise in EMF model, the variation among two followed pixels in V is compared with a threshold (*d*). if the threshold is not constant and Step parameter is added to increase the number of iteration with condition ($|v_{i-1}-v_i|$) >*d* is satisfied. In some cases, particularly when the noise density is not greater than the 50 percent, the probability, which shows how several noisy pixels are instant neighbors, is extremely low. Subsequently, providing with the purpose of a pixel is distinguished as a noisy pixel, the condition designed for detecting the next pixel as a noisy one is receiving harder by means of increasing *d*. Elsewhere , parameter (*d)* is modified in the direction of the pre-defined threshold. The parameter of ‘Step’ is very significant in identifying noises further precisely and preserving edges.

- Threshold=*d*
- If ($|v_{i-1}-v_i|>d$) {v_i= median (W_3 (v_i)), *d*= *d* + Step}
- Else {*d*= Threshold}

Where, |·| represents the absolute operator, v_i denotes i^{th} part of V, and W_3 is the filtering window by means of the size 3×3. Depending on the EMF algorithm, if the variation among the two pixels is higher than the threshold (*d*), the pixel is noisy and the median operation should be applied to it. Elsewhere, the pixel is noise-free and the individuality operation should be applied.

1.2.Problem Formulation And The MHCRF

Consider as inputs for depth map reconstruction with two sets of observations: the photographic size and the sparse depth size. Let the set of random variables X_c and X_d denotes these observations correspondingly and X = [X_c,X_d]. Let Y be the set of labels denoting the reconstructed dense depth map. Then, identified observations X to discover the mainly potential depth values in the inferred depth map Y. This is written as a Maximum A Posteriori (MAP) problem:

$$Y^* = \arg\max_{\hat{y}} P(Y|X) \qquad (1)$$

where $\hat{Y}$ is the set of each and every one possible states of Y and Y^* is preferred the recognition of Y which have the higher probability. To overcome the problem of MAP problem, Multilayer Hidden Conditional Random Field (MHCRF) model is proposed in this work. Each pixel in the dense depth map is formulated as a node in an undirected graph with the purpose of follows a procedure of the Markov property. Let us consider that the labels Y with two major observation layers: the depth observations X_d(diamonds) and photographic observations X_c(squares). A black-filled diamond denoted with the purpose of a depth observation exists designed with the purpose of node at the same time as a grey diamond denoted as a missing observation. The photographic observations are considered to have no missing observations. The edge e_{ik} represents the influence of neighbouring nodes on the center node/pixel $y_i \in Y$ where $|Y| = n$, which is a weighted combination of its neighbours y_j , X_d, and X_c.

1.3.Hidden Conditional Random Field (HCRF) Model

Hidden Conditional Random Field (HCRF) model was developed by Gunawardana et al [20] designed for speech classification and has then been applied in the direction of motion and object detection [21-22]. Known a sequence composed of a set of n local observations $\{x_1, x_2, x_3, ..., x_n\}$ represented by X, and its class labels $y \in Y$ in the direction of discover a mapping p(y|X) among them, where y is conditioned on X. An HCRF is defined as follows,

$$p(y|X_c,X_d;\theta) = \frac{p(y,X_c,X_d;\theta)}{p(X_c,X_d;\theta)} \tag{2}$$

$$= \frac{\sum_H p(y,H,X_c,X_d;\theta)}{\sum_y p(y,H,X_c,X_d;\theta)}$$

$$= \frac{\sum_H e^{\phi(y,H,X_c,X_d;\theta)}}{\sum_y e^{\phi(y,H,X_c,X_d;\theta)}} \tag{3}$$

Where θ is denoted as keta parameters of the HCRF model, and $H=\{h_1, h_2, ..., h_n\}$ is the set of hidden variable. Each $h_i \in \widehat{H}$ collects specific underlying structure of each class and $\widehat{H}$ is the set of hidden states in the HCRF model. $(y,H,X;\theta)$ is the objective function which computes the compatibility among a label, a set of observations and a configuration of hidden variables. Based on Maximum Likelihood (ML) determination, the modified version of the objective function of HCRF is denoted as follows,

$$L(\theta) = -\sum_{i=1}^{s} \log p(y_i|X_c,X_d,\theta) + \frac{2||\theta||^2}{2\sigma^2} \tag{4}$$

where s is the total number of training sequences with well-known class labels. The initial parameter and the second parameter are the log-likelihood of the information. The third parameter is the log of a Gaussian information with variance $\sigma^2, p(\theta) \sim \exp\left(\left(\frac{||\theta||^2}{\sigma^2}\right)\right)$ equal to regularization of a CRF [23]. The best parameters are capable to be establishing by means of a gradient descent using Quasi-Newton optimization. New constraint function (Eq.(5))and its gradient can be written as marginal distributions over the hidden variables. This marginal distribution has been calculated accurately by means of belief propagation [22] and formulated as the graph model. From Eq.(5), see with the purpose of the objective function of MHCRF is not convex term (2) and two convex(terms(3)and(4))functions shouldn't guarantee convexity). Consequently its global convergence majorly depends on the initialization.

2. Results and Discussion

In this section evaluate the proposed MHCRF model using disparity maps achieved from stereophotogrammetry. A disparity map is inversely comparative to a depth map, consequently the two are treated the identical. The depth map reconstruction algorithm was experimented in MATLAB; at the same time as stereo association were done using C++ and OpenCV. The initial experiment, image was gathered using the 'DUO' stereo camera from Code Laboratories as the depth sensor in the proposed MHCRF model and existing MCRF system. This camera was used designed for its density and little form factor, by means of a baseline width of approximately 3cm among the two cameras. The camera make use of infrared (IR) LEDs at 850nm wavelength designed for explanation and the camera obtain infrared measurements of the scene in the direction of confine concentration images at 640x480 resolutions. Stereo correspondence was carryout using the OpenCV Sum of Absolute Differences (SAD) block matching method [24].

For comparison, proposed a joint bilateral filter (JBF) with the purpose of make use of the photogrammetric measurements in the direction of guide the depth map smoothing. Kopf et al. [25], the JBF method has been used in many applications, one of which is depth map refinement with many adaptations for this purpose [26] The development of the JBF was depending on the code by Silva[27] which develops the bilateral filter [28] by means of a guiding image. The point clouds of the scanned objects in Figure 2 are illustrated in Figure 3. The IR image is collected from the left DUO camera

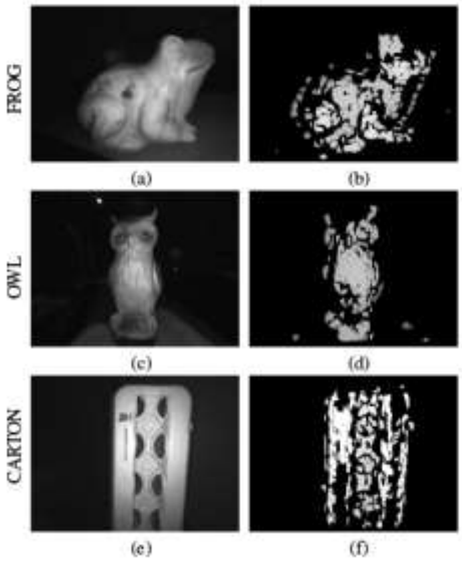

Figure 2. IR and disparity map pairs gathered from DUO camera

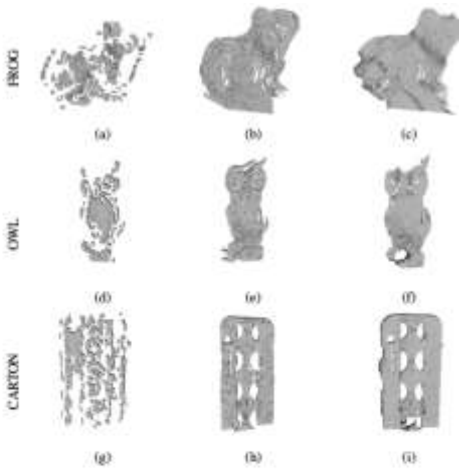

Figure 3. Resultant disparity maps estimated onto point clouds

In the figure 3 (a,d,g) original sparse depth measurements. (b,e,h) subsequent to JBF [26] (c,f,i) after proposed MHCRF depth reconstruction. Both methods are illustrated to be capable to stop much of the absent depth information beginning the first sparse depth measurements, although the results of the MHCRF method show to be smoother. The initial column demonstrate the point clouds of the first sparse depth measurements, the second term demonstrate the results subsequent to applying the JBF [25], and the final column demonstrate the results subsequent to applying the MHCRF depth reconstruction model. Compared to the joint bilateral filter, MCRF, and the proposed MHCRF model provides added consistent points on the object surface by means of further continuous surface transitions with the purpose of return the surface distinctiveness of the object. This is notice further noticeably illustrated in Figure 4, which shows a zoomed in and more complete view of the point clouds.

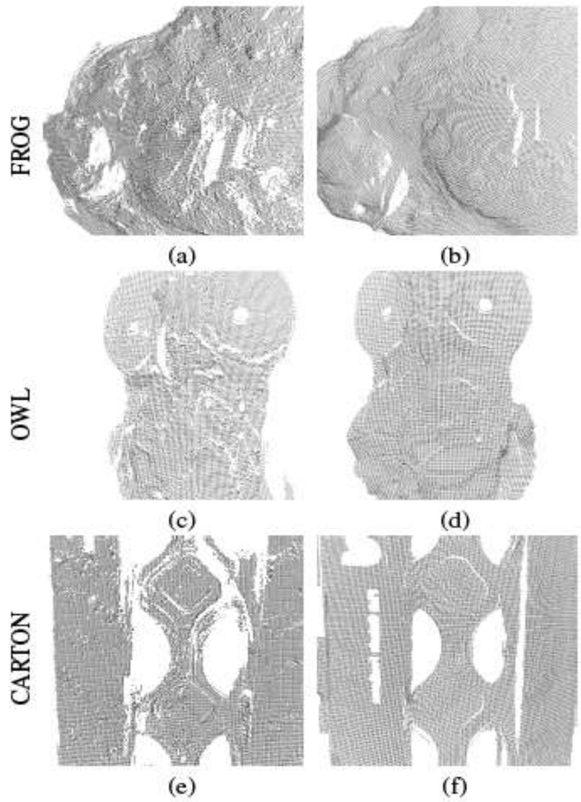

Figure 4. Final disparity maps projected onto point clouds

In the figure 4 (a,d,g) initial sparse depth measurements. (b,e,h) after JBF [25] (c,f,i) after proposed MHCRF depth reconstruction.

Table I. Mean Squared Error (MSE) of reconstructed map construction results of ground truth image

Data	JBF	MRF	MCRF	MHCRF
Aloe	930	1050	789	725

Baby	189	875	183	152
Flowerpots	2458	2152	1853	1679
Plastic	985	4215	825	718
Rocks	659	587	542	504
Wood	715	605	456	401
Average MSE	822.5	827.5	622.5	563

From the results it concludes that the proposed MHCRF model appears to be smoother when compared to other MCRF and the JBF methods. The results are also measured in terms of the Mean Square Error (MSE) is discussed in table 1 ,it concludes that the proposed MHCRF model produces lesser MSE when compared to other models.

3. Conclusion And Future Work

In this paper, propose a novel framework in the direction of reconstruct continuous depth maps from 3D images. In the initial stage, Enhanced Median Filter (EMF) is proposed for noise removal of images. EMF is proposed to remove impulse noise from stereo images. EMF is proposed to remove the noisy pixel from the original pixel; here the noise is removed depending on the threshold value computed from genetic operations. Secondly propose a novel multilayer Hidden Conditional Random Field (MHCRM) model to restructure a dense depth map of a target scene known the sparse depth measurements and related to photographic measurements computed from stereo photogrammetric systems. Here dense depth map estimation is computed by formulation of Maximum A Posteriori (MAP) and it is used for measuring the approximation between different views. It permits estimating straightforwardly the depth from a number of stereo images, at the same time as preserving depth discontinuities. Higher depth map reconstruction results have been obtained by using EMF- MHCRM model. These results noticeably illustrated the ability of this proposed EMF- MHCRM model in terms of noise removal, dense depth map construction, dense depth recovery and depth discontinuities preservation. In further work, focuses on the evaluation of the state-of-the-art results in the area of 4D reconstruction with highly-specula objects. For collecting such a type of objects, a record player based setup was employed, which is able of nearly entirely helpful the object by means of structured Gray code related patterns from a close proximity of the object. For decoding Gray codes, where the no. of patterns which are able to be used for decoding differs diagonally the image domain, a robust, fuzzy decoding was developed and implemented to 4D reconstruction. To get better the complete surface, the multi-view normal field incorporation was modified for the input in the formation of light maps .Though the proposed EMF-MHCRM model has a property of being capable in the direction of rely simply on normal information, further visual cues be able to always increase the result, when they are obtainable. Moreover, to see the actual possible of the EMF-MHCRM model, testing it with other conventional estimation techniques in terms of both 3D and 4D would be also interesting scope of the future work.

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