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A Survey On Depth Estimation Using Vanishing Point

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Abstract: In the field of computer vision, depth estimation plays an important role. Estimating depth from 2D images is a crucial step in scene reconstruction, 3D object recognition, segmentation, and detection. Depth estimation is often described as an ill posed and inherently ambiguous problem. In this paper, convolutional neural network (CNN) model is used to estimate the depth in a given 2D image using the concept of vanishing point by reviewing papers that attempt to solve the depth estimation problem with various methods including structure from motion, stereo vision, camera calibration, depth from focus and also including the convolutional neural network. Additionally, CNN because of its 3 layers embedded outperforms the other methods and detects the important features without human supervision. We then compare these papers and understand the improvements made over one another. Finally, we explore potential improvements that can aid to better solve this problem.

***Index Terms* – Depth Estimation, Vanishing Point, CNN.**

I. Introduction

Digital devices like camera represent the world as two- dimensional (2D) matrix. Since, cameras represent three-dimensional scene in two dimensional matrixes the third-dimension i.e., depth is lost. Recovering scene depth has been a subject undergoing intense study in computer vision and has broad applications. Estimating depth of a scene from a single image is an easy task for humans, but is very challenging for computational models to do with high accuracy and low resource requirements. However, in this paper estimation of depth is performed using a method called vanishing point.

A vanishing point is a point on the image plane which arises from a set of parallel lines as their point of intersection, at an infinite location initially. They are strong cognitive cues for the human visual perception, as they provide characteristic information about the geometry of a scene. Initial work of depth estimation using vanishing point included gathering depth information by stero-vision, structure from motion but those results came out to be ambiguous, further work was in camera calibration where research was done capturing images with a slight displacement of the camera, in turn deriving the relationship between lens and projection plane of the camera. Nevertheless, these methods did not involve direct depth information. Subsequently, a method called depth from defocus/focus was introduced where depth could be inferred focusing only on certain images. However, it failed in textureless images.

Hence, to overcome the drawbacks we are using end-to-end trainable deep network for detecting vanishing points in images using Convolution Neural Network (CNN) and Convolution Random field Network (CRFN) for depth estimation. Given the input image, CNN determines the depth of each image undergoing series of its layers functions and thereafter feeds the output to CRFN which in turn solves the log-likelihood optimization.

Vanishing point being the prominent method in estimating the depth with the help of convolutional neural network has its application in many fields in computer vision and more and works are being done regarding the same.

II. RELATED WORKS TAKEN FOR COMPARISON

Regression Convolutional Network for Vanishing Point Detection [1], This paper provides the detection of the position of the vanishing point using regression convolutional neural network based on Alexnet. This new layer consists of five convolutional layers, four fully connected layers, Tanh activation function and regression loss function. The features from the images are extracted to determine the vanishing point. A small number of training dataset is provided and the result is found. This method is more effective on blurred pictures and complex circumstances.

Three orthogonal vanishing points estimation in structured scene using convolution neural network[2], In this paper, the vanishing point is detected based on Convolutional neural networks approach by constructing the VFO330K database containing street and indoor views, annotated vanishing points, focal length, and the orientation of the camera with respect to the 3D coordinate system of the scene. Convolutional neural networks are explored to learn the vanishing point estimation in an end-to-end paradigm and impose a regularization item derived from the geometric constraint of orthogonal vanishing points which improves the performance of vanishing point prediction by determining the effectiveness of the proposed approach by evaluating with multiple CNNs architectures.

Deep Recognition of Vanishing-Point-Constrained Building Planes in Urban Street Views[3], This paper detects the vanishing point from street view images with fine-grained orientation labels from three different metropolises in the world. A novel convolutional neural network architecture is designed with gating mechanism and deep supervision to improve plane segmentation whose results reveal comparable advancements over state-of-the-art networks for semantic and geometric segmentations. In this paper, they propose to rectify coarse plane segmentations into quads based on their spatial proximity with line segments and demonstrate the use of these rectified quads for overlaying virtual objects on building planes in urban street views.

Non-Iterative Approach for Fast and Accurate Vanishing Point Detection [4], This paper proposed an algorithm that quickly and accurately estimates vanishing points in images of man-made environment which is based on a recently proposed algorithm for the simultaneous estimation of multiple models called J-Linkage. It avoids clustering on the Gaussian sphere and does not require a guess of the number of vanishing points. Based on this algorithm, their approach is fast and accurate. In addition, they gave an approach for determining which of the vanishing points correspond to Manhattan directions. This approach can be future enhanced to estimate vanishing points in images of fish-eyes and catadioptric cameras.

Vanishing point detection with convolutional neural networks [5], In this paper, vanishing point detection was based on convolutional neural networks that does well on road scenes but is not very effective on arbitrary images. To overcome this drawback, they have considered collecting a larger image dataset with variety of scenes including vanishing points and more recent deep learning architectures to improve accuracy. To predict vanishing points in naturalistic environments by training convolutional neural networks in an end-to-end manner by using two popular convolutional neural networks, Alexnet and VGG, for: 1) predicting whether a vanishing point exists in a scene (on a $n \times n$ grid map), and 2) If so, we then attempt to localize its exact location.

NeurVPS: Neural Vanishing Point Scanning via Conic Convolution [6], Detecting vanishing points in images by using an effective end-to-end trainable deep network with geometry inspired convolutional operators. In this paper, they have identified a canonical conic space in which the neural network can effectively compute the global geometric information of vanishing points locally, and they have proposed a geometric operator named conic convolution that can be implemented as regular convolutions in this space by which neural network can find the geometric properties of the vanishing points. This new operator explicitly enforces feature extractions and aggregations along the structural lines. This approach significantly improves the performance of vanishing point detection over traditional methods.

Detecting Vanishing Points using Global Image Context in a Non-Manhattan World [7], A novel vanishing point detection algorithm that obtains state-of-the-art performance on three benchmark datasets which highlights that this method is both fast and accurate. The proposed approach uses global image context to guide precise geometric analysis. It uses a strategy for quickly extracting this context, in the form of constraints on possible horizon lines, using a deep convolutional neural network. It also uses a discrete-continuous method for scoring horizon line candidates. which highlights that our method is both fast and accurate.

Globally Optimal Line Clustering and Vanishing Point Estimation in Manhattan World [8], This paper deals with the fundamental problem of line clustering and orthogonal VP estimation. Given a set of lines extracted from a calibrated image, the goal is to determine the line clustering and estimate the associated orthogonal vanishing points. In this paper they present a mathematical setup that explicitly maximizes the number of clustered lines in a guaranteed globally optimal manner, while inherently enforcing the orthogonality of the VPs. Hence, they formulate a set maximization problem over the rotation search space, and solve it efficiently by combining Interval Analysis theory with a branch-and-bound procedure.

3D Orientation Estimation and Vanishing Point Extraction from Single Panoramas Using Convolutional Neural Network [9], This paper presents a new CNN architecture to estimate the 3D orientation of an omnidirectional camera with respect to the world coordinate system from a single spherical panorama. It proposes an edge extractor layer to utilize the geometric information of panorama, an attention module to fuse different features generated by previous layers. For the panorama with 360 degrees field of view, all of the vanishing points corresponding to three orthogonal directions always appear in a single panorama VOP60K dataset is constructed to estimate the rotation of the omnidirectional camera with respect to the world coordinate system. The input of the network is a panorama, first use several convolution layers to extract the low-level information. Considering the fact that, vanishing points appeared on different locations are interdependent. So, it adopts two blocks based hourglass module to get the global information. The outputs of the network are two probability maps for two vanishing points, each point in probability map denotes the possibility of it being a vanishing point

Combining CNN and MRF for road detection [10], To improve the accuracy and robustness of road detection approaches in complex environments, a new road detection method based on a convolutional neural network (CNN) and Markov random field (MRF) is proposed in this paper. The original road image is segmented into super-pixels of uniform size using the simple linear iterative clustering (SLIC) algorithm. On this basis, we train the convolutional neural network, which can automatically learn the features that are most beneficial to the classification. The trained convolutional neural network (CNN) is then applied to classify road and non- road regions. Finally, based on the relationship between the super-pixel neighborhood, we utilize Markov random field (MRF) to optimize the classification results of the convolutional neural network (CNN).

A Global Approach for the Detection of Vanishing Points and Mutually Orthogonal Vanishing Directions [11], This paper considers the problem of estimating orientation and vanishing points of an intrinsically calibrated camera in a Manhattan world, where the line directions are predominantly orthogonal to each other. The proposed method is validated experimentally on the York Urban Database. This work presents a new method for analytically estimating the optimal (in the least-squares sense) orthogonal vanishing points in a Manhattan world. Specifically, it employs the multiplication matrix to solve the multivariate polynomial system resulting from the optimality conditions of the corresponding constrained least-squares problem and compute all its critical points. Amongst these, the ones that minimize the cost function are the globally optimal estimates of the orthogonal vanishing points. Additionally, it introduces a robust and efficient RANSAC-based line classifier that employs the optimal estimator to generate hypotheses for all three orthogonal points from triplets of line observations.

Efficient Computation of Vanishing Points [12], This paper presents an efficient, completely automated approach for detection of vanishing points from a single view assuming an uncalibrated camera. It proposes an approach for estimation of vanishing points by exploiting the constraints of structured man-made environments, where the majority of lines is aligned with the principal orthogonal directions of the world coordinate frame. It combines efficient image processing techniques used in the line detection and initialization stage with simultaneous grouping and estimation of vanishing directions using expectation maximization (EM) algorithm.

Unstructured Road Vanishing Point Detection Using the Convolutional Neural Network and Heatmap Regression [13], This paper proposes a novel heatmap regression method based on multi-scale supervised learning for unstructured road VP detection. The proposed algorithm firstly adopts a lightweight backbone, i.e., depth wise convolution modified HRNet, to extract hierarchical features of the unstructured road image.

The modified HRNet is firstly utilized as the backbone to extract the image features. Secondly, multiscale heatmap supervised learning is employed to obtain more accurate keypoint (Vanishing Point) estimation. Finally, high precision VP coordinates are obtained using the strategy of coordinate regression. Then, three advanced strategies, i.e., multi-scale supervised learning, heatmap super-resolution, and coordinate regression techniques are utilized to achieve fast and high-precision unstructured road VP detection. The empirical results on Kong's dataset show that the proposed approach enjoys the highest detection accuracy compared with state-of-the-art methods under various conditions in real-time, achieving the highest speed.

Vanishing Point Detection without Any A Priori Information[14], Even though vanishing points in digital images result from parallel lines in the 3D scene, most of the proposed detection algorithms are forced to rely heavily either on additional properties (like orthogonality or coplanarity and equal distance) of the underlying 3D lines, or on knowledge of the camera calibration parameters, in order to avoid spurious responses. In this work, we develop a new detection algorithm that relies on the Helmoltz principle both at the line detection and line grouping stages. This leads to a vanishing point detector with a low false alarms rate and a high precision level, which does not rely on any a priori information on the image or calibration parameters, and does not require any parameter tuning.

Determining Vanishing Points from Perspective Images[15], This paper describes a computationally inexpensive algorithm for the determination of vanishing points once line segments in an image have been determined. The approach is particularly attractive since it has no computationally degenerate cases and the only operations necessary are vector cross products and arc tangents. The need to know the distance to the focal plane is also eliminated thus avoiding tedious calibration procedures.

Road Following Using Vanishing Points [16], We propose an algorithm that uses hypothesized vanishing points to extract the road boundaries. Based on the direction and strength of edges in an area for a hypothesized vanishing point, a performance measure is computed. The vanishing point for the given image, and the corresponding road boundaries is selected by searching for the maxima of the performance measures. The efficiency our approach is demonstrated using several real-world road images.

VPGNet: Vanishing Point Guided Network for Lane and Road Marking Detection and Recognition[17], In this paper, a unified end-to-end trainable multi-task network that handles lane and road marking detection and recognition that is guided by a vanishing point has been proposed where the dataset for those is taken under various weather conditions. The dataset consists of about 20,000 images with 17 manually annotated lane and road markings classes under four different scenarios: no rain, rain, heavy rain, and night. Vanishing point annotation is provided as well. The proposed vanishing point prediction task enables the network to detect lanes that are not explicitly seen.

Block-based Vanishing Line and Vanishing Point Detection for 3D Scene Reconstruction [18], The vanishing line and vanishing point detection can be divided into two kinds. One is the image-based method, and the other is the characteristic-based method. Both have notable amount of disadvantages where the result depends on the on the numbers of iterative training and adjustment, and hence results consume enormous time whereas in the other complicated mathematic calculation approximation steps and includes a lot of work respectively. Hence to overcome these, novel block-based vanishing line and vanishing point was proposed where focus is on the fundamental image structure analysis instead of mathematically sophisticated estimation. This method contains procedures including block object finding, object combination and selection, dominant vanishing lines acquisition and VP detection. Most importantly this paper is about block-based algorithm rather than the pixel-based algorithms and it holds the regular block data flow feature is much faster, simpler and efficient.

Deep Convolutional Neural Fields for Depth Estimation from a Single Image [19], Depth estimation from a single monocular image is a challenging task as no reliable depth cue are available. In this paper deep convolutional neural field model for depth estimations by exploring CNN and continuous CRF has been addressed which is trained by optimizing the well-defined loss function. Given the continuous nature of the depth values, the partition function in the probability density function can be analytically calculated, therefore we can directly solve the log-likelihood optimization without any approximations. This method outperforms state-of-the-art results of depth estimation on both indoor and outdoor scene datasets.

Visualization of Convolutional Neural Networks for Monocular Depth Estimation [20], Visualization of inference of a CNN by identifying relevant pixels of an input image to depth estimation. We formulate it as an optimization problem of identifying the smallest number of image pixels from which the CNN can estimate a depth map with the minimum difference from the estimate from the entire image. Visualization of CNNs is performed for object recognition where an attempt to identify the image pixels that are relevant to depth estimation is performed followed by formulation of the problem of identifying relevant pixels as a problem of sparse optimization particularly estimating an image mask that selects the smallest number of pixels from which the target CNN can provide the maximally similar depth map ,where optimization of backward direction sometimes yields unexpected results, such as noisy visualization. To avoid this issue, an additional CNN to estimate the mask from the input image in the forward computation is used.

Unsupervised CNN for Single View Depth Estimation [21], A unsupervised framework to learn a deep convolutional neural network for single view depth prediction, without requiring a pre-training stage or annotated ground-truth depths is introduced. This is possible by training the network similar to autoencoder. At the training time pair of images source and target is considered with small camera motion between the two. Explicitly there is a generation of an inverse warp of the target image using the predicted depth and known inter-view displacement, to reconstruct the source image.

Deformable Convolutional Networks [22], Convolutional neural networks (CNNs) are limited to model geometric transformations due to the fixed geometric structures. In this work, two new modules to enhance the transformation modeling capability of CNNs are introduced namely, deformable convolution and deformable RoI pooling. In deformable convolution 2D offsets are added to the regular grid sampling locations in the standard convolution. It enables free form deformation of the sampling grid whereas in deformable RoI pooling It adds an offset to each bin position in the regular bin partition of the previous RoI pooling. Both modules are light weight. They add small amount of parameters and computation for the offset learning. They can replace their plain counterparts in deep CNNs and can be easily trained end-to-end with standard back propagation. The resulting CNNs are called deformable convolutional networks.

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II. Summary

This paper presents a survey of depth estimation using vanishing point that has been developed using CNN. Detection of vanishing point is a crucial step in depth estimation which can be done using various ways such as using Alex net [1] which is more effective on blurred pictures, dark scenes, rotating images, by using a single CNN for road scenes [5] and under various weather conditions [17]. Vanishing point can be detected using various networks such as conic convolution network [6], continuous CRF [20], convolutional neural network (CNN) and Markov random field (MRF) [10], deformable convolution and deformable RoI pooling and in an end-to-end paradigm of multiple CNNs architectures [22]. Some of the techniques used for vanishing point detection are line detectors [7], line clustering [8], 3D orientation of omnidirectional camera [9], J-linkage algorithm [4], multiscale heatmap supervised learning [13], least-squares [11], uncalibrated camera [12], Helmholtz principle [14], segmentation of the scene into quads [3], image structure analysis [19], by searching for the maxima of the performance measures.[16], by identifying relevant pixels of an input image [20]. Hence, we can conclude that Vanishing point is the prominent method in estimating the depth with the help of convolutional neural network and works are being done regarding the same in the industry.

Summary Table

S.I. No.	Methods	Pros	Cons	Dataset Used
1	Regression Convolutional Network	Proposed method detects vanishing point by using a new structure of regression neural network based on AlexNet.	1.Extraction of local features is not simple. 2.The training set consists of a lot of images without the vanishing point	The dataset consists of 640 images with a vanishing point.
2	Convolutional Neural Networks	1.Proposed method constructs the VFO330K database containing street and indoor views, annotated vanishing points, focal length, and the orientation of the camera with respect to the 3D coordinate system of the scene. 2.Proposed method also explores CNNs architectures to learn vanishing point estimation in an end-to-end manner.		VFO330K DATABASE
3	Convolutional Neural Networks	The proposed method detects the vanishing point from a single image of street view by using convolutional neural network (CNN) architecture that generates geometric segmentation of per-pixel orientations from a single street-view image and rectify the coarse plane segmentations into quads.	1. Geometry-based approaches relying on geometric primitives are prone to fail for occlusions such as pedestrians and trees. 2. Outdoor scenes typically exhibit much more complex geometry than indoor ones.	Outdoor Street Views
4	J-Linkage	The proposed method is an algorithm that quickly and accurately estimates vanishing points in images of man-made environment which is based on a recently proposed algorithm for the simultaneous estimation of multiple models called J-Linkage.	Resources on devices such as video cameras on cell phones and personal device assistants, applications for single-view reconstruction and pose estimation are limited	York Urban Database
5	Convolutional neural networks	The proposed method predicts vanishing points in naturalistic environments by training convolutional neural networks in an end-to-end	Line clustering and orthogonal VP estimation in modern environments	YouTube videos, MIT saliency benchmark, CAT2000 dataset, Caltech 256, 15 category dataset except the street and highway

		manner by training two popular convolutional neural networks, Alexnet and VGG.		categories, MS COCO and ImageNet.
6	Conic Convolutional Network	Detecting vanishing points in images using a geometric operator named conic convolution by which neural network can find the geometric properties of the vanishing points.	Need of large amount of training data	Natural Scene, Scan Net, SU3 Wireframe
7	Method proposed is a set of horizon line candidates and score each based on the vanishing points it contains.	The proposed method detects horizontal vanishing points and the zenith vanishing point in man-made environments by using a set of horizon line candidates and score each based on the vanishing points it contains.	Formulations significantly increase robustness to noise	Eurasian Cities Dataset and the York Urban Dataset
8	Method proposed is to formulate the task as a consensus set maximization problem over the rotation search space, and further solve it efficiently by a branch-and-bound procedure based on the Interval Analysis theory.	The proposed method finds the line clustering and the associated VPs leading to the globally optimal largest number of clustered lines.	Line clustering and orthogonal VP estimation in modern environments.	Synthetic dataset for synthesized data and York urban database for real images
9	Convolutional Neural Network	The proposed method presents a new CNN architecture to estimate the 3D orientation of an omnidirectional camera with respect to the world coordinate system from a single spherical panorama.		VOP60K dataset with labeled 3D orientation including 50 thousand panoramas for training and 10 thousand panoramas for testing
10	Convolutional Neural Network and Markov Random Field	Presents a new road detection method based on a convolutional neural network (CNN) and Markov random field (MRF). We utilize Markov random field to optimize the classification results of the CNN. The approach provides the better performance.	The proposed algorithm used an open database containing road images with shadows and light, curves, and obstacles; however, there are no road images taken at night, or under rain, snow, or other harsh weather conditions.	CamVid containing 701 road images and their corresponding ground truth (GT) images. The original image size is 960 ×720, and the GT image resolution is 320 ×240.
11	Message Passing Inference	The proposed method outperforms the state-of the-art methods keeping the computation tractable. In addition, we show for the first-time results in simultaneously detecting multiple Manhattan-world configurations that can either share one vanishing direction (Atlanta world) or be completely independent.	Additional VDs that might exist are passed undetected, and the methods cannot handle images with more than one set of Manhattan-world directions for which multi-model fitting is again required	York Urban Database with images pf size 640*480
12	Expectation Maximization	Describes a completely automated process of detecting the vanishing points in the image. The estimated vanishing points can	An assumption that the camera is not calibrated and about structure of manmade environment is made.	Images from uncalibrated camera of 400 * 300 image size

		be used for partial camera calibration yielding more flexible overall system.		
13	Convolutional Neural Network and Heatmap Regression	Proposes a novel heatmap regression method based on multi-scale supervised learning for unstructured road VP detection. It has highest detection accuracy under various conditions in real-time, achieving the highest speed.	Work is still being done to be extended to multiple panoramas	Kong's dataset (containing 1003 images) and Moghadam's dataset (500 images).
14	Vanishing Point Detection without Any A Priori Information	Develops a new detection algorithm that relies on the Helmoltz principle recently proposed for computer vision, both at the line detection and line grouping stages. This leads to a vanishing point detector with a low false alarms rate and a high precision level, which does not rely on any a priori information on the image or calibration parameters, and does not require any parameter tuning.	It is quite difficult to build an experimental setup which allows to fairly compare our method with previously proposed ones.	
15	Determining Vanishing Points from Perspective Images	The algorithm has been tested on real images in which strong sets of parallel lines converge to a vanishing point and correct vanishing points and their associated segments have been extracted.	The speed of the cross-product method is directly proportional to the number of paired lines segments whose projections must be intersected as great circles. This contrasts with Barnard's method which varies in direct proportion with the product of the number of line segments and the fineness of the great circle parameterization of each line.	
16	Road Following Using Vanishing Points	Uses hypothesized vanishing points to extract the road boundaries. The efficacy of our approach is demonstrated using several real-world road images.	We plan to explore this using longer sequences of known roads.	Real-world road image sequences on VAX 11-780 w
17	Vanishing point guided network	Shows robustness under different weather conditions with real-time performance with respect to road and lane detection	The stop line class of the road marking cannot be deducted as they have horizontal edges which are not closely related to VPP	Dataset consist of 20,000 images and 17 annotated points
18	Block based estimation algorithm	The proposed method is feasible for a particular image sequence without prior temporal information and guarantees that dominant vanishing lines are detected correctly with high probability and accuracy		Outdoor images

19	Convolutional neural network	The log-likelihood optimization in this method can be directly solved using back propagation without any approximations required	Deep CNN has been less explored for structured learning problems, i.e., joint training of a deep CNN and a graphical model	Indoor and outdoor scene dataset
20	Convolutional neural network	The optimization problem of selecting the smallest number of pixels from which the CNN can estimate a depth map with the minimum difference to that it estimates from the entire image	Distant scene points tend to yield large errors because of the loss evaluating the difference in absolute depths; then such distant scene regions will be given more weights than others	NYUv2 and KITTI Dataset
21	Convolutional neural network	No need for vast amount of manually annotated training data		NYUv2 and KITTI Dataset
22	Deformable convolution and deformable ROI pooling	CNNs are inherently limited to model geometric transformations due to the fixed geometric structures. Hence 2 new modules are introduced to enhance the transformation modeling capability of CNNs, namely, deformable convolution and deformable RoI pooling	Geometric transformations are assumed fixed and known and prior knowledge is used to augment the data, and design the features and algorithms. This assumption prevents generalization to new tasks possessing unknown geometric transformations	

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