



FakeVP



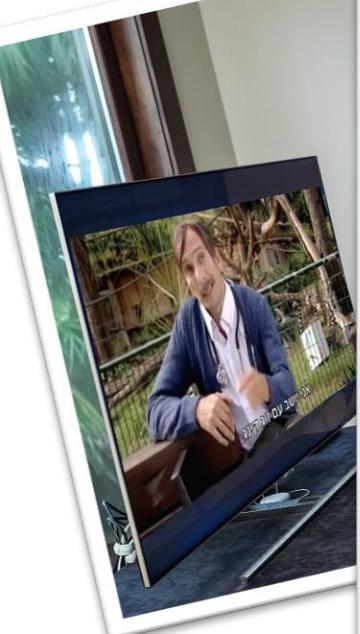
Jonathan Mey-Tal

Itay Katav

Shahar Azoulai



The Problem: Fake Photos



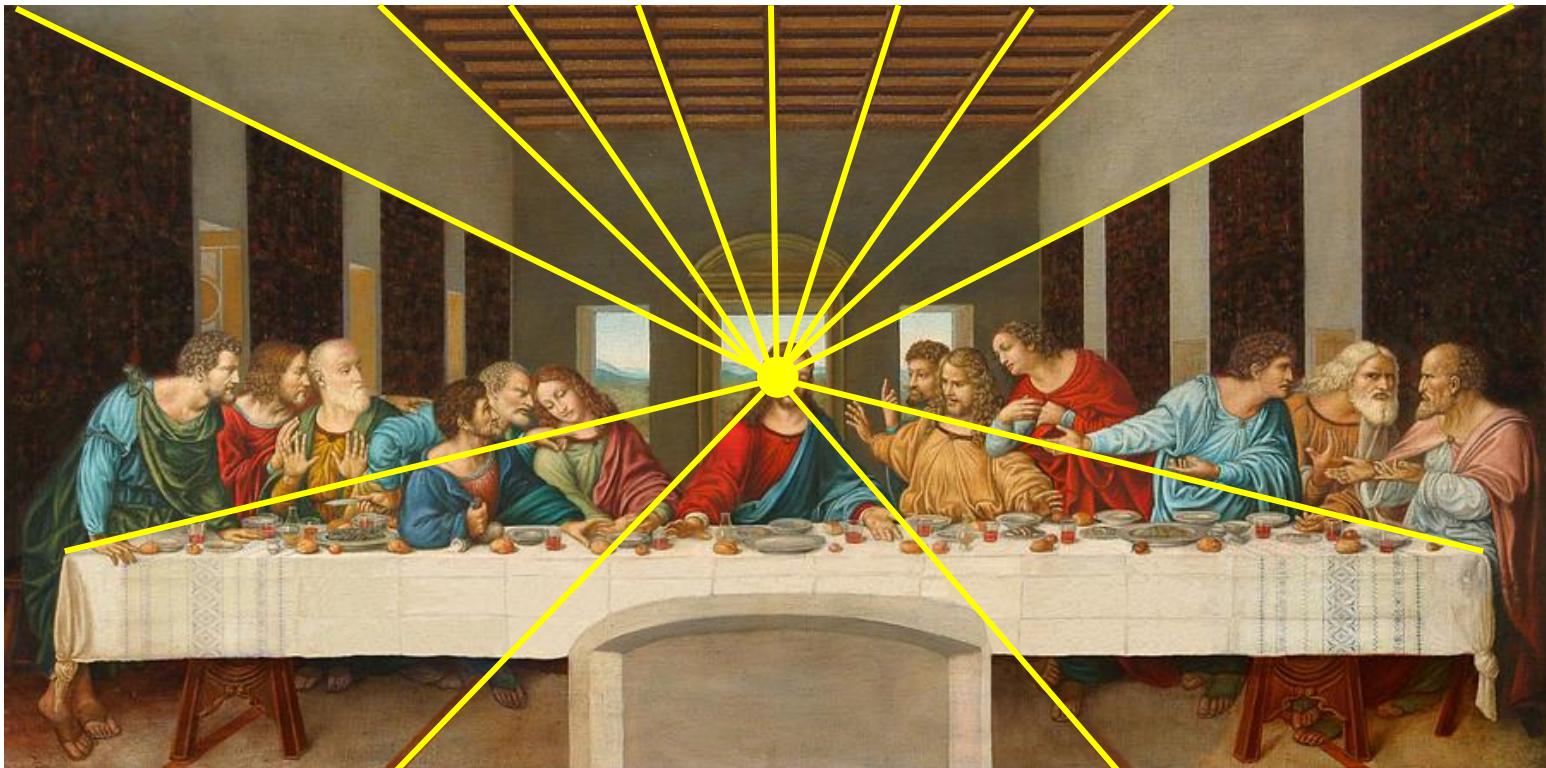


Vanishing Points | What is it?



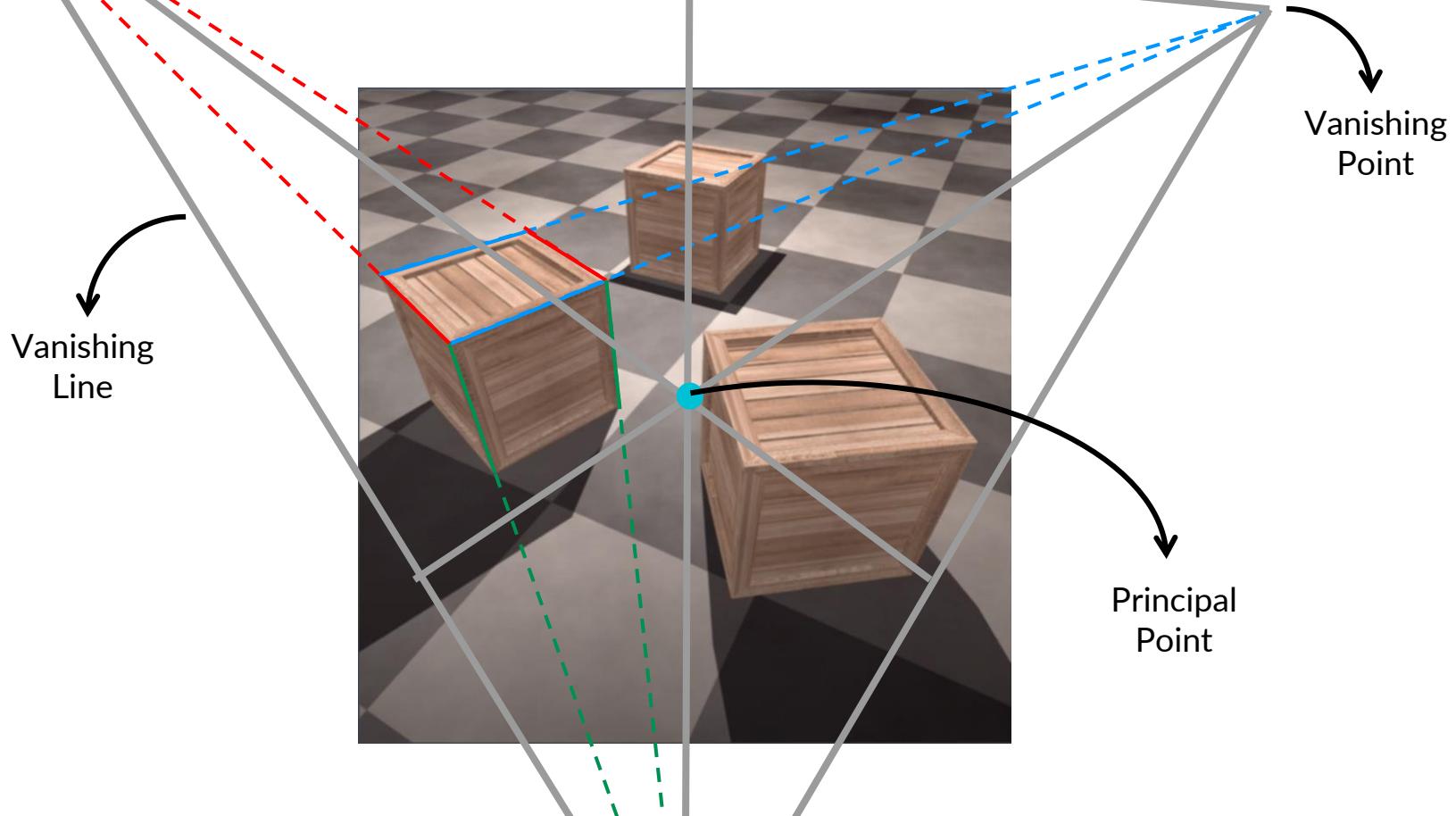


Vanishing Points to create depth





Vanishing Points to find the principal point





Fake Photos Detection Using Principal Point





So What's the Plan

- Calculate the Principal point
 - Finding straight lines
 - Classify the lines
 - Choose three pairs of parallel lines
 - Extending each line to find the Vanishing points
- Do the same thing for the suspected object
- Compare the two Principal points





So What's the Plan

- Calculate the Principal point.
 - **Finding straight lines**
 - Classify the lines
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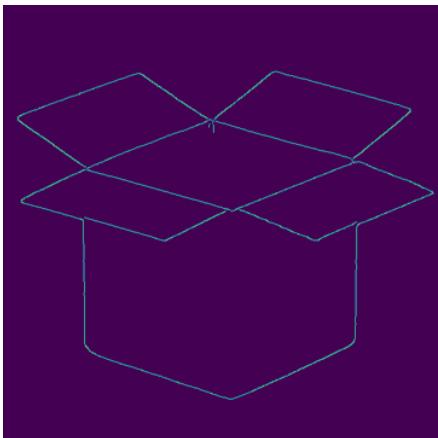




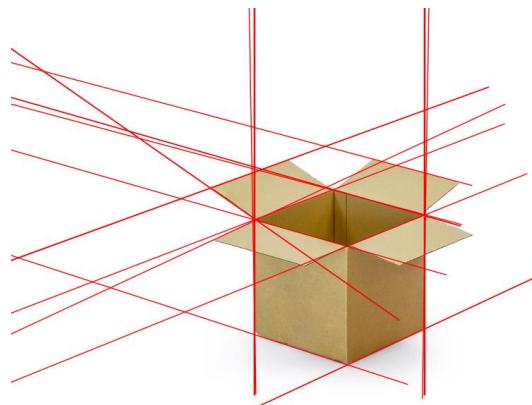
Detecting Straight Lines

- Gaussian Smoothing + Canny + Hough Transform

Canny Output



Hough Transform



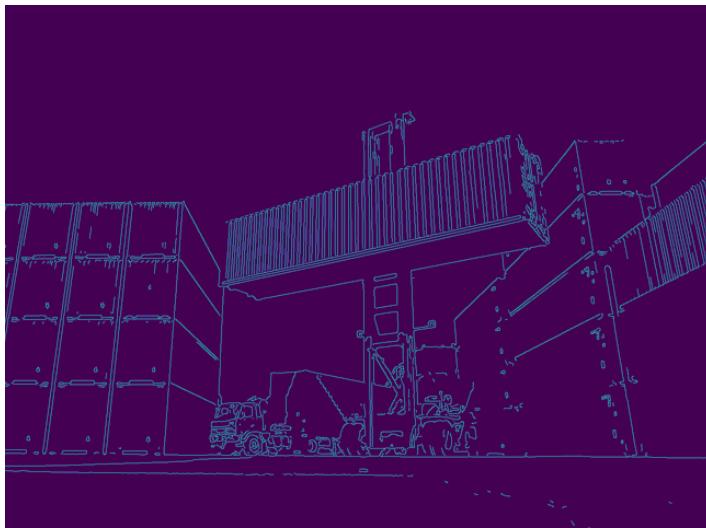
Post Processing





Detecting Straight Lines

- Gaussian Smoothing + Canny + Hough Transform





Detecting Straight Lines

- LSD (Line Segment Detector)





So What's the Plan

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Line Classification

**First, we looked for papers and works in
the area of vanishing points detection**





A new approach to vanishing point detection in architectural environments

Carsten Rother

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Received 10 June 2001; received in revised form 6 February 2002; accepted 14 March 2002

Abstract

A man-made environment is characterized by many parallel lines and orthogonal edges. In this article, a new method for detecting the three mutually orthogonal directions of such an environment is presented. Since real-time performance is not necessary for architectural applications, such as building reconstruction, a computationally intensive approach was chosen. However, this enables us to avoid one fundamental error of most other existing techniques. Compared to theirs, our approach is furthermore more rigorous, since all conditions given by three mutually orthogonal directions are identified and utilized. We assume a partly calibrated camera with unknown focal length and unknown principal point. By examining these camera parameters, which can be determined from orthogonal directions, falsely detected vanishing points may be rejected. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Vanishing points; Vanishing lines; Geometric constraints; Architecture; Camera calibration

1. Introduction

The analysis of vanishing points provides strong cues for inferring information about the 3D structure of a scene. With the assumption of perfect projection, e.g. with a pin-hole camera, a set of parallel lines in the scene is projected

detecting the three mutually orthogonal directions of a man-made environment has raised considerable interest [6,8,16]. After a discussion of existing vanishing point detection methods in Section 2, our method is presented in Section 4 demonstrates the real im-



Vanishing Point Detection with OpenCV, Python & C++



Kedia Rahul · [Follow](#)

2 min read · Jun 7, 2021

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... in the scene is projected

existing vanishing point detection
Section 2, our method is presented
real images.

Computer Vision Methods Applied to Forensic Science

Fernanda A. Andaló, and Siome Goldenstein
Institute of Computing, University of Campinas – UNICAMP

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Abstract—Crimes in our society, increasing in volume and sophistication, have determined the need for knowledge and use of scientific methods to their prevention and investigation. This work presents three Computer Vision methods that can be applied in forensic investigations. In the first method, a new vanishing point detector facilitates the process of making measurements in a single 2D image, and is used to estimate the height of a person in an image, important measurement to corroborate pieces of evidence. In the second method, multiview stereo techniques are used to obtain a three-dimensional model from photographs taken from a footwear impression, evidence commonly found in crime scenes. In the third method, the need for reconstructing shredded images is explored. A photograph can be shredded in order to hide information and it is up to the field of Computer Forensics its automatic reconstruction. Experimental results are provided, showing the effectiveness of the proposed methods when compared to relevant work in the literature.

Keywords—vanishing point; footwear impression; image puzzle; computer forensics; computer vision;

1. INTRODUCTION

Forensic Science is the application of knowledge from several branches of science to answer questions relevant to a legal system. Due to the evolution of criminal activities, more specialized disciplines have been involved, such as Computer Science, Engineering and Economics.

The research field that unites the fields of Forensic Science and Computer Science is called *Computer Forensics* and encompasses the study of research methods, driven by hypothesis, of a specific problem, through the use of computers and computational methods [1].

However, this research area, although promising, requires joint efforts from several disciplines and collaborations are essential. Computer Vision and Forensic Science [2], for example, are two fields that have been combined to solve crimes [3, 4].

methods that can assist traditional Forensic Science procedures. The methods are associated with three main forensic topics:

- Photogrammetry: When photographing a certain region of space, the three-dimensional (3D) points are projected to points in the two-dimensional (2D) image, which causes the loss of depth information. Rests with Photogrammetry the study and the proposition of methods to recover such information, allowing geometric measurements in the image plane.
- 3D reconstruction of impressions: Experts in different localities must collaborate to answer questions pertinent to an investigation and thus they need to share existing physical pieces of evidence. Such collaboration requires the transport of such pieces between several locations. This is an expensive process and fragile pieces can be damaged. It is up to this area of study to propose methods for scanning these pieces of evidence or new methodologies for capturing the 3D shapes directly at the crime scene.
- Reconstruction of fragmented documents and images: It is very common in forensic investigations that examiners depend on the quality of preservation of a document or image, for handwriting analysis or content identification. In some cases, however, these documents and images could have been damaged, torn or obliterated. The reconstruction process when they have been torn, for example, can be done manually, which suggests a tedious and time consuming work. It is up to this area of study to propose methods for the automatic reconstruction of such fragmented documents or images, improving the reconstruction accuracy and efficiency when compared to a manual process.

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on the clustering of line segments in the image plane, which obviates the need for *a priori* camera calibration.

Our method for vanishing point detection is divided in three steps:

- 1) Extraction of line segments on the image plane.
- 2) Clustering of line segments converging to the same vanishing point (repeated until convergence):
 - 2.1. Selection of seeds.
 - 2.2. Grouping of segments based on the seeds and on the distance among intersection points and their corresponding lines on the projective space.
- 3) Detection of a vanishing point to each final cluster.

Fig. 1 illustrates the three steps to estimate the vanishing points, numerated as shown above.

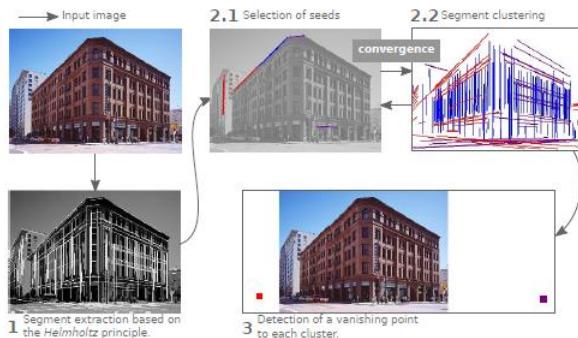


Fig. 1. Steps of the proposed vanishing point detector.

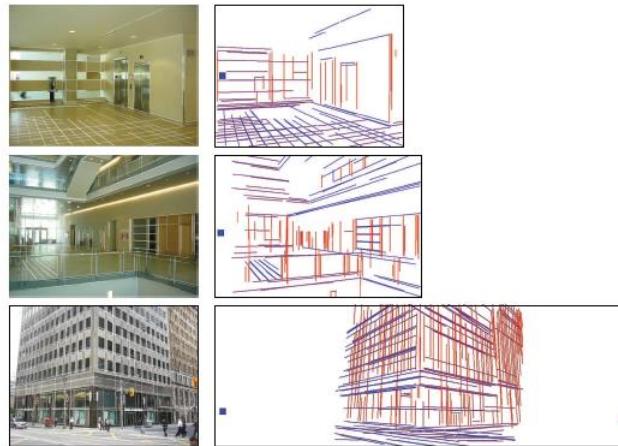


Fig. 2. The first column shows the input image and all detected segments. The second column shows the line clustering result and the detected finite vanishing points. Parallel lines with the same color are associated with a vanishing point at infinity; the other lines are associated with finite vanishing points.

For validation purposes, we compared the obtained results to those of other relevant methods [12], [13], [14]. The first experiment consisted in computing the *orthogonality error* of the detected vanishing points: how much the more orthogonal vanishing points deviate from the real orthogonality on the image plane. The second experiment consisted in computing the *focal length error*: how much the focal length computed from the more orthogonal vanishing points deviates from the

on the clustering
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Our method follows
steps:

- 1) Extraction
- 2) Clustering
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- 2.2. Grouping
the detected
correspondences
- 3) Detection

Fig. 1 illustrates
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Fig. 1. S

Detecting the vanishing point in one-point perspective images using Computer Vision algorithms



Kuoyuan Li · Follow
8 min read · Dec 27, 2021

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An image or photograph is called one-point perspective when it contains one and only one vanishing point. All parallel lines extending into the distance would converge to this vanishing point. This type of perspective is very easy to be found in images of roads, railway tracks or buildings.



shows the input image and all detected segments. vs the line clustering result and the detected finite lines with the same color are associated with a v; the other lines are associated with finite vanishing

poses, we compared the obtained results with relevant methods [12], [13], [14]. The first experiment consisted in computing the *orthogonality error* of the detected vanishing points: how much the more orthogonal they deviate from the real orthogonality on the image. The second experiment consisted in computing the *length error*: how much the focal length computed for the detected orthogonal vanishing points deviates from the real focal length. Such a process is presented in [16, 8, 16].

CONSAC: Robust Multi-Model Fitting by Conditional Sample Consensus

Florian Kluger¹, Eric Brachmann², Hanno Ackermann¹, Carsten Rother², Michael Ying Yang³, Bodo Rosenhahn¹
¹Leibniz University Hannover, ²Heidelberg University, ³University of Twente

Abstract

We present a robust estimator for fitting multiple parametric models of the same form to noisy measurements. Applications include finding multiple vanishing points in man-made scenes, fitting planes to architectural imagery, or estimating multiple rigid motions within the same sequence. In contrast to previous works, which resorted to hand-crafted search strategies for multiple model detection, we learn the search strategy from data. A neural network conditioned on previously detected models guides a RANSAC estimator to different subsets of all measurements, thereby finding model instances one after another. We train our method supervised as well as self-supervised. For supervised training of the search strategy, we contribute a new dataset for vanishing point estimation. Leveraging this dataset, the proposed algorithm is superior with respect to other robust estimators as well as to designated vanishing point estimation algorithms. For self-supervised learning of the search, we evaluate the proposed algorithm on multi-homography estimation and demonstrate an accuracy that is superior to state-of-the-art methods.

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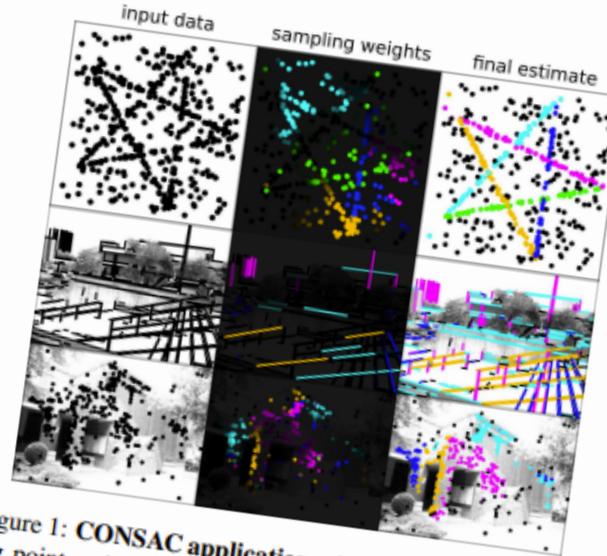
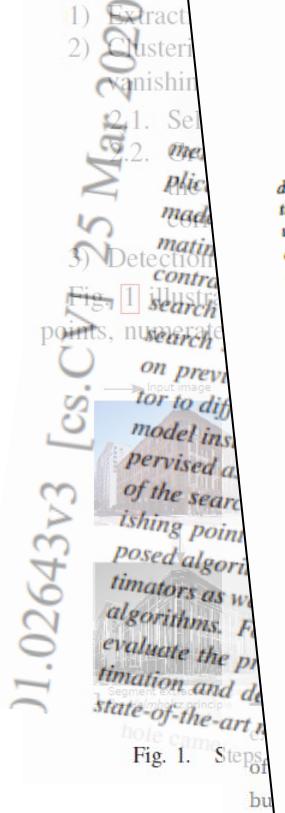


Figure 1: **CONSAC applications:** line fitting (top), vanishing point estimation (middle) and homography estimation (bottom) for multiple instances. Colour hues in column two and three indicate different instances, brightness in column two varies by sampling weight.



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Finding Vanishing Points via Point Alignments in Image Primal and Dual Domains

José Lezama*,†, Rafael Grompone von Gioi*, Gregory Randall†, Jean-Michel Morel*

*CMLA, ENS Cachan, France, †IIE, Universidad de la República, Uruguay
{lezama, grompone, morel}@cmla.ens-cachan.fr, randall@fing.edu.uy

Abstract

We present a novel method for automatic vanishing point detection based on primal and dual point alignment detection. The very same point alignment detection algorithm is used twice: First in the image domain to group line segment endpoints into more precise lines. Second, it is used in the dual domain where converging lines become aligned points. The use of the recently introduced PClines dual spaces and a robust point alignment detector leads to a very accurate algorithm. Experimental results on two public standard datasets show that our method significantly advances the state-of-the-art in the Manhattan world scenario, while producing state-of-the-art performances in non-Manhattan scenes.

1. Introduction

Under the pinhole camera model, 3D lines are transformed into 2D lines. Moreover, parallel lines in 3D are projected into lines that converge on a point (perhaps at infinity) known as a *vanishing point* (VP). In the presence of parallel lines, as is common in human-made environments, VPs provide crucial information about the 3D structure of the scene and have applications in camera calibration, single-view 3D scene reconstruction, autonomous navigation, and semantic scene parsing, to mention a few.

There is a vast literature on the problem of VP detection, starting with the seminal work by Barnard [5] and leading to high-precision algorithms in recent works [20, 21]. Typically, a method starts by the identification of oriented elements, which are then clustered into groups of concurrent lines, and finally refined to get the corresponding vanishing points. The main challenge is to treat segments as ori-

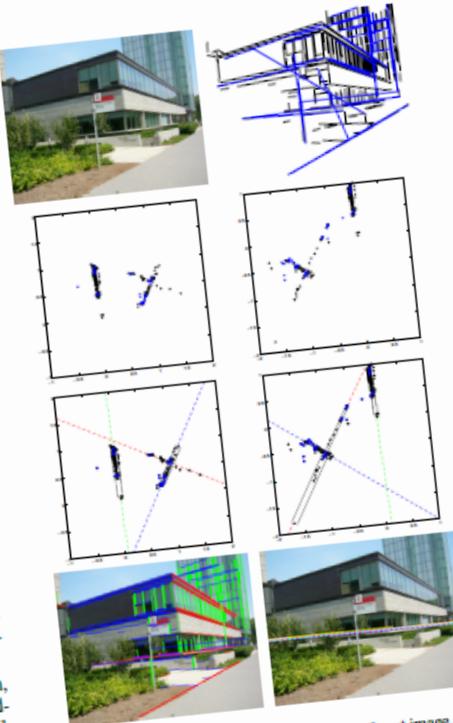


Figure 1. Main steps of our method. Top Left: Input image. Top Right: Line segments (black) and alignments of line segments (blue). 2nd Row: Lines as points in straight (left) and twisted (right) PClines spaces. 3rd Row: Aligned points detections (red) and the ground truth (dashed lines). Some points are colored according to their alignment quality.

Multiple Consensus

ng³, Bodo Rosenhahn¹

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Non-Iterative Approach for Fast and Accurate Vanishing Point Detection

Jean-Philippe Tardif

McGill University, Montréal, QC, Canada

tardifj@cim.mcgill.ca

Abstract

We present an algorithm that quickly and accurately estimates vanishing points in images of man-made environments. Contrary to previously proposed solutions, ours is neither iterative nor relies on voting in the space of vanishing points. Our formulation is based on a recently proposed algorithm for the simultaneous estimation of multiple models called J-Linkage. Our method avoids representing edges on the Gaussian sphere and the computations and error measures are done in the image. We show that a consistency measure between a vanishing point and an edge of the image can be computed in closed-form while being geometrically meaningful. Finally, given a set of estimated vanishing points, we show how this consistency measure can be used to identify the three vanishing points corresponding to the Manhattan directions. We compare our algorithm with other approaches on the York Urban Database and show significant performance improvements.

Vanishing point estimation is a key component of many computer vision systems. Under the perspective projection, parallel lines in the scene are projected into 2D lines forming a grid. The intersection of these lines is the vanishing point (VP). There are several methods to estimate VP, ranging from simple heuristics to complex iterative optimization algorithms. For self-supervised learning, VP detection is often used to evaluate the proposed methods. In this paper, we propose a non-iterative approach for VP detection that is fast and accurate. The proposed algorithm is based on J-Linkage, a clustering algorithm that can handle multiple clusters simultaneously. It uses a geometric consistency measure between edges and vanishing points to identify the three VP corresponding to the Manhattan directions. The proposed algorithm is evaluated on the York Urban Database and shows significant performance improvements compared to other state-of-the-art methods.

Fig. 1. Steps of the proposed approach for vanishing point detection. The process starts by detecting edges in the image, then estimating vanishing points using the proposed algorithm, and finally identifying the three vanishing points corresponding to the Manhattan directions.

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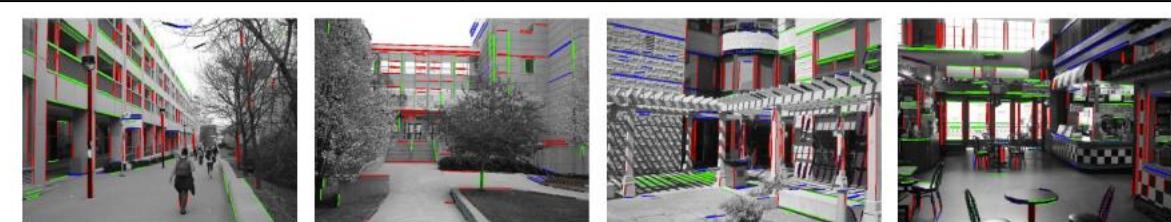
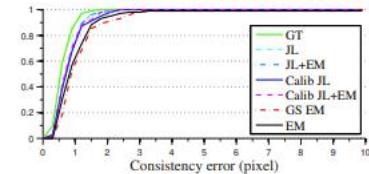
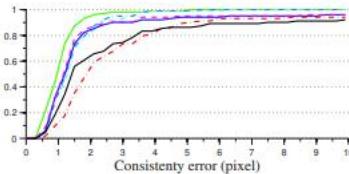


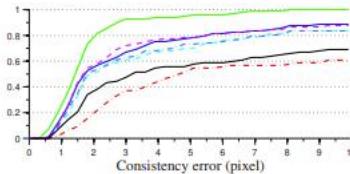
Figure 6. Results given by our algorithm on four images of the York Urban Database [11].



(a) $S_{i,1}$

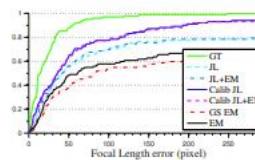


(b) $S_{i,2}$

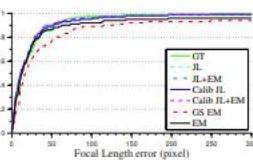


(c) $S_{i,3}$

Figure 7. Cumulative histograms of the error for three groups of ground truth edges (See text for details). The vanishing points were estimated using edges automatically detected.



(a) Edges automatically detected



(b) Ground truth edges

Figure 8. Cumulative histograms of the error on the focal length for the tested algorithms.

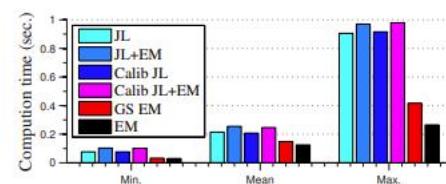


Figure 9. Computation time of the tested algorithms.

VPDETR: End-to-End Vanishing Point DEtection TRAnsformers

National Key Laboratory of General Artificial Intelligence, School of Intelligence Science and Technology, Peking University
chenty@stu.pku.edu.cn, xhying@pku.edu.cn

Abstract

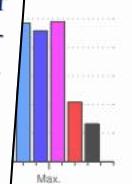
In the field of vanishing point detection, previous works commonly relied on extracting and clustering straight lines or classifying candidate points as vanishing points. This paper proposes a novel end-to-end framework, called VPDETR (Vanishing Point DEtection TRansformer), that views vanishing point detection as a set prediction problem, applicable to both Manhattan and non-Manhattan world datasets. By using the positional embedding of anchor points as queries in Transformer decoders and dynamically updating them layer by layer, our method is able to directly input images and output their vanishing points without the need for explicit straight line extraction and candidate points sampling. Additionally, we introduce an orthogonal loss and a cross-prediction loss to improve accuracy on the Manhattan world datasets. Experimental results demonstrate that VPDETR achieves competitive performance compared to state-of-the-art methods, without requiring post-processing.

et al. 2022; Lin et al. 2022) have shown great potential in this task. Some of the most recent state-of-the-art works suffer from some problems. NeurVPS (Zhou et al. 2019a) and Lin et al. (Lin et al. 2022) need to sample a large number of candidate points in the Gaussian sphere and classify whether they are vanishing points which is slow during inference. TLC (Tong et al. 2022) uses Transformer to classify straight lines into four categories, requiring additional line category annotations. Post-processing is also required to enhance performance. Although these works are capable of end-to-end training, they still require additional post-processing steps to produce the vanishing point as the final output. In other words, they are not entirely end-to-end because the vanishing point is not directly predicted when an image is inputted.

DETR (Carion et al. 2020) is a highly influential work in the field of object detection. It uses a transformer encoder-decoder architecture for end-to-end object detection. In



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(b) Ground truth edges

(b) Ground truth edges

(B) Ground truth edges
endpoints (blue). 2nd Row: Lines as per
3rd Row: Aligned points

the error on the focal length

the error on the focal length, σ_{focal} , and the truth (dashed) are shown.

2-Line Exhaustive Searching for Real-Time Vanishing Point Estimation in Manhattan World

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[†]EMail: jian.yao@whu.edu.cn Web: <http://cvrs.whu.edu.cn>

Xiaofeng Zhang

Institute for Photogrammetry, University of Stuttgart, Stuttgart, Germany

We propose a new method for estimating vanishing points in images. It does not require any prior knowledge about the scene, neither does it need to detect edges or corners. The proposed method is based on a 2-line model, which is more robust than the multi-line model.

Abstract

This paper presents a very simple and efficient algorithm to estimate 1, 2 or 3 orthogonal vanishing point(s) on a calibrated image in Manhattan world. Unlike the traditional methods which apply 1, 3, 4, or 6 line(s) to generate vanishing point hypotheses, we propose to use 2 lines to get the first vanishing point v_1 , then uniformly take sample of the second vanishing point v_2 on the great circle of v_1 on the equivalent sphere, and finally calculate the third vanishing point v_3 by the cross-product of v_1 and v_2 . There are three advantages of the proposed method over traditional multi-line method. First, the 2-line model is much more robust and reliable than the multi-line method, which can be applied in the scene with 1, 2 or 3 orthogonal vanishing point(s). Second, the probability of the 2-line model being formed of inner line segments can be calculated given the outlier ratio, which means that the number of iterations can be determined, and thus the estimation of vanishing points

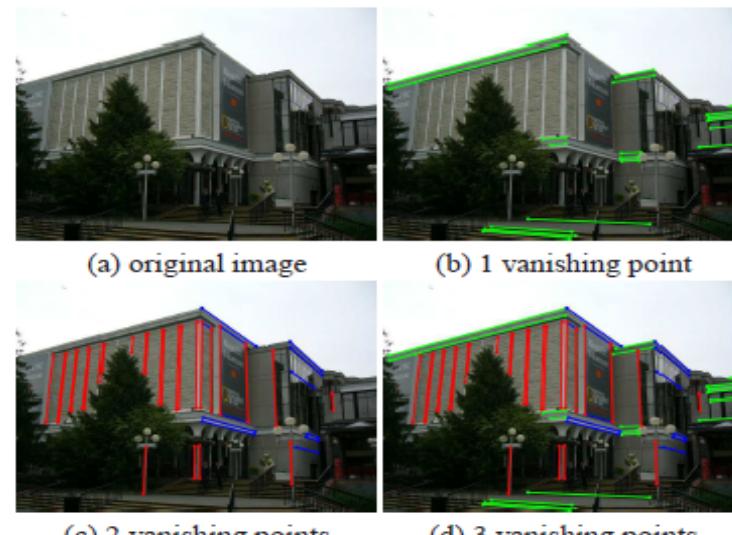


Figure 1. An illustration of vanishing point estimation results of the proposed method in the cases of 1 vanishing point (b), 2 vanishing points (c), and 3 vanishing points (d).



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Line Classification Algorithm

What do they do?





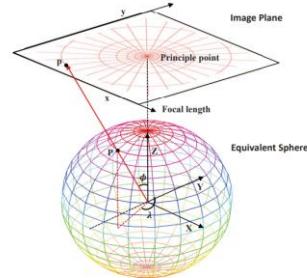
Line Classification Algorithm

How they did it

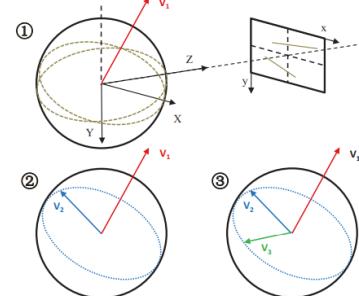
Get the straight lines



Polar grid building



Find the points



Classify the lines





So What's the Plan

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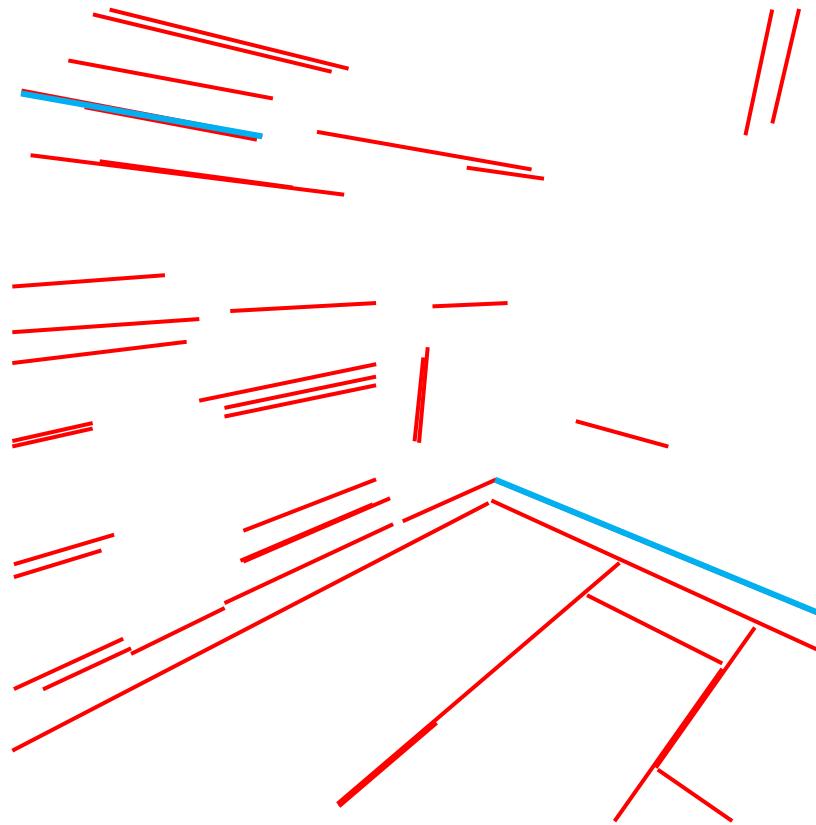
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Filtering and Choosing the Best Lines





Filtering and Choosing the Best Lines





Filtering and Choosing the Best Lines



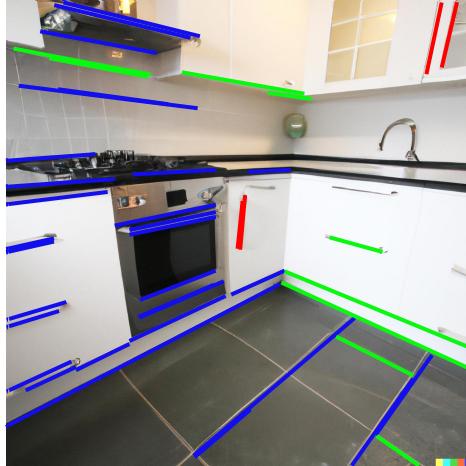


Filtering and Choosing the Best Lines



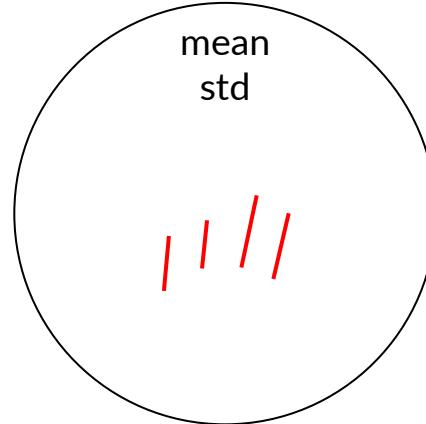
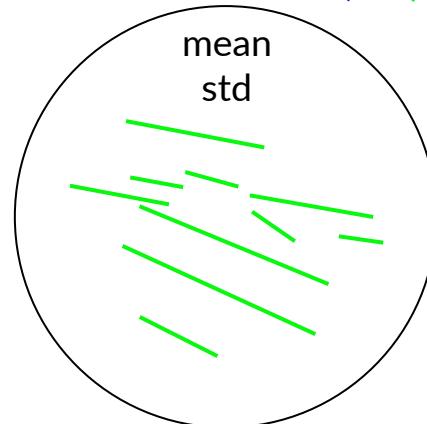
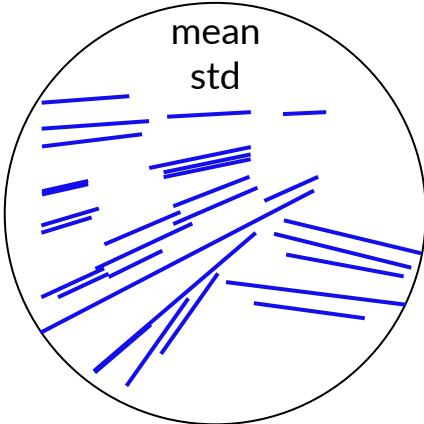


Filtering and Choosing the Best Lines



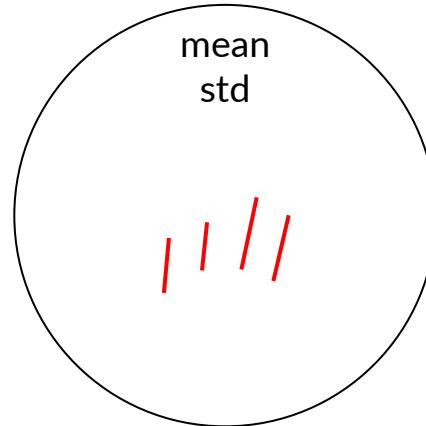
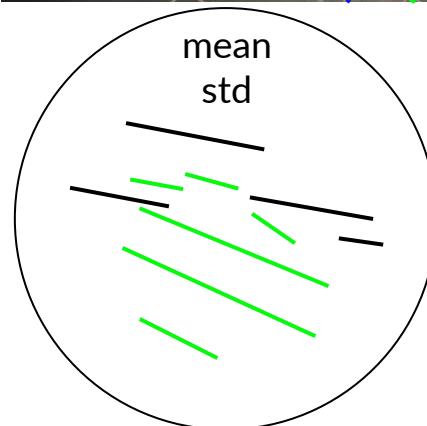
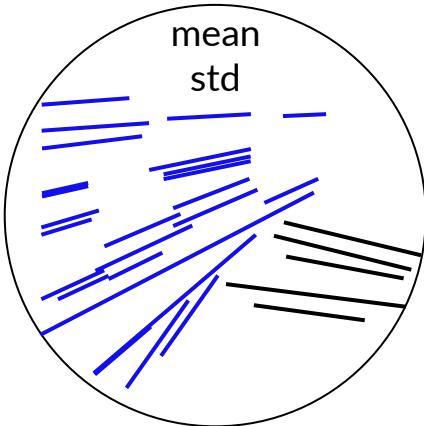


Filtering and Choosing the Best Lines



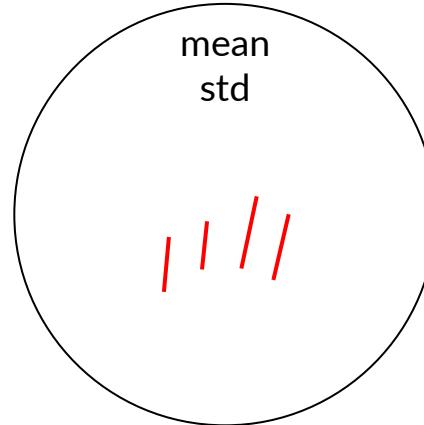
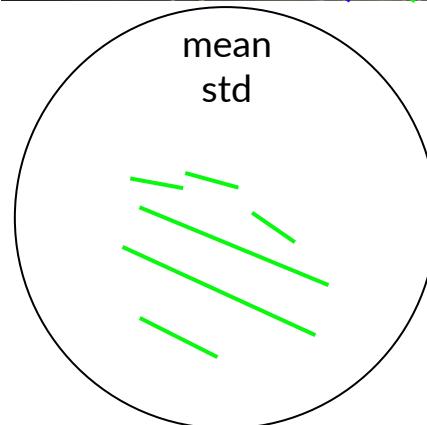
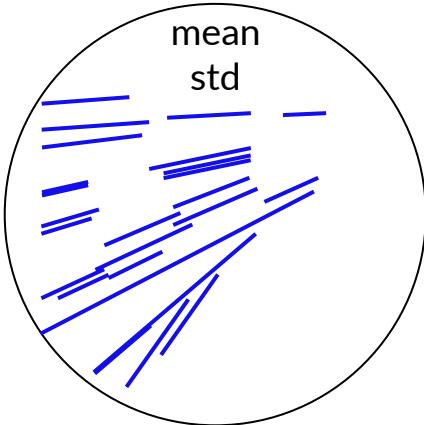


Filtering and Choosing the Best Lines





Filtering and Choosing the Best Lines



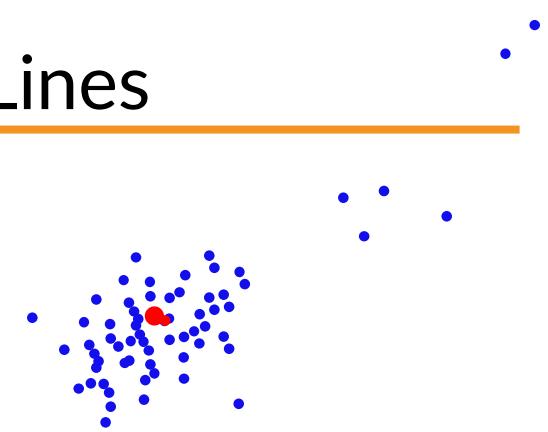
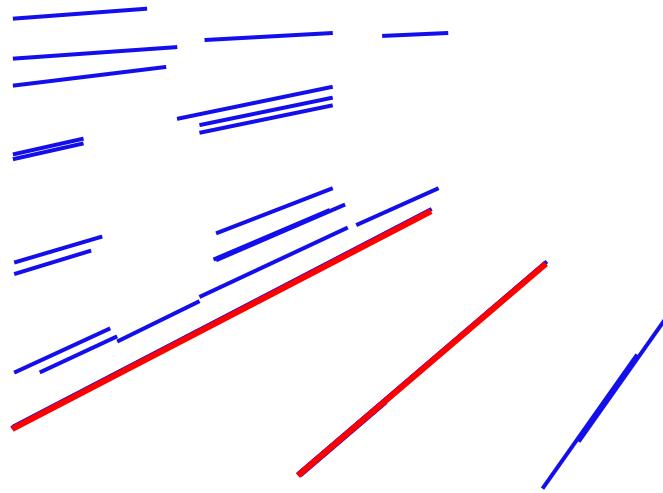


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So What's the Plan

- Calculate the Principal point
 - Finding straight lines
 - Classify the lines
 - Choose three pairs of parallel lines
 - Extending each line to find the Vanishing points
- Do the same thing for the suspected object
- Compare the two Principal points





Simulation



Simulation

Input

```
.imshow(vpd_all.create_debug_VP_image())
.show()
Figure 1
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w out
vanishing_data(pil_img, vanishing_data_out, cluster_lines_object)
```

Zoom & Selection

```
.imshow(vpd_all.create_debug_VP_image())
.show()
Figure 1
cualt
_in =
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hing_
w out
vanishing_data(pil_img, vanishing_data_out, cluster_lines_object)
```



Simulation

Image PP

```
_all.find_vps(input_path)
.imshow(vpd_all.create_debug_VP_image())
.show()
Figure 1
... (code for vp_all, vpd_all, show, Figure 1)

Figure 1 shows a photograph of a shipping container yard. A red dashed line indicates a vanishing point for the perspective. A blue dashed line represents a cluster boundary. A green dashed line shows a cluster line. A blue dot marks a specific point on the red dashed line.


```

Container PP

```
vp_all.find_vps(input_path)
.imshow(vpd_all.create_debug_VP_image())
.show()
Figure 1
... (code for vp_all, vpd_all, show, Figure 1)

Figure 1 shows a photograph of a shipping container yard with a red container being moved by a crane. A red dashed line indicates a vanishing point. A blue dashed line represents a cluster boundary. A green dashed line shows a cluster line. A blue dot marks a specific point on the red dashed line.


```




Simulation



Image PP

VPDetection(length_thresh principal_point_all focal_length_all seed)

Figure 1

```
def VPDetection(length_thresh, principal_point_all, focal_length_all, seed):
    # Implementation details
    pass

    lines_object = line.filter_to_knnim(cluster_lines_object)
```

Fake object PP

VPD
ind_

Figure 1

```
lines_object = [[Line(*line) for line in cluster] for cluster in cluster_out]
```



Questions?