FakeVP

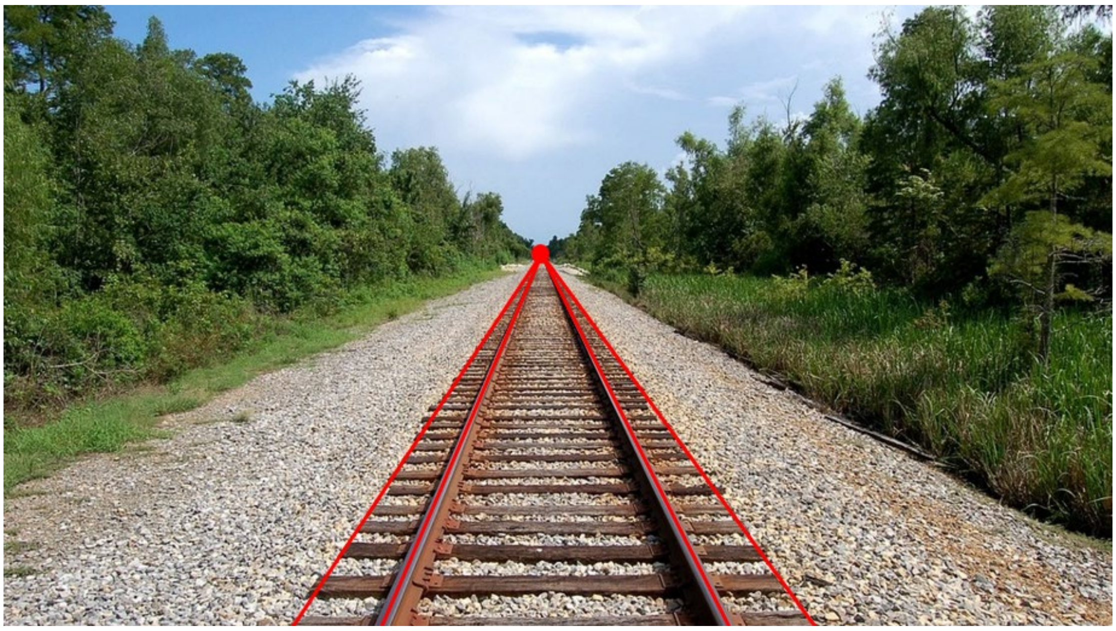
Manipulated Photos Detector Using Vanishing Points

Introduction:

Manipulations on photos is something that exists since the very beginning of photography. With the development of technology, both the methods for manipulation and the methods for detecting them photos have evolved a lot. Today, with the entrance of deep learning and generative models to our lives, the creation of fake photos have become much better and easier in a way that makes it hard to detect, especially in large scales. We chose to focus on a specific method that makes use of vanishing points for the detecting the principal point of the image which is unique.

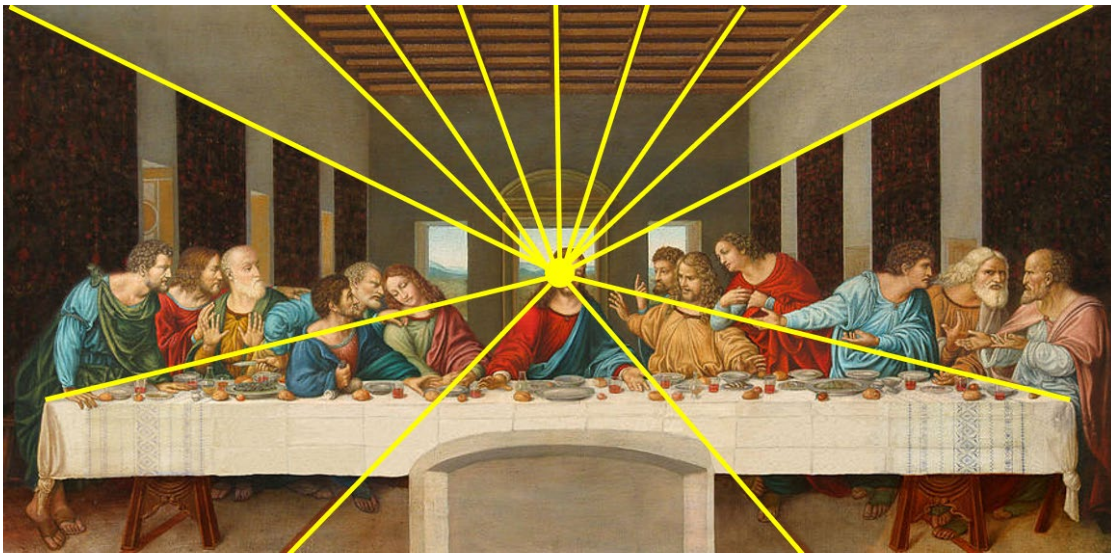
What are vanishing points and the principal point?

If we are looking on two lines that are parallel in the real world, in the 2D image plane they will look like they are crossing a single point. A verry common example is railroad tracks as can be seen in the picture bellow.



The reason why this phenomenon happens is because the perspective projection of straight lines in three-dimensional space (the real world) onto the two-dimensional image plane keeps the lines straight. In addition, more distant objects appear smaller, and the combination creates an effect of lines that get closer and closer towards the horizon.

This idea is known for very long time and is used for centuries by artists that wanted to create depth in their masterpieces. For example, in his famous painting "The Last Supper", Leonardo da Vinci used this idea to create depth and to emphasize the presence of Jesus.

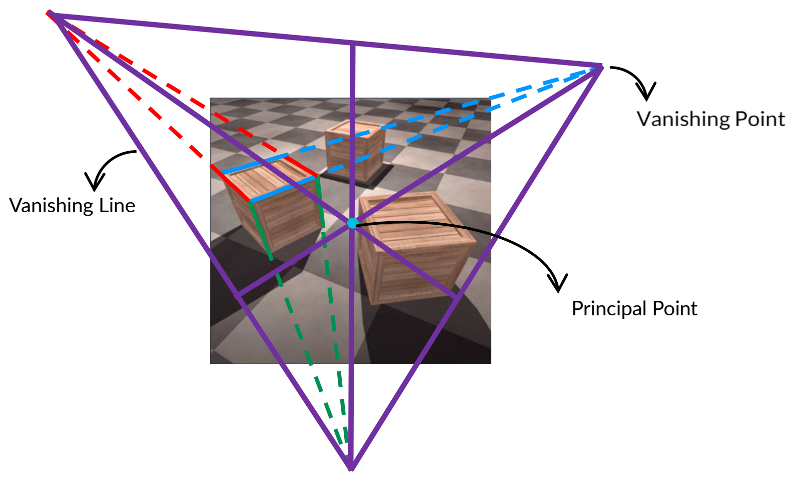


As mentioned, this phenomenon is a core in understanding the depth of a 2D image and it is widely used in fields where understanding the missing dimension is crucial such as 3D modelling, Virtual Reality, autonomous driving and more.

More than one vanishing point

It is possible to have multiple vanishing points in one image. The case that interests us is when it is possible to find three pairs of lines where each pair is parallel to each other and orthogonal to the 2 other pairs. Thus, we will have 3 vanishing points.

Connecting these 3 points will define a triangle which each of its sides is called a vanishing line. The orthocenter of this triangle is called the principal point of the image and it is unique to the specific image i.e.: as long as we choose the 3 pairs as described above we will get the same principal point.



In the method we are implementing in this project we take advantage of the fact that a photo that has not been manipulated has only a single principal point. That means that if we choose different sets of lines from different object in the photo and we get two different principal points, then we can say that the photo has been manipulated.

Our approach:

Our plan is:

1. Finding the principal point of the image. To be able to do it we need to:
    a. Find all the straight lines in the photo.
    b. Classify the lines to three class that each class contains set of parallel lines that orthogonal to all the lines in the other two class in the real world.
    c. Choosing a pair of lines from each class.
    d. Finding the vanishing point that corresponding to each class.
    e. Calculate the principal point according to the method we discuss above.
2. Doing the first step one time with lines of a suspected object and the other time with lines from the rest of the image.
3. Compare the two principal points to decide whether the image has been manipulated.

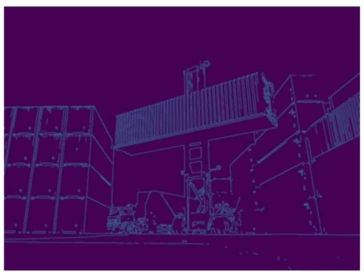
1st Step - Finding the straight lines in the photo:

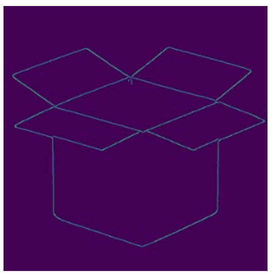
Given an image we want to detect straight lines in it. To do so we tried two methods:

First method: Gaussian smoothing + Canny edge detection + Hough transform

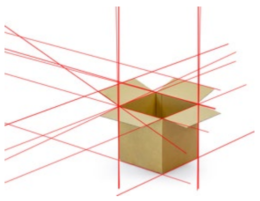
- Gaussian Smoothing which performs a weighted average of surrounding pixels based on the Gaussian distribution, this method removes the noise in the image and will help Canny algorithm to perform better.
- Canny edge detection to find the edges in the image which using them we can try to extract lines.

Canny edge detection output

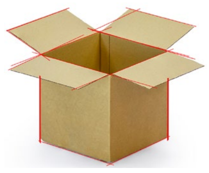




We can see that Canny output is quite good and can be helpful for our purpose.
We used Hough Transform algorithm to detect the lines, we can see the Hough transform algorithm on the box:



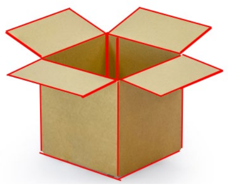
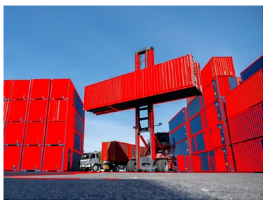
The output is good but we just need to do some post proccessing to remove the lines that are not on the edges. What we did is that if a Hough transform line is not on the canny edge then we removed it. Here's an example of such output:



The problem with Hough tranform is that when we want to use it on different images we need to adjust the hyperparameters, if we use the same hyperparameters from the box example on the containers image we get the output bellow which is useless:

Thus, we tried to find another method that will work without adjusting the hyperparamters.

Second method: Line Segment Detection (LSD)
Using the LSD we don't need to adjust the hyperparamters for different imges, the output for the LSD algorithm with the same hyperparamters and we received some good results:

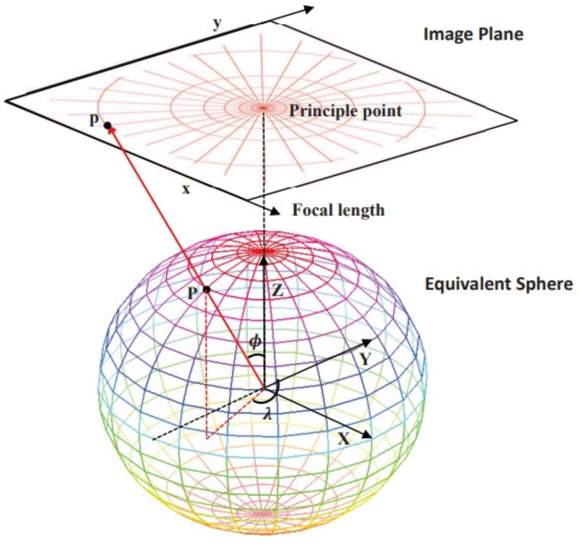



2nd <u>Step - Classify the lines</u>:

Given all the lines from the LSD algorithm, we need to classify them into 4 classes.
3 classes which each line in these classes is parallel to all the other lines in its class and orthogonal to all the other 2 classes' lines, the last class is the outliers which we cannot give a good prediction for. Just when we start to think about this problem, we realized that this is a hard task. When examining pairs of lines in the 2D image space without a semantic context, it is very difficult to decide what was the relationship between them (parallel or orthogonal or neither) in the 3D world.

Therefore, we accessed the internet and the academic literature to check and understand how the problem is dealt with and which existing works are already successful in this task. We were surprised to discover the amount of research, and the wide use in a variety of fields that try to solve the problem (finding vanishing points). Such fields include virtual reality, autonomous driving, 3D reconstruction, and for our case, fake photos detection. After thorough research we decided to dive into a specific article that seemed to solve the problem well given the information we have, the article is called: " 2-Line Exhaustive Searching for Real-Time Vanishing Point Estimation in Manhattan World " by Xiaohu Lu, Jian Yao†, Haoang Li, Yahui Liu School of Remote Sensing and Information Engineering, Wuhan University, Wuhan, Hubei, China. So indeed, in this paper they try to classify the straight lines in the picture in the same way we detailed above. The way they do it is as following:

First, they build a polar grid by extending the unit vectors on the equivalent sphere to intersect with the image plane. The equivalent sphere is a unit sphere which centers in the focal point of the camera (in practice we don't know yet the focal point, so we used the center of the image) the distance of the sphere from the image plane is the focal length of the camera (also this value we didn't always had) as the following figure is shown.

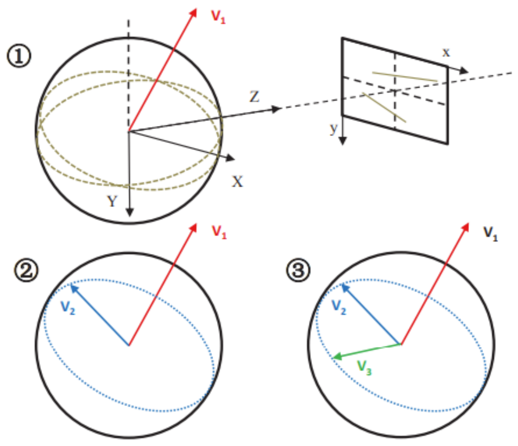


They showed how they find points and straight lines on the polar grid that correspond to points and lines from the image plane and vice versa. After they looked for potential set of three vanishing points on the polar grid.

To find the first point, they calculated the probability that given a random selection of two lines from the set of lines (by making assumptions regarding the distribution of the lines between the different classes) how many guesses are needed for at least one of the pairs to intersect at the vanishing point, over all 105 hypotheses of v1.

For the second vanishing point considering the orthogonal constraint of the three points, given the first vanishing point v1 = (X1, Y1, Z1), the second vanishing point must lie on the great circle of v1 in the equivalent sphere as shown in the figure. So, they split the circle in to 360 points (accuracy of 1 degree). Finally, with both the hypothesis for V1 and

V2 the third vanishing point can be obtained as v3 = v1 × v2. there will be totally 105 × 360 = 37800 hypotheses for three orthogonal vanishing points, which will then be validated to choose the best ones.

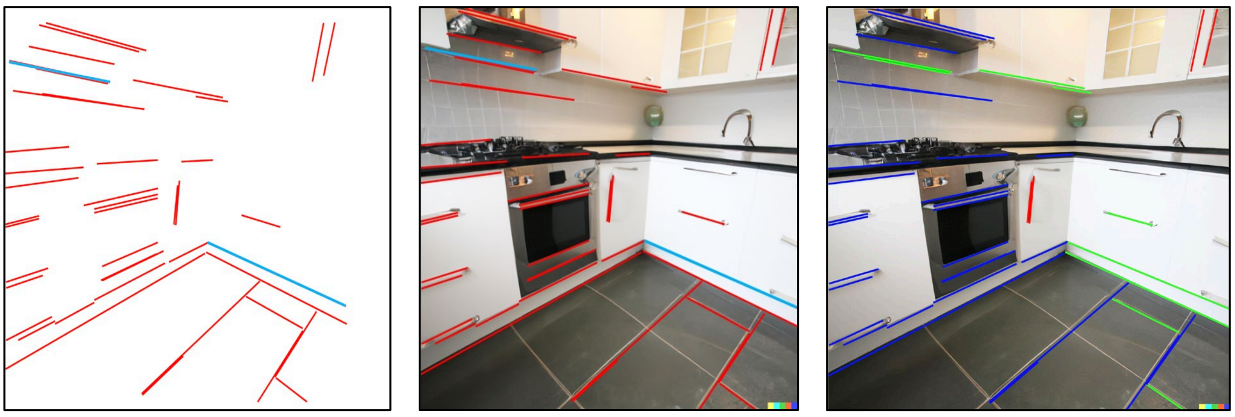


The final step of the method is to choose the best hypothesis. The choosing of the best hypothesis preforming via "vote" mechanism which each line is "voting" for a vanishing point if cross it. The hypothesis of the set of the three points that gets the most votes is the one that chooses, and the classification of the lines are according to these points.

In our case we only used the classification that the algorithm performs and calculated the vanishing points in a different way that resulted in better results for our case.

3rd Step - Choosing a pair of lines from each class:

Though the classification algorithm performs pretty well, there are still some failures that in our case may cause a high rate of false-positives (stating that the image has been manipulated when it wasn't). Below we can see lines detected by the LSD algorithm for an image of a kitchen. Without the context (left image), it might be hard to conclude which lines are parallel. For example, the 2 lines highlighted in blue may seem parallel without the background of the input image.

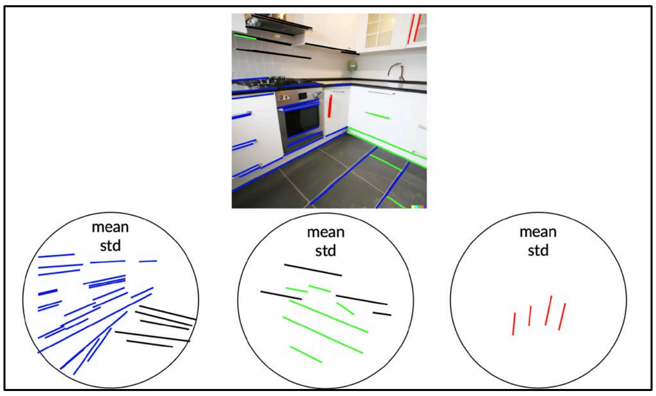


The classification algorithm falls short and indeed classifies these pair of lines as parallel even though they belong to different perpendicular planes.

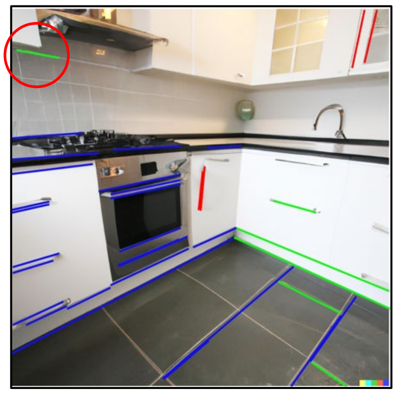
To overcome this problem we added two steps, filtering and choosing:

1. **Filtering**

   Parallel lines in the 3D scene shouldn't be parallel in the image plane (they can be but in our case, we don't want such cases). However, in most cases we would expect parallel lines in the 3D world to have a relatively close orientation in the 2D image plane. Thus, we have taken each cluster of lines and calculated the mean and the standard-deviation of the slope values of the lines assembling it. Then, we removed lines that have a slope that is far from their cluster's mean (>2*std) and close to some other cluster's mean (<1*std). In other words, if a line is an outlier in its associated cluster and is an inlier in another, we say that we have a low confidence about it and we don't want to use it at all.



Black lines are ones with low confidence.



After filtering. Still not perfect.

2. **Choosing**

   Filtering is doing pretty well as we can see in the given image, but it is still not perfect (marked in red circle). Fortunately, to find the principal point of an image we only need a pair of lines from each cluster so choosing wisely should overcome inaccuracies in the classification to this point.

   Under the assumption that in each cluster the majority of lines are indeed parallel to each other we do the following steps:

   a. Foreach possible pair ($\binom{n}{2}$ pairs overall) we calculate the intersection of the two. If the lines are parallel in the 3D world, then this point is a vanishing point.
   b. Given all possible intersection points (a total of $\binom{n}{2}$), the median in all x coordinates and the median in all y coordinates are calculated. Let's notate the medians by $med_x,\ med_y$ respectively.
   c. We define a new point $\tilde{p} = (med_x, med_y)$.
   d. Then we look for the intersection point which has the minimal Euclid distance to $\tilde{p}$. The pair which is associated with that intersection point is chosen.
   e. We perform the same scheme for every cluster.

   Comment: At first we did the same process using the average point instead of the median. However, in many cases there are outliers and in some cases, they can approach infinity (when a pair of lines is parallel). Such cases affected the average point heavily and therefore we used the median instead, which performed much better.

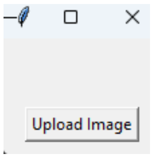
4th Step: Finding the vanishing points and principal point

After we integrated all the parts together, we saw that the classification algorithm from the paper doesn’t perform well on pictures with only one object. The paper aims to work on images called "Manhattan" images, meaning images of an urban environment, and our problem happened because of the way the algorithm works, it needs a lot of lines from each orthogonal space to choose the right classification. In our case when we needed to determine the principal point according to the lines of only the selected object, we couldn't make it work properly so eventually we decided that for this project the lines of the selected object will be chosen manually.

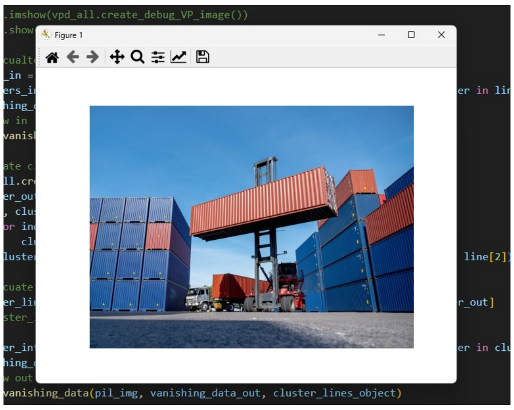
To find the vanishing point we choose the intersection point of each two lines, now we have three intersection points to find the principle point of them we need to take the center of the tringle that they create, and this is the principal point.

Simulation:

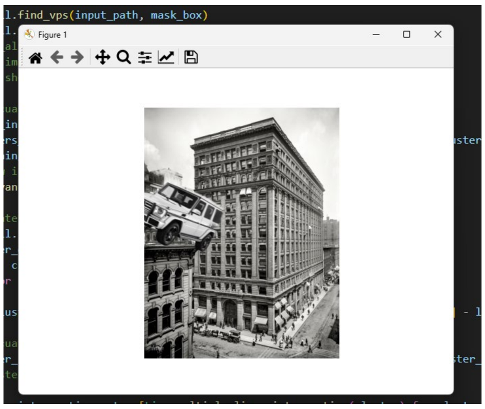
When we run the exec or the code we will be asked to upload image:



then we will see this window:

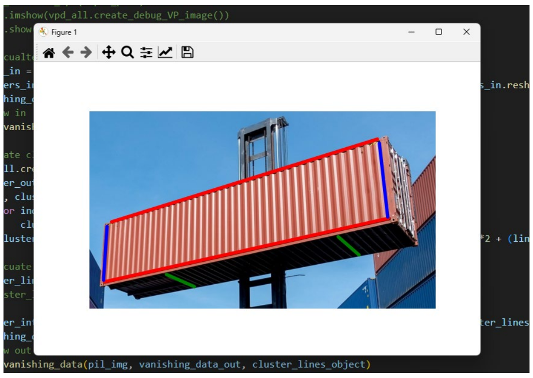


```
.imshow(vpd_all.create_debug_VP_image())
vanishing_data(pil_img, vanishing_data_out, cluster_lines_object)
```

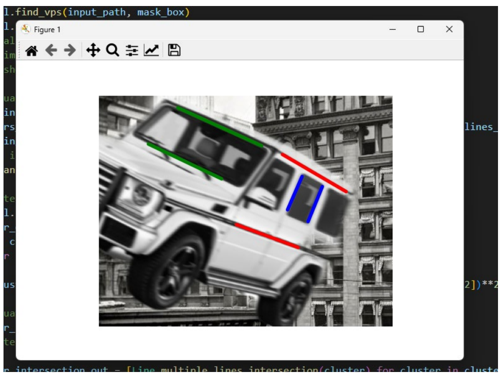


```
l.find_vps(input_path, mask_box)
```

then to select the object that we want to check his principal point agist the background (all the not selected area) and select three sets of two lines which the two lines are parallel to each other and the sets are orthogonal to each other:



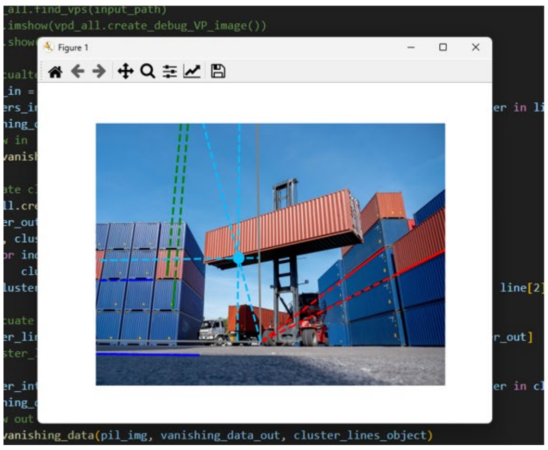
```
.imshow(vpd_all.create_debug_VP_image())
vanishing_data(pil_img, vanishing_data_out, cluster_lines_object)
```



```
l.find_vps(input_path, mask_box)
```

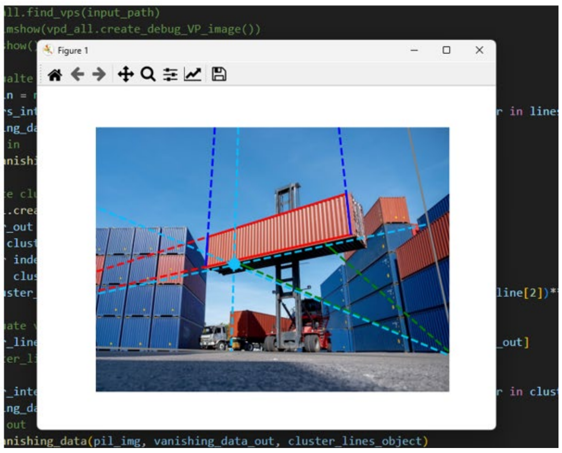
The algorithm will return the principle points of the image and the object and will classify if the object is fake or we cant decide if it is fake,
for the continer example we got that we cant decide if the continer is not belong to the image:

Image PP



```
all.find_vps(input_path)
.imshow(vpd_all.create_debug_VP_image())
vanishing_data(pil_img, vanishing_data_out, cluster_lines_object)
```

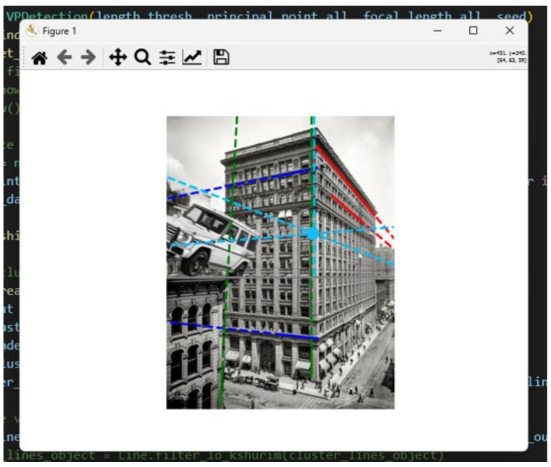
Container PP



```
ll.find_vps(input_path)
mshow(vpd_all.create_debug_VP_image())
nishing_data(pil_img, vanishing_data_out, cluster_lines_object)
```

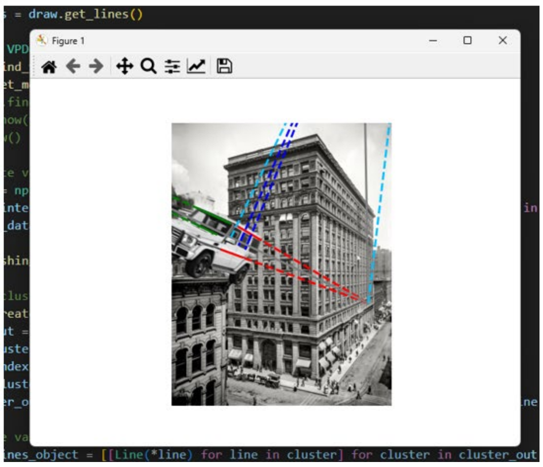
And for the "flying jeep" we classified it as FAKE! Because the principle points are far away from each other.

Image PP



```
VPDetection(length_thresh, principal_point_all, focal_length_all, seed)
lines_object = Line.filter_lo_kshurim(cluster_lines_object)
```

Fake object PP



```
= draw.get_lines()
ines_object = [[Line(*line) for line in cluster] for cluster in cluster_out
```

Note that to classify if the object is fake or not we used a threshold of the distance between the two principle points, the threshold is defined as proportion of the image weight and length combination, so in that way the algorithm is defined for each image size.