INDIAN INSTITUTE OF ENGINEERING SCIENCE AND TECHNOLOGY, SHIBPUR

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"IMAGE SPLICING DETECTION AND LOCALISATION USING DIGITAL FORENSICS"

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We, the undersigned, solemnly declare that the project report "*Image Splicing Detection and Localisation using Digital Forensics*" is based on our work carried out during the course of our study under the supervision of Dr. Ruchira Naskar. We assert the statements made and conclusions drawn are an outcome of our work. We further certify that the work contained in the report is original and has been done by us, under the general supervision of our supervisor. The work has not been submitted to any other institution for any other degree/diploma/certificate in this university or any other university of India or abroad. We have followed the guidelines provided by the university in writing the report. Whenever we have used materials (data, theoretical analysis, and text) from other sources, we have given due credit to them in the text of the report and given their details in the references.

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CERTIFICATE

It is certified that the work contained in the project report titled "*Image Splicing Detection and Localisation*", by "*Kunal Ojha*", "*Anindya Kundu*", "*Diksha*", and "*Rishabh Chandani*", has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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ABSTRACT

The authenticity of digital images has been seriously challenged, with the development of computer and artificial intelligence technology. Image splicing is one of the most common image tampering methods. Different photographic sources (cameras, scanners, etc.) have different noise levels; this project builds on a scheme to locate image splicing using the inconsistencies in local noise levels of the image.

To start with, the image is segmented into blocks of pixels with similar features, called superpixels using a superpixel segmentation algorithm called SLIC (Simple Linear Iterative Clustering). Thereafter, local noise levels of the superpixels are estimated using algorithms based on some denoising methods like Principal Component Analysis (PCA) or Robust wavelet-based method. Finally, the noise estimate values of each superpixel are clustered using k-means clustering to generate regions of similar noise levels. We mark the region with less number of pixels as the spliced region.

INTRODUCTION

In recent years, with the development of network sharing platforms and digital cameras, digital images have become an important source of information. Because of its unique advantages, it is used in many fields, such as the court, medicine, journalism and military. But digital images face many new challenges — it is difficult to guarantee their authenticity. Criminals use the tampered image for fraud. Therefore, how to judge the authenticity of the image and how to locate the tampered area of the image have become an essential part of the digital images research field.

Digital image forensics is divided into initiative forensic and passive forensic. According to the different embedded information, initiative forensic can be divided into digital signature, digital watermarking, and digital fingerprinting. However, the limitation of these methods is that the information must be embedded in advance. The passive forensic technology can judge the authenticity and the source of images without any prior knowledge. The mainstream image tampered methods include splicing, copy-move, double JPEG compression and fuzzy. Among them, splicing and copy-move are the most common tampered methods. Copy-move is homologous tam-pering by copying areas of an image and pasting it onto another disjoint area in the same image. Compared with copy-move, splicing is heterogeneous tampering, which is to crop and paste areas from different images.

In the process of imaging, digital images are influenced by camera components, camera settings, or environmental factors, which will introduce noise. Noise differences are typically introduced during the imaging process or caused by intentionally adding noise to hide the tampered trace of the image. For original images, there is little difference in noise among different areas. However, for tampered images, since different images have different noise levels, the inconsistency of local noise levels becomes convincing evidence for detecting image splicing.

APPROACH

The process we have implemented is based on segmentation of an image into superpixels which can be defined as a group of pixels that share common characteristics (like pixel intensities). We then estimate the standard deviation of the noise in each superpixel. Finally, we do a 1D binary clustering of the noise values, and group the superpixels into two classes. We guess the smaller cluster of superpixels to be the spliced image portion. The idea is that two image sources might have different noise values, which can be used to identify them separately.

SUPERPIXEL SEGMENTATION

We followed the algorithm proposed by Achanta et al for SLIC (Simple Linear Iterative Clustering) superpixel segmentation. SLIC algorithm for superpixel generation generates superpixels by clustering pixels based on their color similarity and proximity in the image plane. This is done in the five-dimensional [*labxy*] space, where [*lab*] is the pixel color vector in CIELAB color space and [*xy*] is the pixel position. We need to normalize the spatial distances in order to use the Euclidean distance in this 5D space because the maximum possible distance between two colors in the CIELAB space is limited whereas the spatial distance in the xy plane depends on the image size. Therefore, in order to cluster pixels in this 5D space, a new distance measure that considers superpixel size was introduced.

N	Number of pixels in the input image
K	Number of Superpixels used to segment the input image
N/K	Approximate size of each superpixel
$S = \sqrt{N/K}$	For roughly equally sized superpixels there would be a superpixel centre at every grid interval S

This algorithm takes as input a desired number of approximately equally-sized superpixels K. At the onset of the algorithm, K superpixel cluster centers C = [l , a , b , x , y] are chosen with k= [1, K] at regular grid intervals S. Since the spatial extent of any superpixel is approximately S^2 (the approximate area of a super-pixel), it is safely assumed that pixels that are associated with this cluster center lie within a 2S × 2S area around the superpixel center on the xy plane. The normalized distance measure (D) to be used in the 5D space is defined as :

$$D = d_{a\beta} + (m/S) * d_{x\gamma} \;....$$

where $d_{a\beta} = \sqrt{(l - l_i)^2 + (a - a_i)^2 + (b - b_i)^2}$, $d_{x\gamma} = \sqrt{(x - x_i)^2 + (y - y_i)^2}$ and D is the sum of the lab distance ($d_{a\beta}$)and the xy plane distance ($d_{x\gamma}$) normalized by the grid interval S. A variable m is introduced in D allowing us to control the compactness of a superpixel. The greater the value of m, the more compact the cluster. This value can be in the range [1, 20].

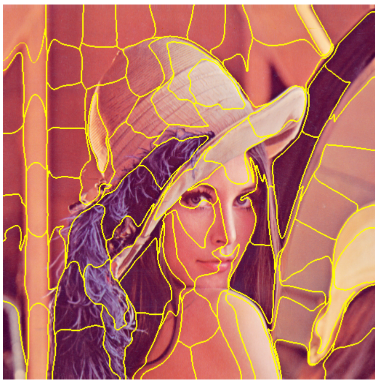
The SLIC algorithm can be summarised as:

Algorithm 1 Efficient superpixel segmentation

```
Initialize cluster centers C_k = [l_k, a_k, b_k, x_k, y_k]^T by sampling pixels at regular grid steps S.
Perturb cluster centers in an n × n neighborhood, to the lowest gradient position.
repeat
    for each cluster center C_k do
        Assign the best matching pixels from a 2S × 2S square neighborhood around
        the cluster center according to the distance measure (Eq. 1).
    end for
    Compute new cluster centers and residual error E {L1 distance between previous
    centers and recomputed centers}
until E ≤ threshold
Enforce connectivity.
```

We observed that the final splicing detection result depends on the factor K. Usually, the larger the K (smaller superpixels), the better is the precision. But, smaller superpixels have higher degrees of variation of noise estimates between them, which decreases the accuracy of detection.

We concluded that the K value for which the average superpixel sizes approximate the artifacts in the image gives better results, e.g. for images that have smaller artifacts, larger values of K is generally better. For our tests, we used 512 × 512 3-channel coloured images, and generally a K value of 100 (which results in around 85-95 actual number of segments) yields good results.



K = 100 (actual 85)

K = 200 (actual 166)

K = 300 (actual 255)

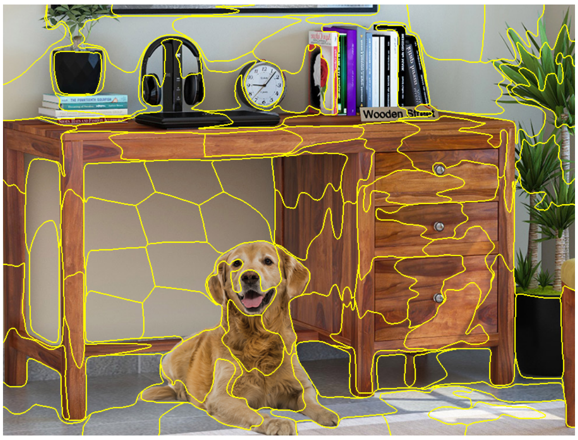
NOISE ESTIMATION

Our goal was to find the standard deviation (σ) of noise in each superpixel. We tried 3 techniques. We first tried two variants of algorithms based on Principal Component Analysis denoising. Then, we tried robust wavelet-based denoising algorithm to estimate the same. In our testing, the latter was significantly faster, so we went with it.

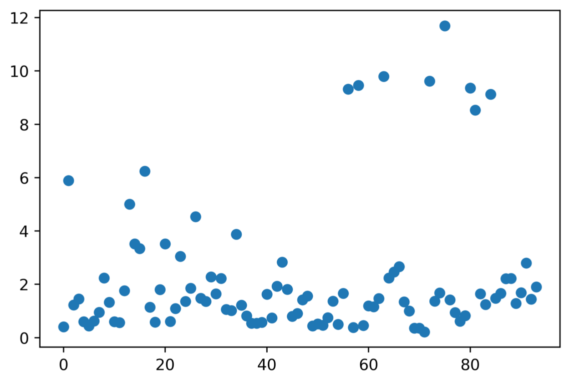
Superpixels are much smaller than the actual image. We tried two variations of estimating noise from the superpixels. In the first approach, we have a superpixel mask — the image has the same dimensions as the original image but only the area of each superpixel has the pixel values from the original image, while the rest is back (0 intensity). In another variation, we cropped this masked image to the tightest bounding box of the superpixel. We noticed that there is often a slight improvement in the detection result if we estimate the noise from the cropped superpixel masks. However, in some cases, the results don't improve at all, and in a few cases the result is worse.

Noise (σ): 0.6639336909287843

Noise (σ): 2.707748035318859



Superpixels K = 100 (actual 94)



Superpixel vs Noise (σ) Scatter Plot

Our conclusion is that the result again depends on the size of each superpixel, especially in images with smaller artifacts. But, since there is a high degree of variation in the noise values of smaller superpixels, detection results worsen, and somehow the full size masks yield better. If the artifacts are relatively larger and the degree of variation of noise in the spliced region and the non-spliced region is lower individually, there is a good result.

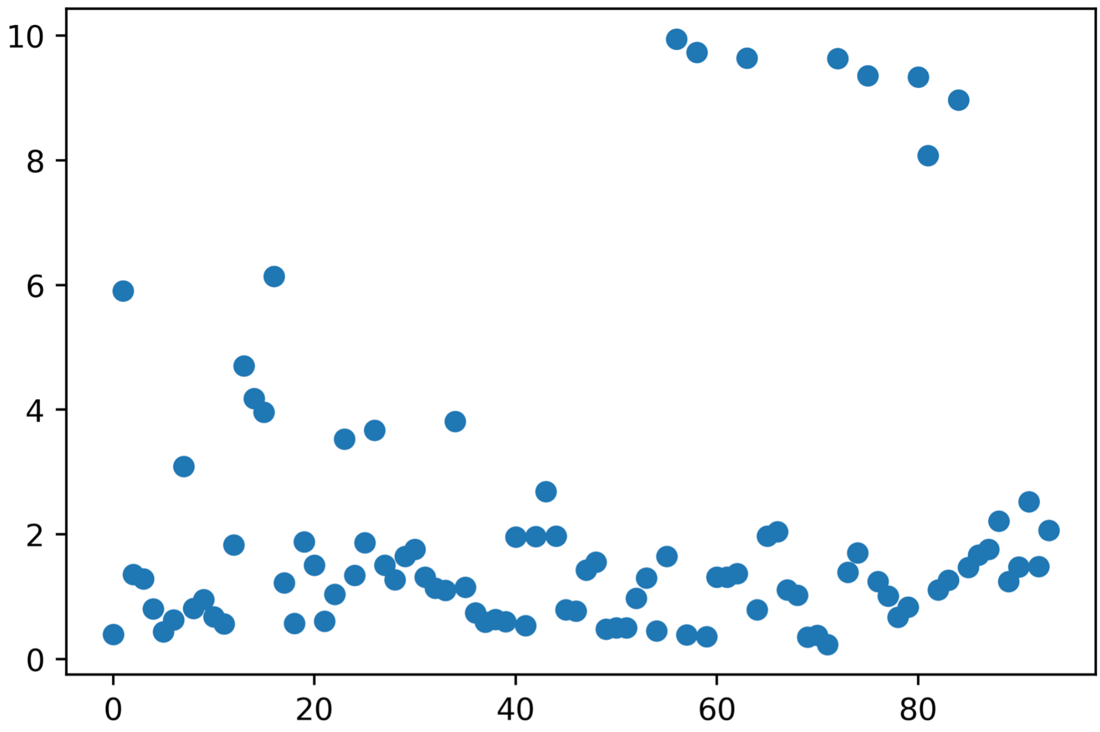
(K = 100) *True positives* in *green*, *False positives* in *red*, *False negatives* in *blue*

Uncropped | Cropped to bounding box

K-MEANS CLUSTERING

After we have the noise estimates of each superpixel, we do a binary k-means++ clustering of the values and classify them into two classes. We guess the cluster with a smaller number of pixels to be the spliced region.

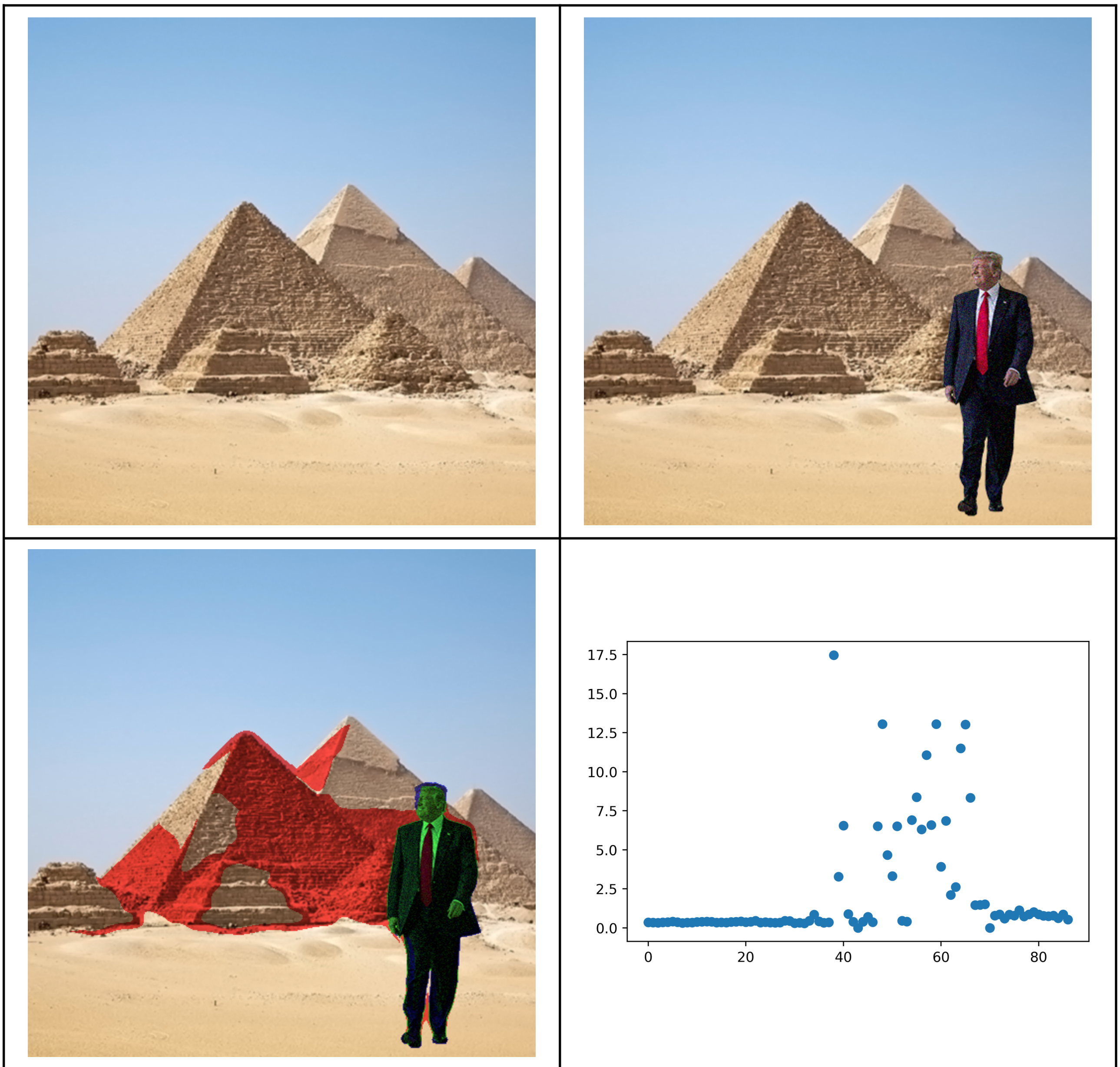
Our heuristic is subjective though. In addition, we explicitly do a binary clustering, implying that the correctness of the algorithm is based on our image having two groups of noise values. If there are more, we can increase the number of clusters, and generally with good noise separation between the spliced regions and the non-spliced region the segmentation will yield good results, but we cannot guess which are spliced and which are not. We can still do a guess by finding the segment with the most number of pixels and considering it the non-spliced region and other clusters with significant difference in noise standard deviations with it and each other be the spliced regions, but it is only a guess.



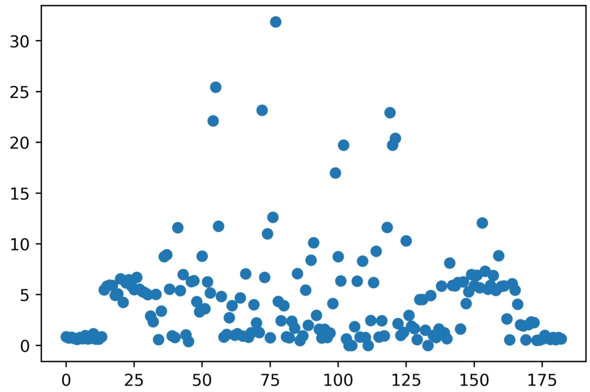
Superpixels vs Standard Deviation (σ) Scatter Plot

Detected Splicing (in yellow), *True Positives* (in green), *False Positives* (in red), *False Negatives* (in blue)

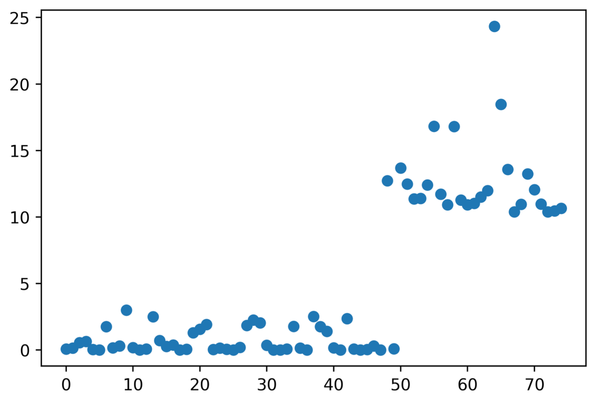
Precision: **0.81**, *Recall*: **0.95**, F_1 *score*: **0.87**



(512 × 512, k = 100), *Precision*: **0.29**, *Recall*: **0.85**, F_1 *score*: **0.44**
High texture in non-spliced region

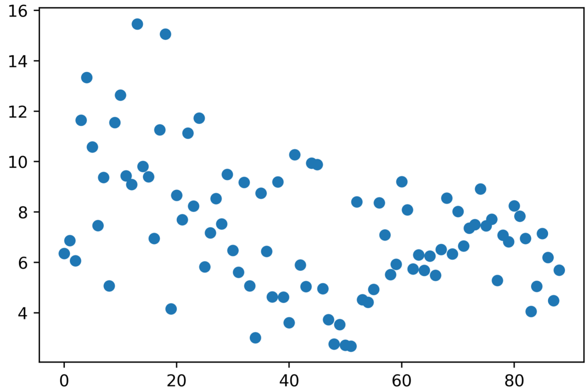


(325 × 768, k = 200), *Precision*: **0.86**, *Recall*: **0.59**, F_1 *score*: **0.69**
Artifacts are very small



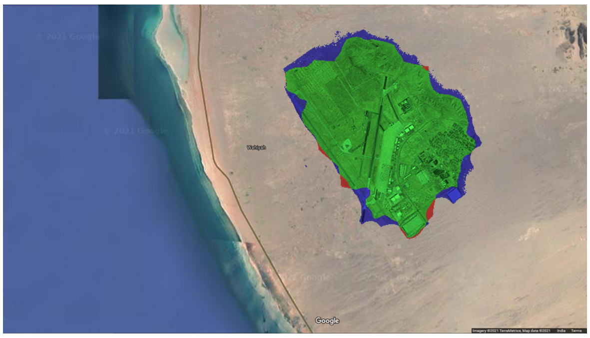
(509 × 463, k = 100), *Precision*: **1.00**, *Recall*: **0.95**, F_1 *score*: **0.97**

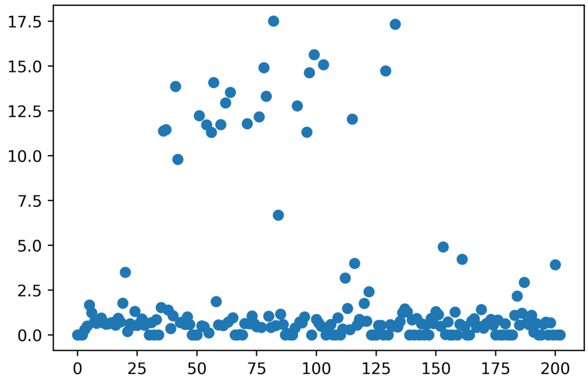
Significant difference in noise estimates of spliced and unspliced regions



(512 × 512, k = 100), *Precision*: **0.29**, *Recall*: **0.93**, F_1 *score*: **0.44**

High standard deviation in noise estimates of unspliced region's superpixels





(512 × 911, k = 200), *Precision*: **0.98**, *Recall*: **0.87**, F_1 *score*: **0.93**
Clear separation of spliced region from unspliced region

Copy-move splicing; copied regions are in same cluster, but splicing undetected

CONCLUSION

- The method is applicable for image splicing from two or more sources of which at least either the non-spliced region (the template) or the spliced regions, or both need to be from photographic sources (camera, scanner, etc.) and not CGI such that there is a random Gaussian (or spot noise — Poisson approximated to Gaussian for not very high intensities) noise in the images.

- The sources need to be different such that the noise values between the spliced and the non-spliced regions are distinguishably different.

- k value used for segmentation should be decided such that the resulting superpixel sizes are a good approximation of the artifacts in the images — for smaller artifacts, higher k values and smaller superpixel sizes, and vice versa.

- Even though noise in the spliced and unspliced regions are expected to be Gaussian, there needs to be a small variance (or standard deviation) between the noise values of the spliced and unspliced regions, and there must be a differentiable difference between the two which needs to be more than the standard deviations of each set.

- Binary clustering's accuracy depends on the noise clusters. Two differentiable noise clusters yield good results.

- The precision of the splicing detection depends on the superpixel sizes — smaller sizes approximate better to the spliced region, but may decrease noise clustering accuracy.

- Copy-move splicing isn't handled; all copy-move instances will be in the same cluster.

- Images with varying artifact sizes (or texture) often yield a high standard deviation in the noise estimates of the corresponding region, which decreases the chances of effective noise region clustering.

- Non-binary source splicing can be clustered but guessing the spliced regions is only heuristic. For binary sources too, it is only guessed that the smaller region is the spliced region. Irrespective, if there is effective noise separation, good clustering can however be done even if identification is heuristical.

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