# **Sparse Edge Encoder (SEE) for natural images**

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## Natural images in our daily lives

Without any priors of an image,  $256 * L^2$  different images can be generated with the fixed image size  $L^2$ , the possible image space is very large. However, most of the samples will not be observed in our daily lives. The images which can be observed are called the **natural images**, which are rare events in the image space. The rareness implies us particular type of structure inhabit the natural images. Here we would like to ask: What is the particular structure or constraint of the natural images? Once the constraint is known, the degree of freedom of the image space is reduced.

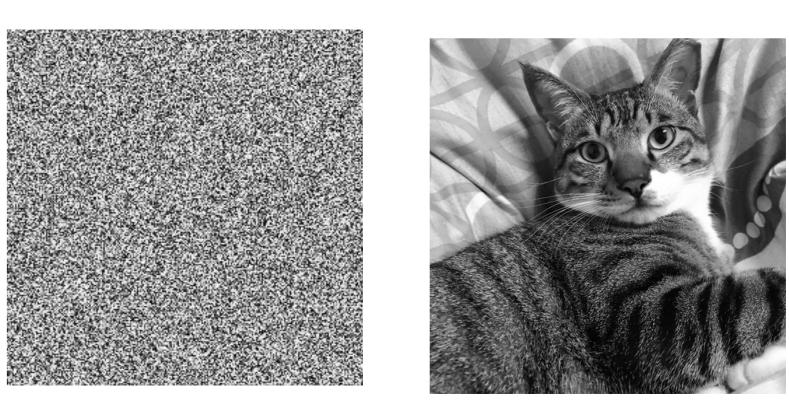


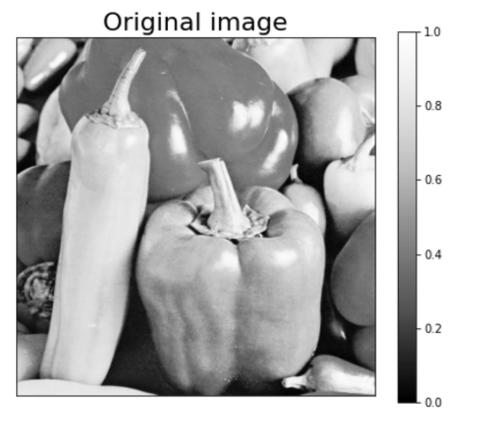
Figure1: What is the difference between these two images?

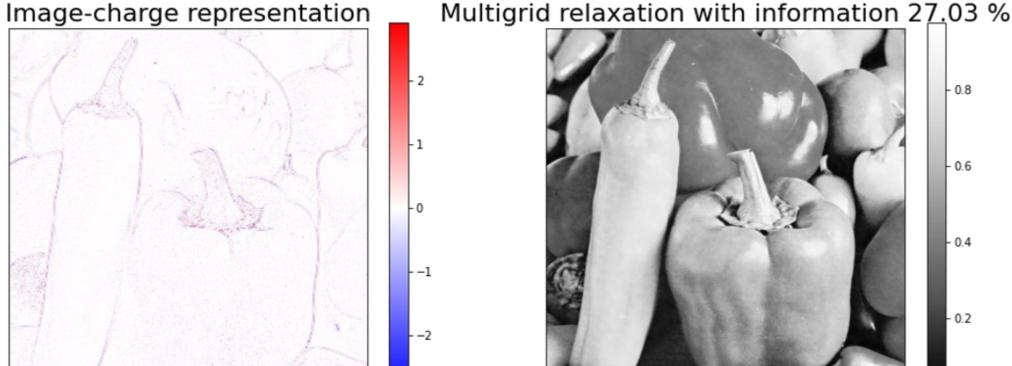


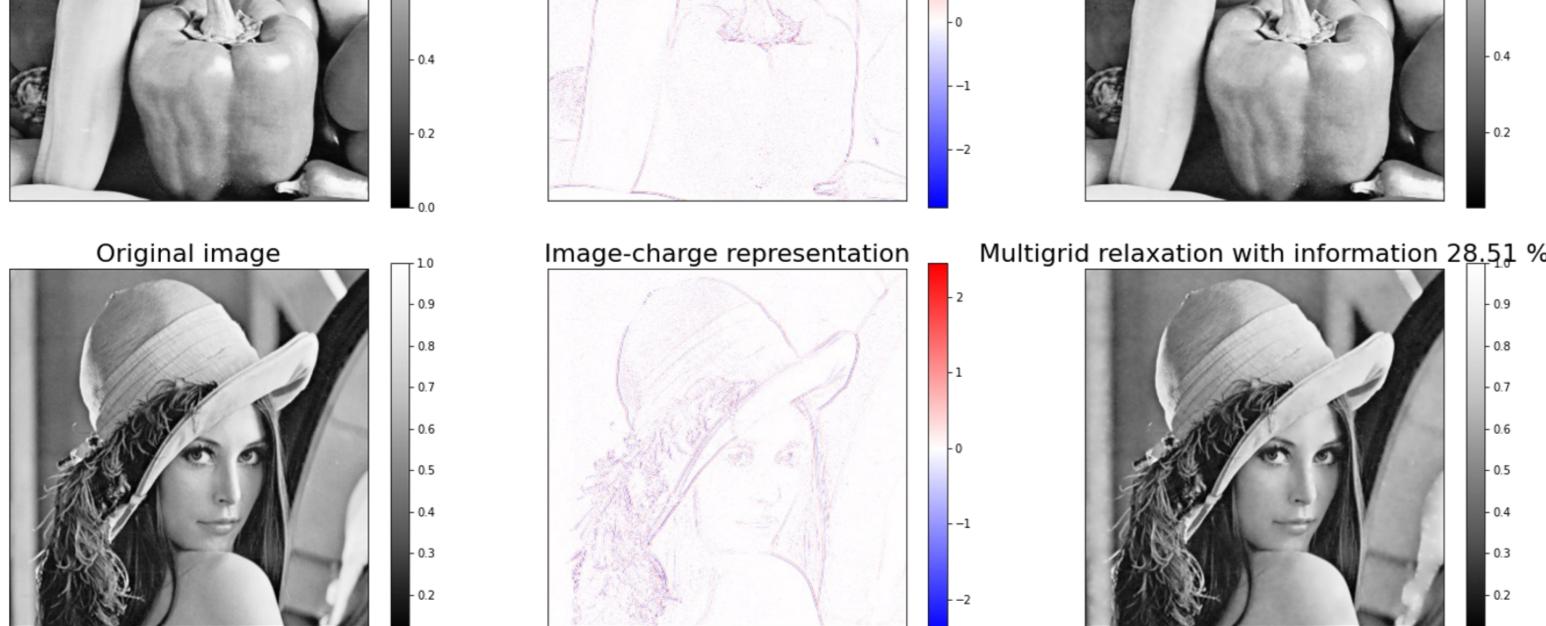
### **Image charge representation**

		гсррсі	LCIIG
	Pixel representation	0.089	0.069
Hoyer sparseness	Image charge representation	0.35	0.37
	Ratio(%)	396.02	540.58

Tabel1: The great enhancement of Hoyer sparseness after the Loperation.







Inspired by the principle of physical imaging(the diffusive reflection), we proposed a local filter L representing the local correlation between nearing pixels. (This concept and below details are recommended by NTHU for the patent application.)

The **image charge representation** is obtained by the *L*-operation, and the original image can be reconstructed by the multigrid relaxation method. Notice that this kind of architecture is called the encoderdecoder structure in deep learning which aims to learn the data representation in the layer of bottleneck between the encoder and decoder. Specifically, the encoder-decoder architecture we proposed here is called **Sparse Edge Encoder(SEE)**.

It is worth noting that the value of the image charges is almost zero everywhere except the appearance of image dipoles near the edges i.e.  $L\phi \approx 0$  (sum rule for natural images). A great enhancement of Hoyer Sparseness (larger than 300%) is showed up because most of the pixel information already described by the local filter L. (see Table 1.) The sparsity of the representation implies the dimension reduction of the image may be done, good data representation helps us to cutdown the redundant information.

Figure 2: The lossy image compression demonstrated by the image charge representation. (a) Pepper; (b) Lena.

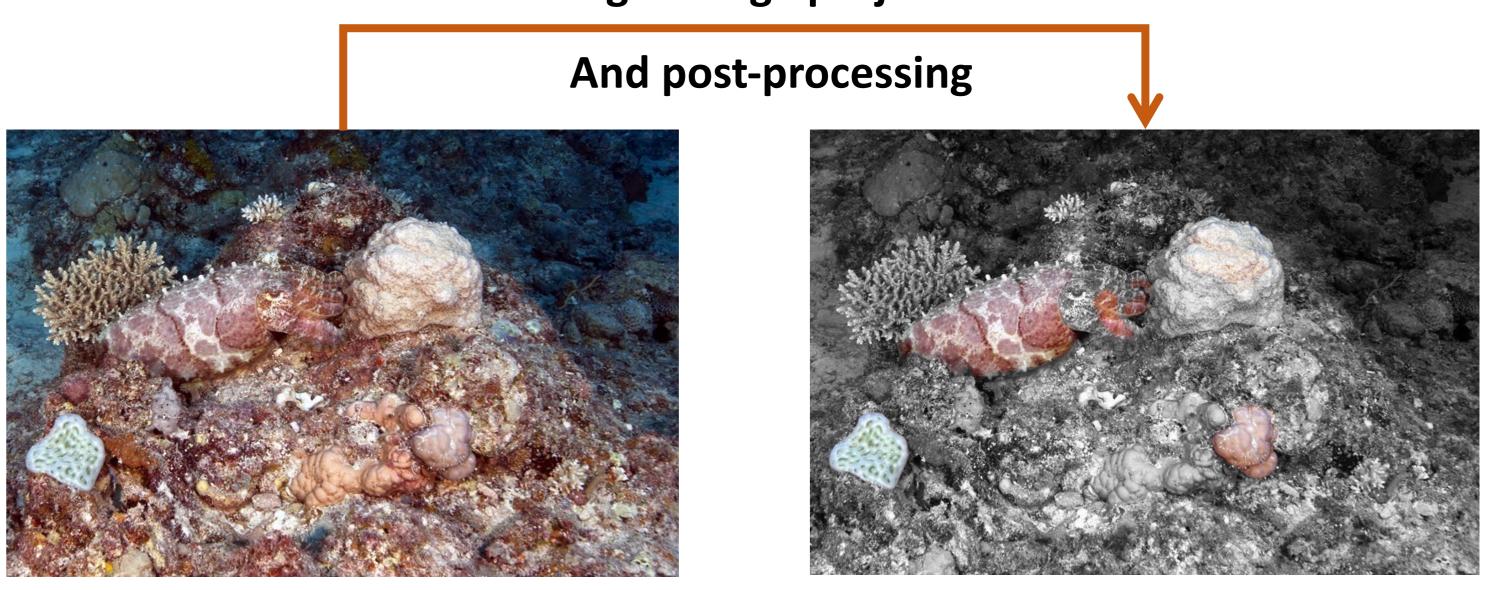
Image	Information (%)	PSNR(dB)
Pepper	27.03	35.49
Lena	28.51	32.11

Tabel2: The compressed ratios and the corresponding PSNR values for the demonstration of Figure 2.

### **Applications for the SEE**

#### **Anomaly detection and medical image analysis**

By the hierarchy that the magnitude of image charges provides, singularities of the image which break the sum rule can be easily picked up. We simply project out the charges containing small magnitude, reconstruct the image successfully by less than 30% pixel information with PSNR value higher than 30dB. (see Table 2.) Note that here we demonstrate the lossy image compression, which means although the PSNR value measures the pixel-pixel error between two images, but human eyes are not sensitive with the loss. (see Figure 2.) Here shows the difference between pixel information and visual information, the image charge priority provides us the strategy to extract the visual information among the vast amount of pixel information. Image charge projection



While image dipoles exist at the edges of objects mainly, carry the information of the object existence that human eyes sensitive to, the image charges spread through the bulk of object and reflect the texture information of the object. Figure 3. demonstrates a feasible anomaly detection by SEE: It is difficult to discover the target object (cuttlefish) from the left side photo because the shape of the target object is not obvious (i.e. Image charges with order of magnitude equals to the target dipoles spread through most part of the picture), human eyes should be confused. As image charges are everywhere now, demonstration of Figure 2. should be destroyed. However, the anomalies (smooth surfaces) are highlighted by SEE since the charge distributions are different from the most part. The stage-0 tumors without shape but deteriorate tissue are not easy to detect by the human eyes as Figure 4. shown, with the texture information SEE provide, the anomaly tissue might be picked up by SEE image-processing.

Figure3: Left: The cuttlefish, a master of camouflage, mimicking its environment; Right: Anomaly detection by SEE and post-processing.

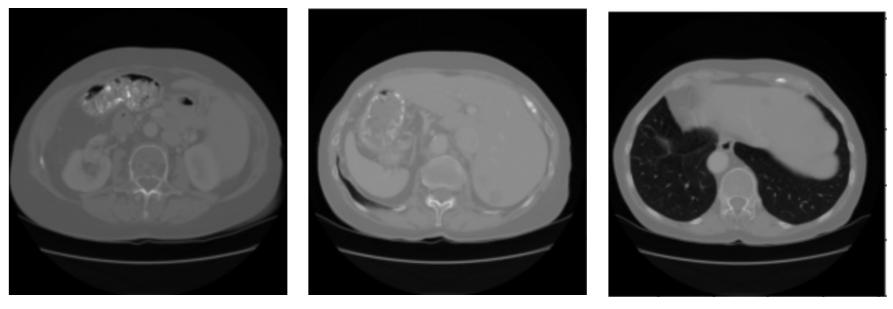


Figure 4: Liver CT scan. Where is the cancer?