A Canonical Image Set for Examining and Comparing Image Processing Algorithms

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***Abstract*—The purpose of this paper is to introduce a set of four test images containing features and structures that can facilitate effective examination and comparison of image processing algorithms. More specifically, the images are designed to more explicitly expose the characteristic properties of algorithms for image compression, virtual resolution adjustment, and enhancement. This set was developed at the Naval Research Laboratory (NRL) in the late 1990s as a more rigorous alternative to Lena and other images that have come into common use for purely ad hoc reasons with little or no rigorous consideration of their suitability. The increasing number of test images appearing in the literature not only makes it more difficult to compare results from different papers, it also introduces the potential for cherry-picking to influence results. The key contribution of this paper is the proposal to establish *some* canonical set to ensure that published results can be analyzed and compared in a rigorous way from one paper to another, and consideration of the four NRL images is proposed for this purpose.**

***Index Terms*—test images, image compression, image superresolution, image enhancement, image processing**

I. Introduction

This paper proposes a set of four specially-generated test images as candidates for general use in the qualitative assessment of image processing and related algorithms. The goal is to establish a consensus standard so that results from published experiments can be more easily and reliably compared. In other words, the objective is to promote greater consistency in the assessment and presentation of results in the literature.

Presently there are many de facto standard test images from which to choose when assessing a given image processing algorithm. One example is the image *Barbara*, shown in Fig. 1a. This image has very distinctive parallel line structures that can be presumed useful for revealing clearly visible artifacts, e.g., in the form of moire patterns, after processing by a given algorithm. The image *Baboon* (aka *Mandrill*), Fig. 1b, is another widely-used test image which has appeal because of its distinctive mix of colors and textures.

What is important to note is that the assumed useful features of *Barbara* and *Baboon* were determined *post hoc*, i.e., they were subjectively judged to have those features rather than being intentionally produced to exhibit those features in a rigorous form. Intentionally-produced test images have been used in the past, especially in the early days of television broadcasting. Fig. 2a shows an early RCA test pattern that was designed to reveal artifacts of incorrect brightness and/or camera calibration [1]. Fig. 2b shows color bars similar to those used later for calibration of NTSC color television signals and color rendering of computer monitors [2].

The structure of this paper is as follows: Section 1 discusses the difference between identifying the qualitative *properties* of a given algorithm versus making a qualitative *assessment* of those properties for a given application. Section 2 formally introduces the four proposed test images. Section 3 provides examples involving image super-resolution and image compression. And Section 4 concludes with a brief summary and discussion.

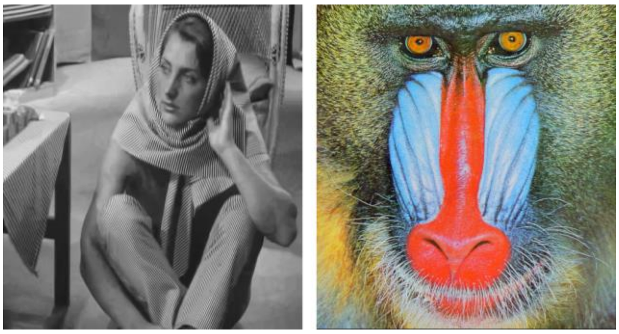

Figure 1. Widely-used test images *Barbara* (left) and *Baboon* (right).

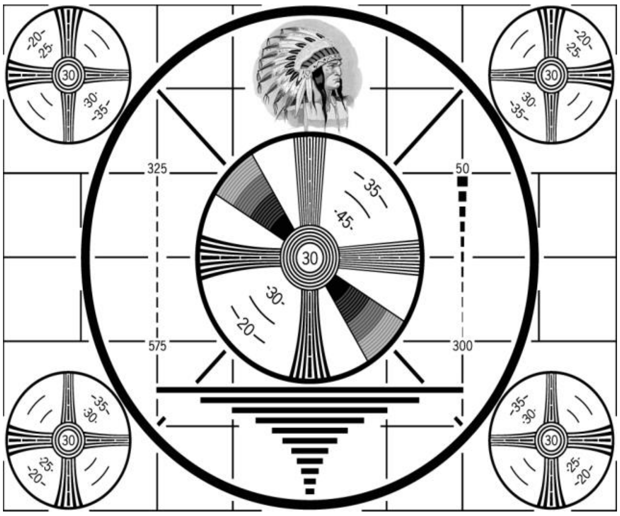

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Figure 2. Widely-used test images from the early days of television: *RCA Test Pattern* (top) and *Color Bars* (bottom).

II. Assessing Image Processing Algorithms Using Test Images

Image processing algorithms can be assessed using purely subjective qualitative judgments or by applying objective quantitative formulas that may not accurately measure the salient properties relevant to the intended application of interest. For example, suppose that decompressed results from image compression algorithms *A* and *B* reveal that *A* is superior in most cases to *B* in terms of RMS error while the soft blurring introduced by *B* is judged in almost all cases to be aesthetically superior to the characteristic artifacts (e.g., ringing or blockiness) produced by A. Assuming that the algorithms offer comparable compression ratios, which is "better"?

Image Super-Resolution (ISR) provides an illustrative example of the challenges that can arise when assessing competing approaches. ISR is an inherently ill-posed problem in that it requires the generation of intensity/color values for unobserved pixels, so in some sense there is no "correct" or "incorrect" solution. Fig. 3 shows results for three methods for synthetically increasing the resolution of a 25x25-pixel image by a factor of 16. The first method applies simple replication of pixels, the second performs cubic polynomial interpolation between adjacent pixels, and the third represents a result that might be generated using a machine-learning algorithm based on a large database of faces.

Pixel replication can be regarded as a very conservative approach to ISR that is unwilling to mix/combine intensities of adjacent pixels to estimate intensities between them whereas cubic interpolation assumes smooth intensity gradations between pixels and generates unobserved pixel intensities accordingly. One appealing property of replication is that all information about the original image is preserved, i.e., the original image can be recovered exactly. On the other hand, it introduces uniform, high-frequency, rectilinear features that are purely artifacts of the algorithm in that they appear in all nontrivial images processed by the method. Cubic interpolation, by contrast, introduces a blurring effect that in some sense is suggestive of the fact that image detail is unavailable.

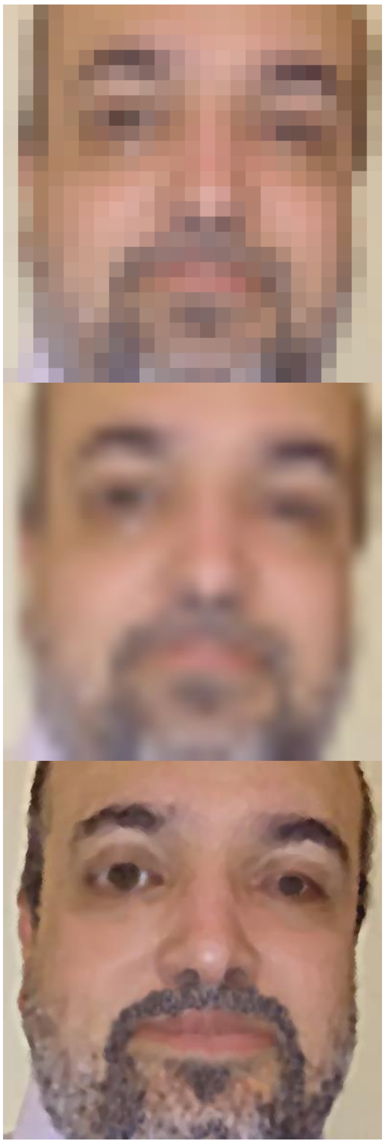


Figure 3. Top-to-bottom shows ISR results from replication, cubic interpolation, and possible from machine learning.

At first glance the machine-learning result in the example of Fig. 3 may appear "best" in that it resembles an in-focus photograph of a face, but much of the detail of that face is *not real* and thus may be misleading for applications in which the generated image is intended to assist in the identification of the actual human subject of the original image. In a different application, however, aesthetic considerations may be more important than whether or not the synthetic face closely resembles the original subject (it does not). The conclusion to be drawn is that while image processing algorithms can be assessed in terms of their characteristic properties, the qualitative ranking of different algorithms typically only makes sense with respect to application-specific criteria.

Over the years many images have become de facto standards simply because they were used in papers that proved to be influential in the field. This is not unreasonable because subsequent researchers would naturally be motivated to compare their alternative algorithms to the prior state-of-the-art using the same images for comparison. In fact, if a later paper were to use different images, questions might be raised as to whether those images were selectively chosen to yield more favorable results. Of course, similar questions could also be raised about the choice of images used in the original papers.

Attempts have been made to establish collections of "standard" test images (often including labels, e.g., *faces* [3], *textures* [4], etc.), and these are valuable resources for deriving statistical measures of performance over many images that share a set of common features of interest. More specifically, they can be used to show that some characteristic of a given algorithm that is observed when applied to a few well-known standard images is robustly exhibited when applied to a larger set of images. However, the availability of a large number of images in a collection introduces opportunities for selection bias. What is needed is a small set of images that collectively captures the most critical features of relevance to general image processing and thus may be used as a common basis for comparing different algorithms across a range of application domains.

III. Considerations for Choosing "Standard" Test Images

The "*Lena*" image (Fig. 4) has been in widespread use for decades and is the most widely used standard in the field of image processing. A major reason why *Lena* has been adopted so widely is because it contains many of the feature types that are most commonly examined when assessing image processing algorithms [5]. Specifically, the hat contains repetitive parallel weave structures; the feather contains complex textures; the skin of the face and shoulder show smooth intensity gradations; and the eyes include familiar small-scale features in the iris and lashes. Common undesirable artifacts generated from compression or ISR processing of the *Lena* image include the appearance of checkerboarding in the weave of the hat; strong intensity discontinuities (banding) on the skin; and blurring of detail in the eyes.

Instead of seeking out details (subregions) that exhibit features of interest, e.g., edges, smooth intensity gradations, etc., a reasonable question to ask is whether it might be preferable to construct a small set of synthetic images, each element of which is tailored to clearly exhibit a particular class of feature, in place of a "real" image such as *Lena*. Also, is it prudent to use images that include human faces, or text in a particular language, when there is potential for evolutionary and/or cultural experience to influence interpretation? In the case of text, for example, strokes comprising characters in different languages often include ornamental flourishes (e.g., serifs) that native speakers may unconsciously ignore, i.e., the relative attention given to distinct textual features of similar size is culturally influenced. This obviously suggests that the assessed "significance" of artifacts introduced by algorithmic processing of text may be culturally biased.

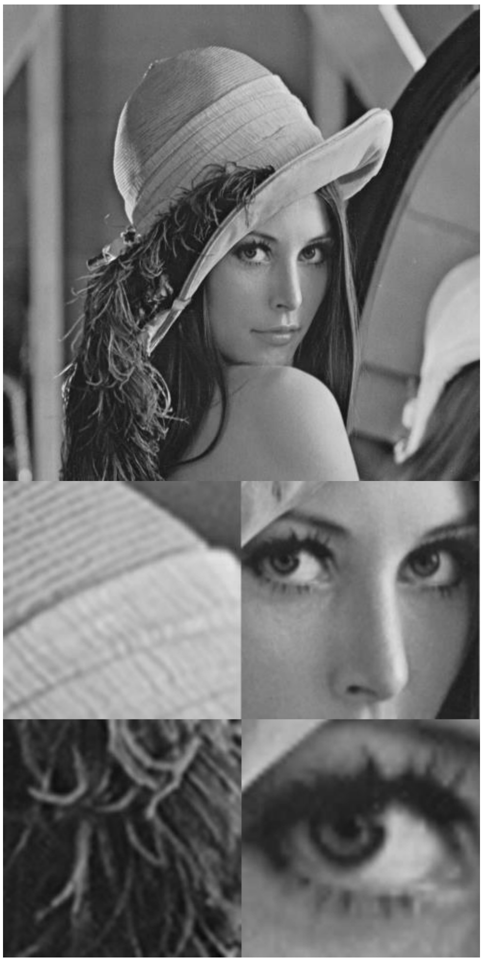


Figure 4. *Top* is the standard Lena image and *Bottom* are four commonly examined details from it.

More generally, the problem posed by most natural images is that visual examination tends to be distracted by interpretable content. For example, a compression algorithm that identifies and attempts to preserve approximately-straight lines may introduce significant artifacts into the feather strands of Lena's hat that may be hardly noticeable under casual inspection if the more easily-interpretable features of the face and shoulder are rendered accurately. Of course this behavior of the algorithm could be an advantage in some applications, but it is typically best to understand the properties of a given algorithm first and then identify the applications for which those properties are best suited. With this in mind, four images are proposed as candidates for standards for identifying and comparing properties of image processing algorithms.

IV. Four Images

The four images described in this section are 1024 pixels in height, 2048 pixels in width, with 256 greyscale intensities. The dimensions are chosen to facilitate factor-of-2 decimations and to offer typographical formatting flexibility in landscape format, or vertical in multi-column format (as used in this paper). Each image can also be subdivided into separate 1024x1024 sub-images as needed.

The first image, "*Basic*", consists of contiguous regions of uniform intensity with boundaries of varying curvature. It is suitable for revealing aliasing, pixelation, and ringing artifacts. As can be seen in Fig. 5, Basic is a relatively low-information image and thus can be highly compressed. Because its information content is largely focused along high-contrast curved edges, it is well-suited for comparing compression algorithms at very high compression ratios because artifacts can be expected to be most pronounced along those edges.

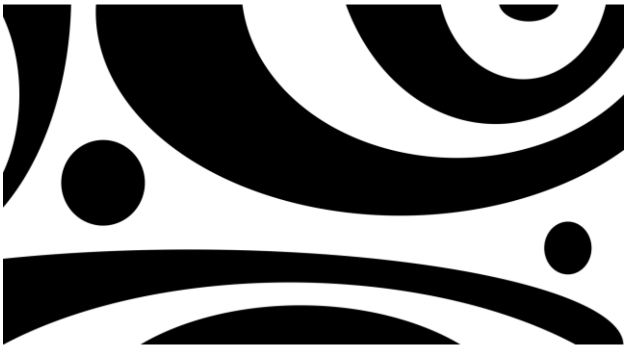


Figure 5. "Basic" - A simple set of contiguous regions of pure black and pure white.

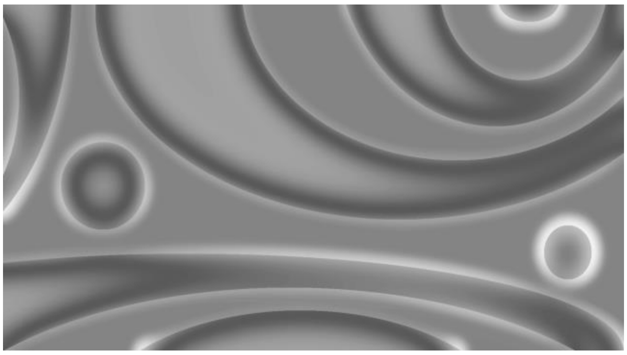


Figure 6. "Platonic" - Smooth intensity gradations.

The second image, "*Platonic*", has smooth gradations of intensity along contours of varying curvature. This image was constructed so that intensity variations are at the limit for visual smoothness given the available resolution and discrete intensity values. It can reveal, for example, an algorithm's use of global contrast enhancement to mask its blurring of edge detail. As can be seen in Fig. 6, *Platonic* contains a broad range of strong and weak intensity gradients that vary with respect to boundary directions of curvature in such a way that can further enhance contrast and edge-enhancement artifacts. Interfaces between the bright diffusive regions around the circles and those of surrounding structures can be particularly revealing of such artifacts.

The third image, "*Natural*" (Fig. 7), includes basic features found in natural images such as approximately-repeating structures with subtle variations in texture and illumination. This image is particularly tailored to reveal properties of an algorithm that are relevant to its use with radiological and multi-spectral imaging. Noise and defocusing artifacts can be introduced to this image (or its intensity inverse) to model application-specific characteristics of an assumed sensing modality.

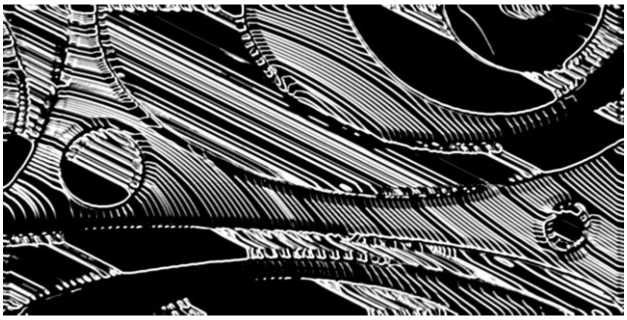


Figure 7. "Natural" - Structures common to natural images.

As can be seen in Fig. 7, *Natural* includes parallel structures of varying width, separation, and curvature with smooth but nonlinear drop-offs in illumination. This image is suitable for identifying loss of visibility or spurious presence of features that may be diagnostically important, e.g., when interpreting X-ray images.

The fourth image, "*Synthetic*" (Fig. 8), is designed to reveal artifacts that may be generated by an algorithm when applied to a complex texture such as sand, grass, fur, cloth, etc., or to a complex repeating pattern when viewed under perspective transformations or physical deformation (e.g., a quilted blanket draped over a person), within which random variations may produce coherent structures at different length scales[1]. Subtle directional biases introduced by an algorithm may visibly alter or spuriously introduce such structures, and this image is designed to be sensitive to such biases even though it is not "texture-like" in appearance.

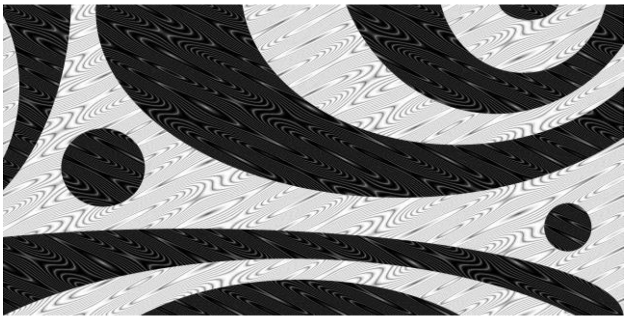


Figure 8. "Synthetic" - Complex patterns.

As can be seen in Fig. 8, *Synthetic* has a repeating pattern of radially-parallel structures that are at the resolution and intensity-discretization limit, i.e., visible artifacts are unavoidable under spatial and/or intensity decimation. As such it is sensitive to a class of artifacts that largely subsumes those that are likely to be revealed by the previous three images. This is a limitation in that it may reveal artifacts for which the source may be difficult to identify in the algorithm under examination. On the other hand, its complexity of structural detail provides sensitivity to artifacts with multivariate dependencies that may not be revealed by the other three images.

The next section provides illustrative examples involving use of the proposed image set.

[1] It must be noted that *Synthetic* is extremely sensitive and will tend to show artifacts such as spurious moire patterns if scaled, e.g., for this paper.

V. Examples

There are clearly too many kinds of image processing operations and algorithms to permit any sort of comprehensive examination using the proposed image set. However, ISR and image compression represent good candidates for consideration given their widespread use and the familiar and well-studied artifacts produced by various algorithms. To further narrow the scope of consideration, examples involving image compression are restricted to only two generic approaches: decimation-based local compression, e.g., JPEG [6], and spectral-based global compression, e.g., using information based on only the largest singular values from a singular-value decomposition (SVD) of the image [7].

Typical artifacts of JPEG and SVD in the high-compression regime[2] are exhibited in the subregion of Basic shown in Fig. 9.

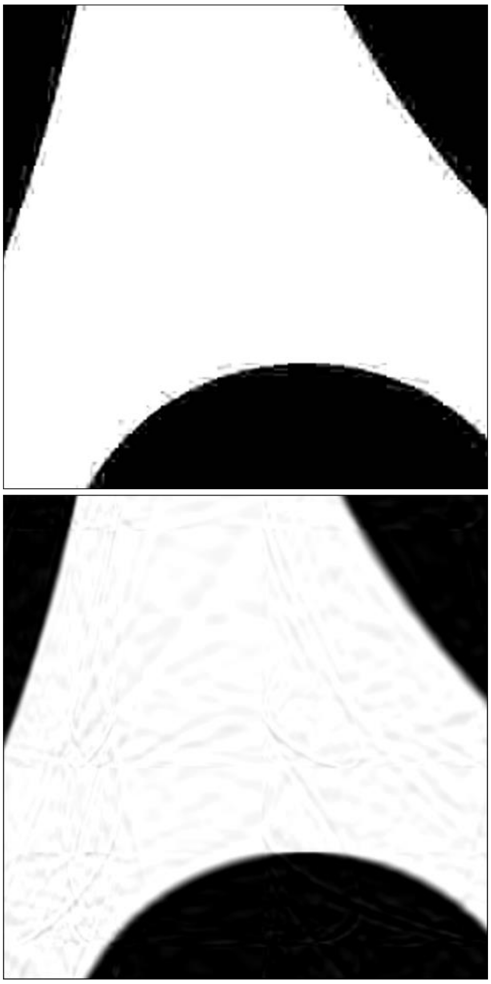


Figure 9. Characteristic artifacts from JPEG (top) and SVD (bottom) associated with very high compression in a subregion of *Basic* image.

The subregion of Basic in Fig. 9 shows that JPEG produces artifacts localized around edges while SVD tends to preserve smooth edges but introduces artifacts globally throughout the image. The JPEG-produced artifacts around the edges are sometimes referred to as “chin whiskers” in still images or “mosquito noise” in video [8], which shows they have distinctive and recognizable characteristics. The SVD-produced artifacts also have recognizable characteristics but are more uniformly distributed, i.e., more noise-like.

Fig. 10 shows JPEG and SVD high-compression artifacts in the lower-right-hand corner of *Platonic*. Again, the two algorithms produce very different, highly distinctive artifacts.

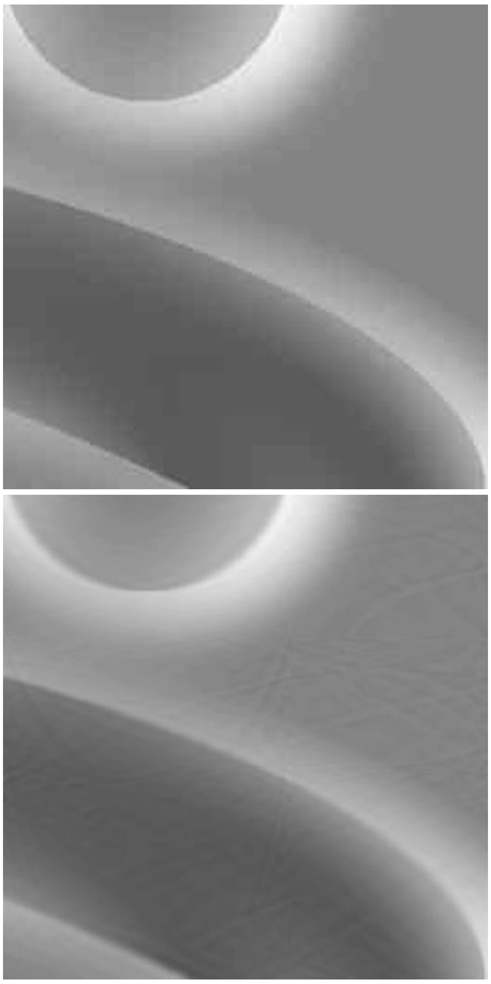


Figure 10. High-compression results from JPEG (left) and SVD (right) in a subregion of *Platonic* image.

Fig. 11 shows the effect of increasing contrast[3] to a subregion of *Platonic*. Specifically, applying an increase in contrast to *Platonic* produces significant banding in regions of smoothly-varying intensity and saturation artifacts in the corona at the center-top of the image. Fig. 12 shows the same increase in contrast applied to *Lena*, resulting in no clearly-visible generation of artifacts.

Fig. 13 shows high-compression artifacts from JPEG when applied to *Natural*.

Fig. 14 shows results from the application of a cubic 4x axis decimation (down-res) of *Natural* followed by

[2] Because there is no standardized codec for SVD compression (e.g., with defined bit-depth optimization of floating-point numbers), examples of SVD and JPEG applied to the same image in this section do not necessarily correspond to equal optimally-achievable compression ratios.

[3] All examples involving contrast enhancement were produced by GIMP at level 30.

cubic up-res (super-resolution/interpolation) back to its original dimensions.

Fig. 15 shows the same operation as Fig. 14 but applied to *Synthetic*.

Lastly, Fig. 16 and Fig. 17 respectively show high-compression results from applying JPEG and SVD to *Synthetic*. In both cases the distinctive artifacts associated with JPEG and SVD compression are clearly visible. In the case of JPEG the artifacts are manifest in multiple ways, including moire patterns, while the SVD artifacts are of a form that resembles scratches and surface dust.

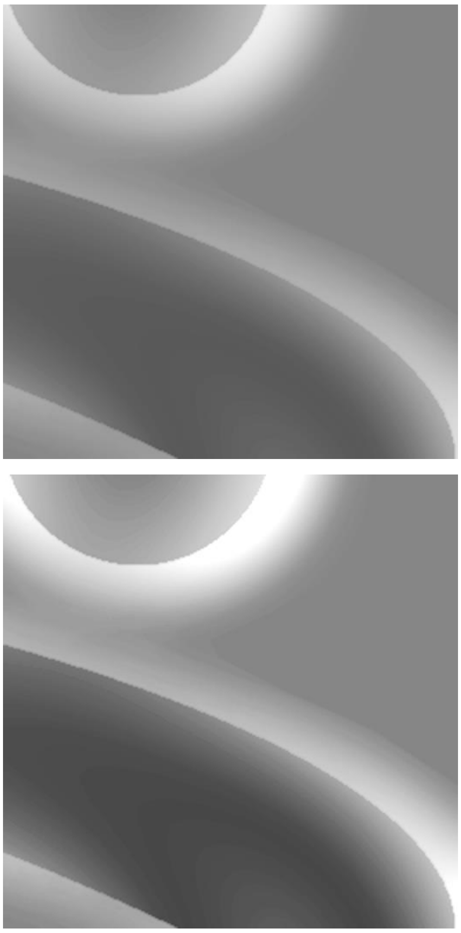
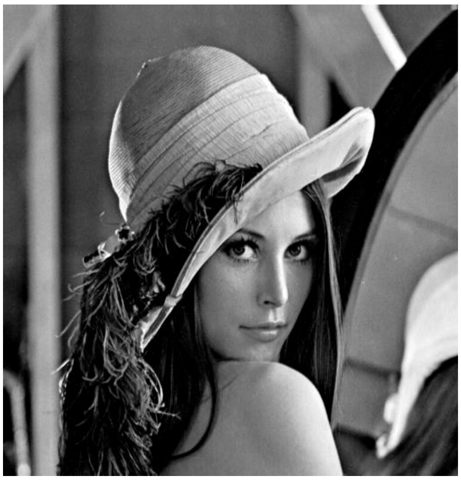


Figure 11. Detail of *Platonic* (left) and the same subregion with an increase in contrast (right) showing spurious contour layering. (Note: Jagged edges are due to magnification of subregion for easier viewing.)



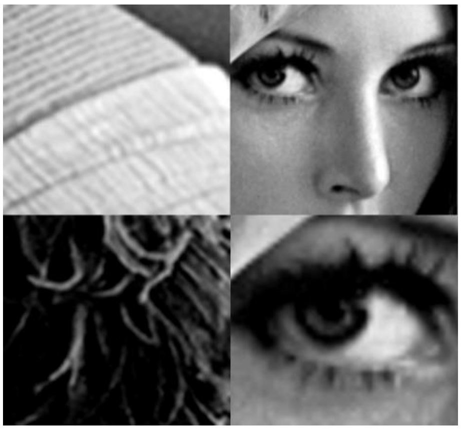


Figure 12. Contrast enhancement of *Lena* does not produce any clearly-visible artifacts that are not present in the original image.

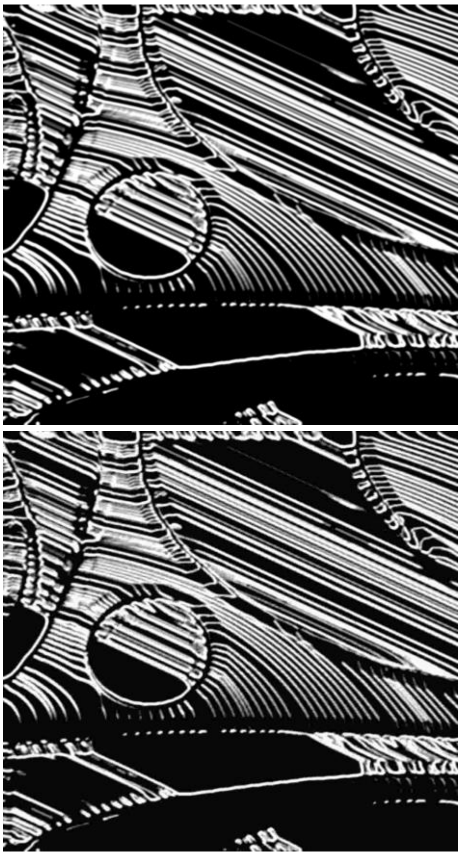
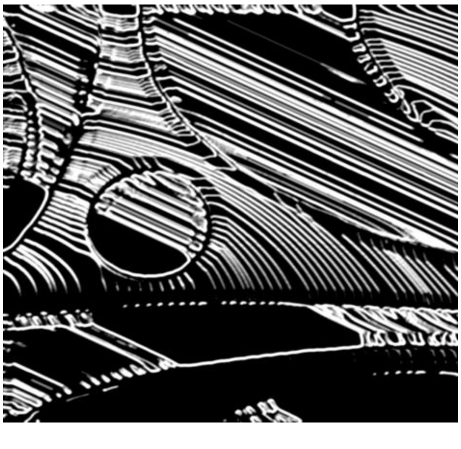


Figure 13. Left half of *Natural* image (top) and high-compression results from JPEG (bottom) with visible pixelation noise and aliasing.



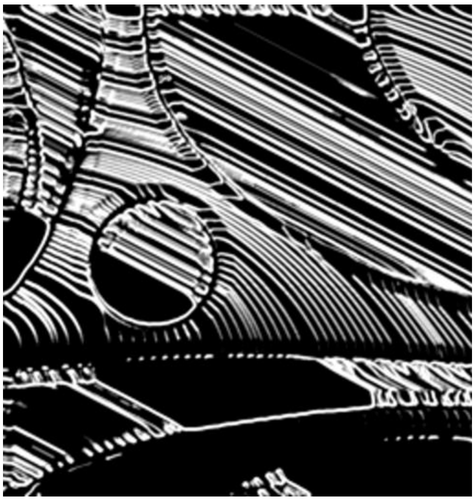


Figure 14. Left half of *Natural* image (top) and the result of a 4x down-res followed by a 4x up-res (bottom) with clearly-visible pixelation and aliasing artifacts.

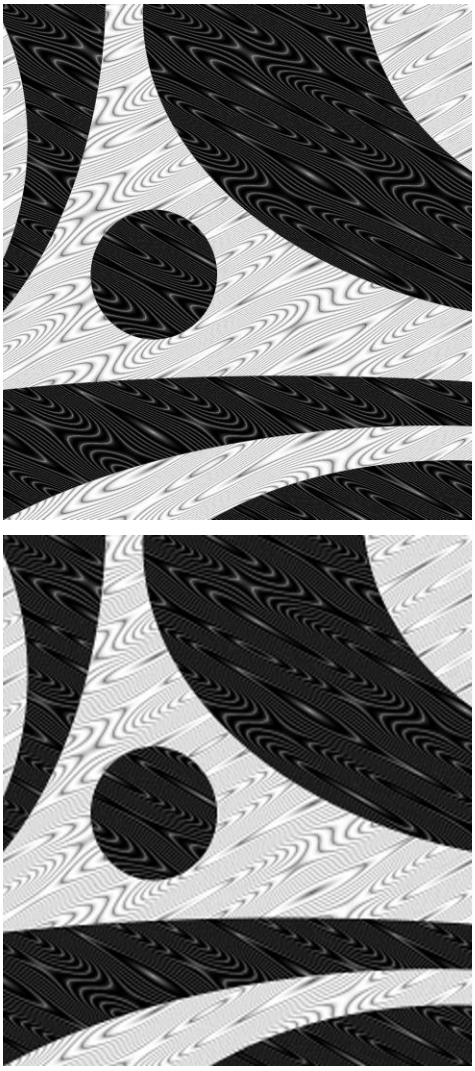


Figure 15. Left half of *Synthetic* image (top) and the result of a 4x down-res followed by a 4x up-res (bottom) with clearly-visible pixelation and aliasing artifacts.

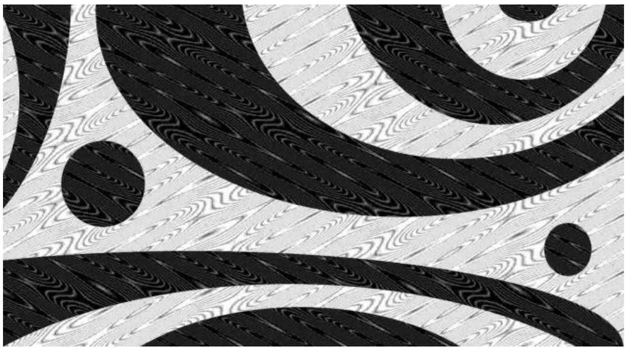


Figure 16. JPEG high-compression of *Synthetic*.

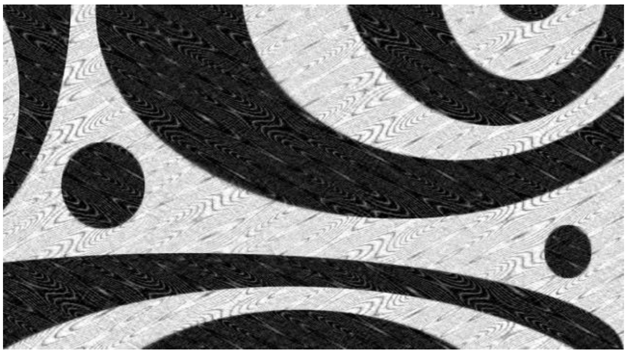


Figure 17. SVD high-compression of *Synthetic*.

VI. Discussion

Four artificially-generated images have been proposed as candidate test images for assessing and comparing the qualitative behaviors of different image processing algorithms. These images have been examined in a wide variety of contexts since they were developed at the Naval Research Laboratory (NRL) in the 1990s. There is no rigorous and general statement that can be made except that the four images have been found to be distinct in their specificity to different types of artifact. It is clearly also the case that they do not contain (by design) interpretable content that can lead to subjective bias when applied to qualitatively assess the properties of a given algorithm. Anecdotal experience motivates significantly stronger claims, but here we only put forth this set of images as candidates for consideration as potential standards for the image processing community.

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