Understanding visual complexity with statistical physics
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We attribute a notion of lost information (entropy) to digital images based on considering pixel value fluctuations that are considered imperceptible or irrelevant to understanding the content of an image. This information is precisely defined in the framework of information theory, and is influenced by an analogous situation in statistical physics. Using this analogy enables us to compute the entropy using the Wang-Landau algorithm for the density of states developed for use in statistical physics. Given the results, we discuss limitations of the model in comparison to the known physical and biological processes that take place in the visual system.

CONTENTS

I. INTRODUCTION

The human visual system is crucial for survival. While this system gathers useful information from our environment, it remains imperfect. A precise understanding of the information lost in sensation may guide future understanding of the information we do gather, as well as inform the design of image compression and reconstruction algorithms for human consumption.

As a simple model for this lossy process, we consider slightly varying the pixel values of a grayscale image to produce different images that are not perceived to be different, or that are not different enough to change the qualitative impression of the image on an observer. The freedom to choose different modified images represents information that is lost. What follows is a description of how we can quantify this information, and then how we can calculate it for particular images.

We first define what we mean by information, complexity, and entropy in Sec. II. With this backdrop in place, we then look at different perspectives on visual complexity. We start with the *psychophysical perspective* and consider the human visual system in Sec. III. The *natural perspective* looks at images of the environment that the visual system processes. These images have well-studied statistics that we will discuss in Sec. IV. Another approach is to study differences between images. To this end, we propose an ensemble of images that are different from a given image in Sec. V. This *ensemble perspective* considers the information to describe the modification to be much like the information to specify a microstate in statistical physics. The natural and ensemble perspectives usually work with grayscale images. The complications associated with considering color arise from the choice of coordinates for the color space. This is addressed by the *coordinate perspective* in Sec. VI. Finally, we look past data on lattices like the fovea or sets of pixels, and instead hold the processes that create the data to be responsible for their complexity. The *algorithmic perspective* of Sec. VII considers programs as explanations of complexity, with commonly-used computer graphics techniques serving as upper bounds on the true algorithmic complexity. All of these perspectives contribute to defining the notion of visual complexity.

II. INFORMATION, ENTROPY, AND COMPLEXITY

We generally use these terms as synonyms for the same kind of idea, but with different connotations from information theory, statistical physics, and computer science, respectively.

A. Information Theory

A mathematical notion of information is provided by the work of Shannon [1]. In the view of classical information theory, *information* is a property of an event, in the sense of a random process. To this end, we consider a random variable X with support $\mathcal{X}$ and probabilities $p(x)$ for $x \in \mathcal{X}$. As regards communication, the information $I(x)$ required to describe the event $X = x$ should satisfy intuitive axioms:

- If $p(x) = 1$, the event is certain to happen and no information is required to describe its occurrence: $I(x) = 0$.
- If $p(x) < p(x')$, then x is less likely to happen, and ought to require more information to describe: $I(x) > I(x') \geqslant 0$. As an analogy, compare the phrases "nightly" and "once in a full moon:" The less probable event has a longer description.
- For independent events x and y, it makes no difference to describe the combined event (x, y) instead of each event individually: $I(x, y) = I(x) + I(y)$.

Given these axioms, the only solution is the *self-information* (Theorem A.1)

$$I(x) = -\log p(x), \tag{1}$$

where the base of the logarithm determines the units of information: base two (lg) gives *bits* and base e (ln) gives *nats*. The information of the entire random variable may then be defined as the average of (1) over all events, which is known as the *Shannon entropy*

$$H = -\sum_{x \in \mathcal{X}} p(x) \log p(x). \tag{2}$$

The Shannon entropy may also be derived from intuitive axioms similar to those for the self information [1, 2]. The continuous version of (2) is known as the *differential entropy*

$$h = -\int_{\mathcal{X}} p(x) \log p(x) \,\mathrm{d}x\,,$$

which is insufficient as a notion of information because it may change with different coordinates. Instead, we consider the *relative entropy* or *Kullback-Leibler divergence* from a reference distribution q to p defined by

$$D_{KL}(p \parallel q) = \int_{\mathcal{X}} p(x) \log \frac{p(x)}{q(x)} \,\mathrm{d}x\,,$$

which is invariant under parameter transformations and nonnegative [3, p. 243].

B. The maximum entropy principle (MaxEnt)

A physicist familiar with statistical mechanics might wonder why Shannon's entropy (2) has the same mathematical form as the thermodynamic state variable for temperature

$$S = -k_B \sum_{x \in \mathcal{X}} p(x) \ln p(x),$$

which we may call the *Gibbs entropy*. This connection between information theory and statistical physics was developed by E. T. Jaynes to produce the maximum entropy principle (MaxEnt) [2]. We would like to make predictions about systems given some macroscopic quantities that we observe. To do so, we must assign probabilities to microstates, which we ought to do in an unbiased way, subject to the constraints that average macroscopic quantities take their observed values. Jaynes argues that this unbiased assignment corresponds to maximizing the entropy, and describes how this subjective assignment can be expected to make physical predictions, while an objective assignment of probabilities is required to understand the microscopic mechanisms behind these predictions. In particular, maximizing the entropy with constrained average energy produces the canonical distribution [2]

$$p(x) = \frac{1}{Z} e^{-\beta E(x)},$$

where $\beta = 1/k_B T$ and the *partition function* is

$$Z = \sum_{x \in \mathcal{X}} e^{-\beta E(x)},$$

with the variates x being different states of a system.

C. Algorithmic entropy

A more general notion of entropy is found in an algorithmic approach. We say a *computer* takes a finite binary string $p \in \{0, 1\}^*$ called a *program*, and either produces a finite string as output or produces an infinite string and does not halt.

Definition. Given an object x (representable as a binary string), its *Kolmogorov complexity* $K(x)$ is defined as the length of the shortest program that outputs the object when executed on a computer.

The canonical choice of computer is a universal Turing machine $\mathcal{U}$, but the complexity from different computer $\mathcal{A}$ (like a Python interpreter) differs by only a constant: $K_{\mathcal{U}}(x) \leqslant K_{\mathcal{A}}(x) + c_{\mathcal{A}}$ [3, p. 467]. That is, the universal computer $\mathcal{U}$ may compute x by simulating $\mathcal{A}$. For long strings x, the constant is insignificant. We may also define the *conditional Kolmogorov complexity* $K(x \mid l(x))$, where the computer already knows the length of x.

The generality of Kolmogorov complexity is apparent when we consider stochastic processes. Similar to in Sec. II A, consider a stochastic process $\{X_i\}$ with the X_i drawn IID from the finite set $\mathcal{X}$ with PMF $p(x)$ for $x \in \mathcal{X}$. Then [3, p. 473]

$$H(X) = \lim_{n\to\infty} \frac{1}{n} \langle K(X^n \mid n) \rangle .$$

The length of an optimal compression program approaches the entropy limit. In this sense, the Kolmogorov complexity is a generalization of entropy.

In practice, we do not use minimum-length programs or know Kolmogorov complexities, since in general they are not computable [3, p. 482]. However, they are useful in applications of Occam's razor. To avoid multiplying our explanations beyond necessity, we choose the least complex explanation that is correct.

III. HUMAN VISION

The psychophysical perspective on visual complexity focuses on the light entering the eye and the various responses generated in different regions of the brain.

A. The light field

We may describe the light field from a scene impinging upon the eye with the *plenoptic function* L. This function gives the spectral radiance of light with wavelength λ along a ray specified by spherical angles θ and φ at a given point $(\boldsymbol{x}, t)$ in space and time. All of the information about how a scene looks is contained in the function $L(\boldsymbol{x}, t, \theta, \varphi, \lambda)$. The creation of *light field cameras* to capture the whole light field that would enter the eye is a topic of active research [4]. While our eyes and conventional cameras use many photosensitive elements, significant capture of the light field may be done with only one intensity-sensitive element. This is simple enough that the author previously created a proof of concept *single-pixel camera* for an undergraduate laboratory project [5, 6]. Such a *single-pixel camera* and advances in light-field cameras are made feasible by a *compressive sensing* technique which leverages the statistics of natural images discussed in Sec. IV [7].

B. The visual system

The early stages of processing in the visual system recognize local properties like color, edge orientation, motion, and binocular disparity. These properties arise naturally from the plenoptic function, as discussed in [8]. More precisely, one may show simple images to an animal and probe the responses of neurons in affected regions of the brain, like the lateral geniculate nucleus (LGN) and primary visual cortex (V1). By varying the stimulus, one may develop a map of how the neuron responds as a function of position in θ and φ. This map, called the *receptive field* of the neuron, is generally set up to capture an aspect of the plenoptic function. For example, the receptive fields of *simple cells* in V1 are similar

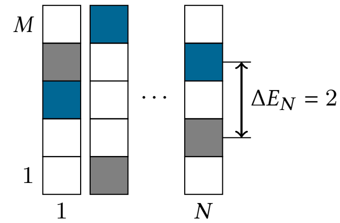

FIG. 1. The energy difference between base image pixel values (■) and modified image pixel values (■).

to Gabor filters, and are used to detect edges with a particular orientation [8]. Van Hateren and Ruderman have shown that the independent components of natural image sequences give similarly shaped filters, supporting the hypothesis that the simple cell receptive fields are tuned to encode natural images well [9].

IV. NATURAL IMAGE STATISTICS

Images of the natural world are easily distinguishable from man-made images or random noise. This difference is reflected in the statistical structure of natural images, and is generally robust across variations in subject matter or lighting. For example, the power spectrum of a natural image (averaged over orientations), scales like $k^{-2+\eta}$, where k is the spatial frequency and η is small. This and the other statistics discussed in [10] establish that natural images are approximately *scale-invariant*. The scale invariance of natural images is mostly explained by occlusion [11]. Different objects appear to be different sizes and occlude one another, causing an image to depict multiple scales. However, the scale invariance of a natural image may also reflect the scale invariance of objects it depicts: nature is full of fractals [12].

V. AN ENSEMBLE OF IMAGES

TODO: Introduce idea and reorient supporting text towards the *ensemble of different images* rather than towards error and "lost information."

A. Theory

Given a base image A with N pixels which take integer gray values $1 \leqslant a_i \leqslant M$, we define the *energy* of a different image B with gray values $1 \leqslant b_i \leqslant M$ as

$$E_A(B) = \sum_{i=1}^{N} |a_i - b_i|,$$

as depicted in Fig. 1.

We would like to consider all possible modified images, but focus on images with a typical value for the energy which indicates the size of fluctuations we are considering. We do this by assigning a probability distribution to the images with constrained average energy. Given the results of Sec. II B, we choose the MaxEnt distribution, which we may consider as a canonical ensemble. By thinking of our images as a physical system, we may apply tools from statistical mechanics. We would like to know the entropy of the MaxEnt distribution, which we will compute with the partition function as

$$S/k_B = \beta E + \ln Z. \tag{3}$$

In turn, we obtain the partition function

$$Z = \sum_{E \in E(\mathfrak{X})} g(E) e^{-\beta E}$$

from the number of states $g(E)$ with energy E (the *density of states*). For the case where the base image is all black ($a_i = 1$) or all white ($a_i = M$), we may explicitly count that the density of states is (Theorem A.2)

$$g(E) = \sum_k (-1)^k \binom{N}{k} \binom{N+E-Mk-1}{E-Mk}.$$

However, the situation for general grayscale images becomes more complicated. For this reason and the ability to analyze more complex systems, we determine the density of states numerically using the Wang-Landau algorithm [13].

B. Methods

The Wang-Landau algorithm (WL) was implemented to determine the density of states for grayscale image fluctuations. Our implementation adapts the algorithm described by Wang, Landau, et al. in [13, 14] for lattice models to work on the image fluctuation model we have described (Appendix B). The offset of the log density of states was set by ensuring that the number of states from $\sum_E g(E)$ gave the total number of states M^N. We then computed the entropy from the numerical density of states with (3).

C. Results

The log density of states from WL for a black image is given in Fig. 2. Since this is indistinguishable from the exact result, we quantify the error by running 1024 simulations for a black image with the same parameters for histogram flatness and f tolerance as in [14]. The resulting relative errors are given in Fig. 3. This relative error is consistent with that in [14] for a similarly-sized 2D Ising ferromagnet, which establishes that the implementation of the algorithm is correct and has the expected error characteristics.

We now consider the desired calculation of the entropy for random grayscale images. The WL densities of states for 1024 random grayscale images is given in Fig. 4. The corresponding entropies (Fig. 5) represent the lost information that we seek. The entropies for different grayscale images are similar, since the local energy landscapes for gray pixels are close

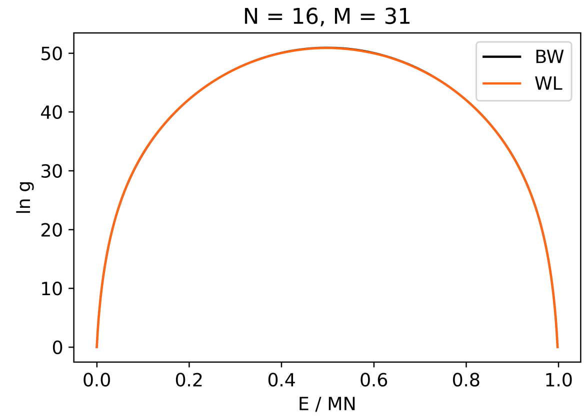

FIG. 2. The log density of states for a black image from the Wang-Landau algorithm (WL), compared to the exact result (BW). The two densities of states are indistinguishable.

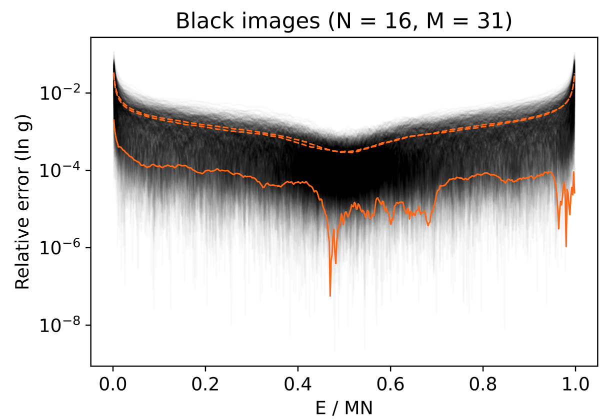

FIG. 3. The relative error in the log density of states for 1024 black image Wang-Landau simulations. The mean density of states is indicated in orange and the composite densities of states one standard deviation away are dashed.

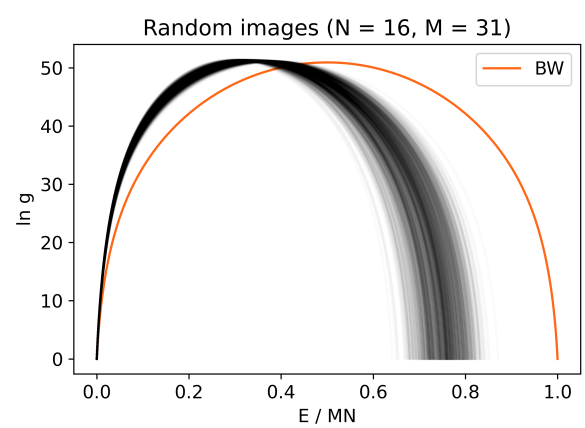

FIG. 4. The log density of states for 1024 random grayscale image Wang-Landau simulations. The black image result is provided as reference in orange (BW).

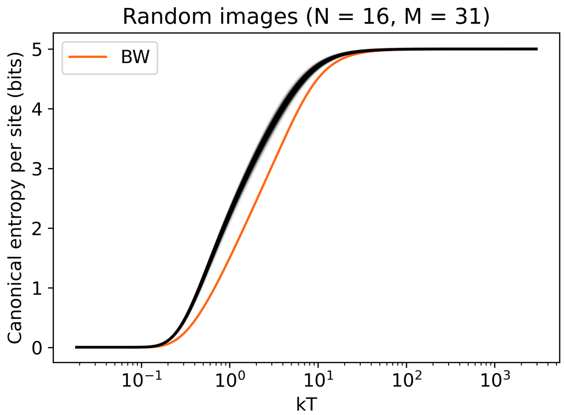

FIG. 5. The canonical entropy computed from the simulation density of states for 1024 random grayscale images. The entropy from the exact result for a black image is shown in orange (BW).

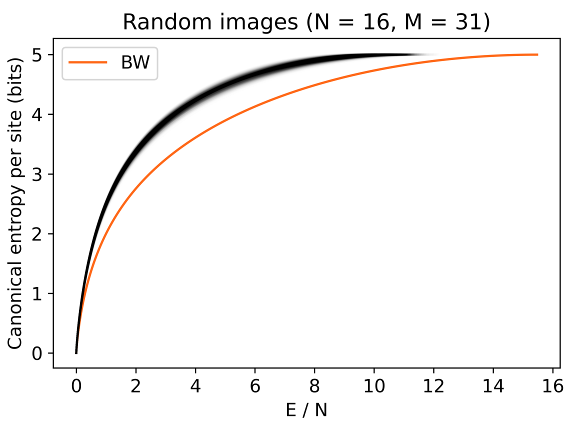

FIG. 6. The canonical entropy for grayscale images increases quickly with energy before saturating at the maximum. The entropy from the exact result for a black image is shown in orange (BW).

to the same. The entropy for a black image is lower than for a grayscale image by almost 1 bit, which reflects that the black pixel values may only fluctuate up in value, rather than in both directions for a gray pixel value. We may also see how the entropy depends upon the average energy, which is the quantity we originally considered (Fig. 6). As expected, this tends towards the log density of states as the canonical and microcanonical ensembles coincide in the thermodynamic limit of large N and M.

D. Discussion

Now that we have computed the lost information as the entropy of a fluctuating grayscale image, what can we learn from it? The immediate answer is nothing, since an empirical determination of the average energy E where the difference between images is barely noticeable is required. However, given such a prescription, we may regard our results as an approximation to the information lost in visual perception.

The greatest limitation of this approximation is of course the use of a digital image instead of considering the light impinging on the retina. The pixels in an image may be considered as averages of the true continuous intensity over a small solid angle. However, considering a static grid of pixels in a digital image differs from our foveated imaging process, which features multiple saccades around a scene to refine points of interest.

Another issue is the arbitrary number of values M for the number of gray values, which affects the entropy value. The simplest solution is to instead consider the intensive quantity $S/\lg M$, but it is unclear how to best generalize this to the case of color, where discretizations of different color spaces may produce different results. This problem of color is avoided in the case of scotopic (night) vision.

Despite these issues, the model of fluctuating pixel values serves as a simple idealized system that is computationally tractable. This allows us to precisely specify the problem at hand and begin to work towards a solution.

VI. COLOR AND CHOICE OF COORDINATES

TODO.

VII. ALGORITHMIC COMPLEXITY OF NATURAL IMAGES

TODO.

VIII. CONCLUSION

We have described a process for computing the lost information in a fluctuating digital image. This simplified model serves as a small step towards knowing how much information our eyes can gather from what they are viewing. While this model is significantly different from a model of the retina and rest of the visual system, the approach taken through information theory and statistical physics may prove to be applicable in more complex models.

Looking at lost information also helps to guide a quantitative understanding of the qualia we do see. We are able to recognize objects and faces despite varying noise, lighting conditions, viewing angles, and other factors. While our model has essentially focused on noise, a broader concept of irrelevant information could serve as a negative definition of the information gained in viewing an object. Such a concept would have strong applications in computer vision, as many systems struggle with recognition after simple irrelevant transformations like rotation.

IX. ACKNOWLEDGEMENTS

TODO.

Appendix A: Theorems

Theorem A.1. *The only twice continuously differentiable function $I(x)$ that satisfies the axioms in Sec. II A is the self-information $I(x) = -\log p(x)$.*

Proof. Consider independent events x and y with probabilities p and p'. The axioms only concern the probabilities of the events, so we may express the information as $I(x) = \tilde{I}(p(x))$. Then as proposed,

$$I(x, y) = \tilde{I}(pp') = \tilde{I}(p) + \tilde{I}(p')$$

by independence. Taking the partial derivative with respect to p gives

$$p'\tilde{I}'(pp') = \tilde{I}'(p),$$

and then taking the partial derivative with respect to p' gives

$$\tilde{I}'(pp') + pp'\tilde{I}''(pp') = 0.$$

We may then define $q = pp'$ to obtain the differential equation

$$\frac{\mathrm{d}}{\mathrm{d}q}\left(q\tilde{I}'(q)\right) = 0,$$

which has solution

$$\tilde{I}(q) = k \log q$$

for real k. The condition that $\tilde{I}(q) \geq 0$ requires $k > 0$, which is equivalent to a choice of base for the logarithm. □

Theorem A.2. *The number of tuples $(a_1, \ldots, a_N)$ with $0 \leqslant a_i \leqslant M - 1$ and $\sum_i a_i = E$ is*

$$g(E) = \sum_k (-1)^k \binom{N}{k} \binom{N + E - Mk - 1}{E - Mk}.$$

Proof. Ordinary generating functions provide the solution [15]. We represent the sum E as the exponent of an integer polynomial in z in the following way. For the tuple (x_1, x_2), we represent x_1 as z^{x_1} and x_2 as z^{x_2}. Together, we have $z^{x_1} z^{x_2}$, which gives the monomial $z^{x_1 + x_2} = z^E$ for this tuple. We may then find $g(E)$ as the coefficient of z^E in

$$\left(1 + \cdots + z^{M-1}\right)^N.$$

Expanding using the binomial theorem gives

$$\begin{aligned} \left(\frac{1 - z^M}{1 - z}\right)^N &= \sum_{k=0}^{N} (-1)^k \binom{N}{k} z^{Mk} \sum_{j=0}^{\infty} (-1)^j \binom{-N}{j} z^j \\ &= \sum_{k=0}^{N} \sum_{j=0}^{\infty} (-1)^k \binom{N}{k} \binom{N + j - 1}{j} z^{Mk + j}. \end{aligned}$$

The value of j for z to have exponent E is $j = E - Mk$, so the coefficient of z^E in the polynomial is

$$g(E) = \sum_k (-1)^k \binom{N}{k} \binom{N + E - Mk - 1}{E - Mk},$$

where the limits of summation are set by the binomial coefficients. □

Appendix B: Wang-Landau algorithm implementation

The relevant core of the Wang-Landau algorithm implementation is reproduced below. For the full code, see the REU project repository [16], which includes both the code and a notebook of all progress, including other approaches than the one described in this report.

```
def simulation(system, Es,
               max_sweeps = 1_000_000,
               flat_sweeps = 10_000,
               eps = 1e-8,
               logf0 = 1,
               flatness = 0.2
              ):
    """
    Run a Wang-Landau simulation on system with energy bins Es to determine
    the system density of states g(E).

    Args:
        system: The system to perform the simulation on (see systems module).
        Es: The energy bins of the system to access. May be a subset of all bins.
        max_sweeps: The scale for the maximum number of MC sweeps per f-iteration.
            The actual maximum iterations may be fewer, but approaches max_sweeps
            exponentially as the algorithm executes.
        flat_sweeps: The number of sweeps between checks for histogram flatness.
            In AJP [10.1119/1.1707017], Landau et. al. use 10_000 sweeps.
        eps: The desired tolerance in f. Wang and Landau [WL] use 1e-8 in the original
            paper [10.1103/PhysRevLett.86.2050].
        logf0: The initial value of ln(f). WL set to 1.
        flatness: The desired flatness of the histogram. WL set to 0.2 (80% flatness).

    Returns:
        A tuple of results with entries:
        Es: The energy bins the algorithm was passed.
        S: The logarithm of the density of states (microcanonical entropy).
        H: The histogram from the last f-iteration.
        converged: True if each f-iteration took fewer than the maximum sweeps.

    Raises:
        ValueError: One of the parameters was invalid.
    """
    if (max_sweeps <= 0
        or flat_sweeps <= 0
        or eps <= 1e-16
        or not (0 < logf0 <= 1)
        or not (0 <= flatness < 1)):
        raise ValueError('Invalid Wang-Landau parameter.')

    # Initial values
    M = max_sweeps * system.sweep_steps
    flat_iters = flat_sweeps * system.sweep_steps
    logf = 2 * logf0 # Compensate for first loop iteration
    logftol = np.log(1 + eps)
    converged = True
    steps = 0

    E0 = Es[0]
    Ef = Es[-1]
    N = len(Es) - 1
    S = np.zeros(N) # Set all initial g's to 1
    H = np.zeros(N, dtype=np.int32)
    i = binindex(Es, system.E)

    while logftol < logf:
        H[:] = 0
        logf /= 2
        iters = 0
        niters = int((M + 1) * np.exp(-logf / 2))
        while (iters % flat_iters != 0 or not flat(H, flatness)) and iters < niters:
            system.propose()
            Ev = system.Ev
            j = binindex(Es, Ev)
            if E0 <= Ev < Ef and (
                S[j] < S[i] or np.random.rand() <= np.exp(S[i] - S[j])):
                system.accept()
                i = j
            H[i] += 1
            S[i] += logf
            iters += 1
        steps += iters
        if niters <= iters:
            converged = False

    return Es, S, H, steps, converged
```

[1] C. E. Shannon, A mathematical theory of communication, The Bell system technical journal **27**, 379 (1948).

[2] E. T. Jaynes, Information theory and statistical mechanics, Phys. Rev. **106**, 620 (1957).

[3] T. M. Cover and J. A. Thomas, *Elements of Information Theory*, 2nd ed., Wiley Series in Telecommunications and Signal Processing (Wiley-Interscience, 2006).

[4] K. Marwah, G. Wetzstein, Y. Bando, and R. Raskar, Compressive light field photography using overcomplete dictionaries and optimized projections, ACM Trans. Graph. **32**, 10.1145/2461912.2461914 (2013).

[5] A. Striff, jfjhh/csjlab.jl: Submitted project (2020).

[6] T. A. Kuusela, Single-pixel camera, American Journal of Physics **87**, 846 (2019).

[7] D. L. Donoho, Compressed sensing, IEEE Transactions on Information Theory **52**, 1289 (2006).

[8] E. H. Adelson, J. R. Bergen, *et al.*, *The plenoptic function and the elements of early vision*, Vol. 2 (Vision and Modeling Group, Media Laboratory, Massachusetts Institute of Technology, 1991).

[9] J. H. van Hateren and D. L. Ruderman, Independent component analysis of natural image sequences yields spatio-temporal filters similar to simple cells in primary visual cortex, Proceedings of the Royal Society of London. Series B: Biological Sciences **265**, 2315 (1998).

[10] D. L. Ruderman, The statistics of natural images, Network: Computation in Neural Systems **5**, 517 (1994).

[11] A. B. Lee, D. Mumford, and J. Huang, Occlusion models for natural images: A statistical study of a scale-invariant dead leaves model, International Journal of Computer Vision **41**, 35 (2001).

[12] M. F. Barnsley, *Fractals everywhere* (Academic press, 2014).

[13] F. Wang and D. P. Landau, Efficient, multiple-range random walk algorithm to calculate the density of states, Phys. Rev. Lett. **86**, 2050 (2001).

[14] D. P. Landau, S.-H. Tsai, and M. Exler, A new approach to monte carlo simulations in statistical physics: Wang-landau sampling, American Journal of Physics **72**, 1294 (2004).

[15] H. S. Wilf, *Generatingfunctionology*, 3rd ed. (A K Peters, 2006).

[16] A. Striff, jfjhh/rpi-reu-notebook: Midterm report (2020).