EE 604
Digital Image Processing

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Lecture outline

- Assignment 2
- Brief review
- Information theory basics
- Image compression (Contd.)

Autoenhance

 

- Denoising
- Contrast adjustment
- Sharpening

Red eye correction

- Eye detection
    - use eye detectors or iris detectors
- Detect brightly red pixels
- Correction
    - Hint: modify only the red component in the image

Red eye correction

Automated red-eye detection and **correction** in digital photographs
L Zhang, Y Sun, M Li, H Zhang - Image Processing, 2004. ICIP' …, 2004 - ieeexplore.ieee.org
Abstract: Caused by light reflected off the subject's retina, **red-eye** is a troublesome problem in consumer photography. Although most of the cameras have the **red-eye** reduction mode, the result reality is that no on-camera system is completely effective. In this paper, we
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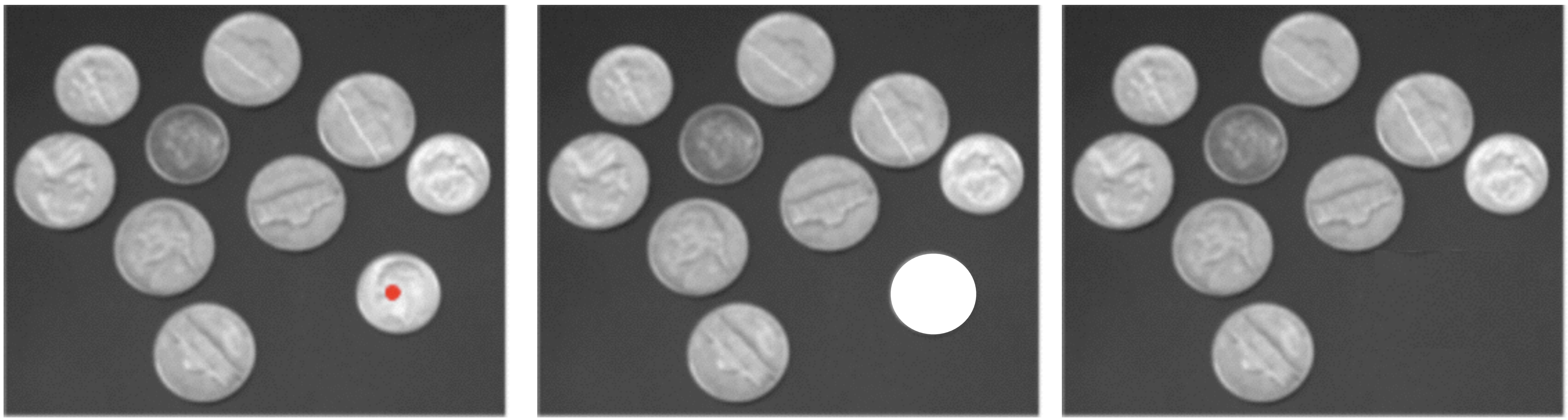
Probabilistic automatic **red eye** detection and **correction**
J Willamowski, G Csurka - Pattern Recognition, 2006. ICPR …, 2006 - ieeexplore.ieee.org
... 4] L. Zhang, Y. Sun, M. Li, and H. Zhang, **Automated Red-Eye** Detection and **Correction** in Digital Photographs, ICIP 2004 [5] B. Smolka, K. Czubin, J. Hardeberg, K. Plataniotis, M. Szczepanski, K. Wojciechowski, Towards automatic **redeye** effect **removal**, Pattern recognition ...
Cited by 54 Related articles All 6 versions

Automated in-camera detection of flash-**eye** defects
P Corcoran, P Bigioi, E Steinberg… - IEEE Transactions on …, 2005 - ieeexplore.ieee.org
... REFERENCES [1] K. Acker, D. Bien, and D. Lawton, "**Automated removal** of **red eye** effect from a digital ... [4] J. Wang and H. Zhang, " Apparatus and a method for automatically detecting and reducing **red-eye** in a ... [5] M. Gaubatz and R. Ulichney, "Automatic **redeye** detection and ...
Cited by 54 Related articles All 8 versions Web of Science: 7

Selective blur

- Region selection
- Segment foreground from background
- Add motion blur to background
- Add the foreground back

Object removal



- Object selection
- Object segmentation
- Fill up the missing pixels

Lecture outline

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- **Brief review**
- **Information theory basics**
- **Image compression (Contd.)**

What is information?

- Can we measure information?

  There was an accident in Kanpur

  There was an accident in IIT Kanpur

- The second sentence contains more information.
- Why? Is it the length (number of letters, may be?)

What is information?

- Can we measure information?

  There was an accident in IIT Kanpur

  There was an accident in IIT Delhi

- Which sentence contains more information? Not clear.

What is information?

- First attempt to quantify information [Hartley 1928]
  - Each symbol has N possible states
  - A given data consists of l symbols
  - The data has N^l possible states
  - Information measure:

$$I = \log(N^l) = l\log(N)$$

What is information?

- **Shannon** (1948) proposed to measure information in terms of uncertainty or randomness.
- Generation of information is seen as a random process.
- Consider a source X (a random variable), which takes a value x with probability p_x
- Event $\mathrm{E} : X = x$
- Information content:

$$I(\mathrm{E}) = \log \frac{1}{Prob(\mathrm{E})} = \log \frac{1}{p_x}$$

Shannon's entropy

- **Shannon's entropy** is the number of bits required to represent the amount of uncertainty (randomness) in a data source.

$$H = -\sum_{x \in \mathcal{X}} p_x \log_2(p_x)$$

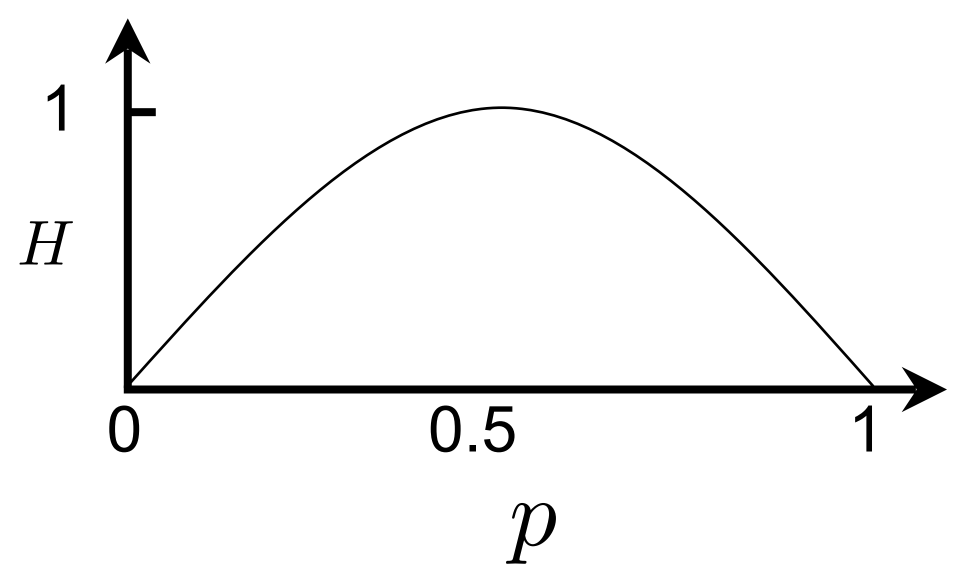
- H is the average information generated by a source.

- Note that the only thing we need to characterize the information content in a data source is its probability distribution.

Shannon's entropy

- A source $\mathbf{z}$ generates two symbols: a_1, a_2
- Probabilities: $Prob(a_1) = p, Prob(a_2) = 1 - p$

$$H(\mathbf{z}) = p\log\frac{1}{p} + (1-p)\log\frac{1}{(1-p)}$$



Shannon's entropy

- Fair coin: P(heads) = P (tails) = 0.5, the amount of information is **1 bit.**
- If we already know that it will be heads, P(heads) = 1, the amount of information is **0!**
- Throw M Fair coins, amount of information?
- A fair dice with M faces has entropy?

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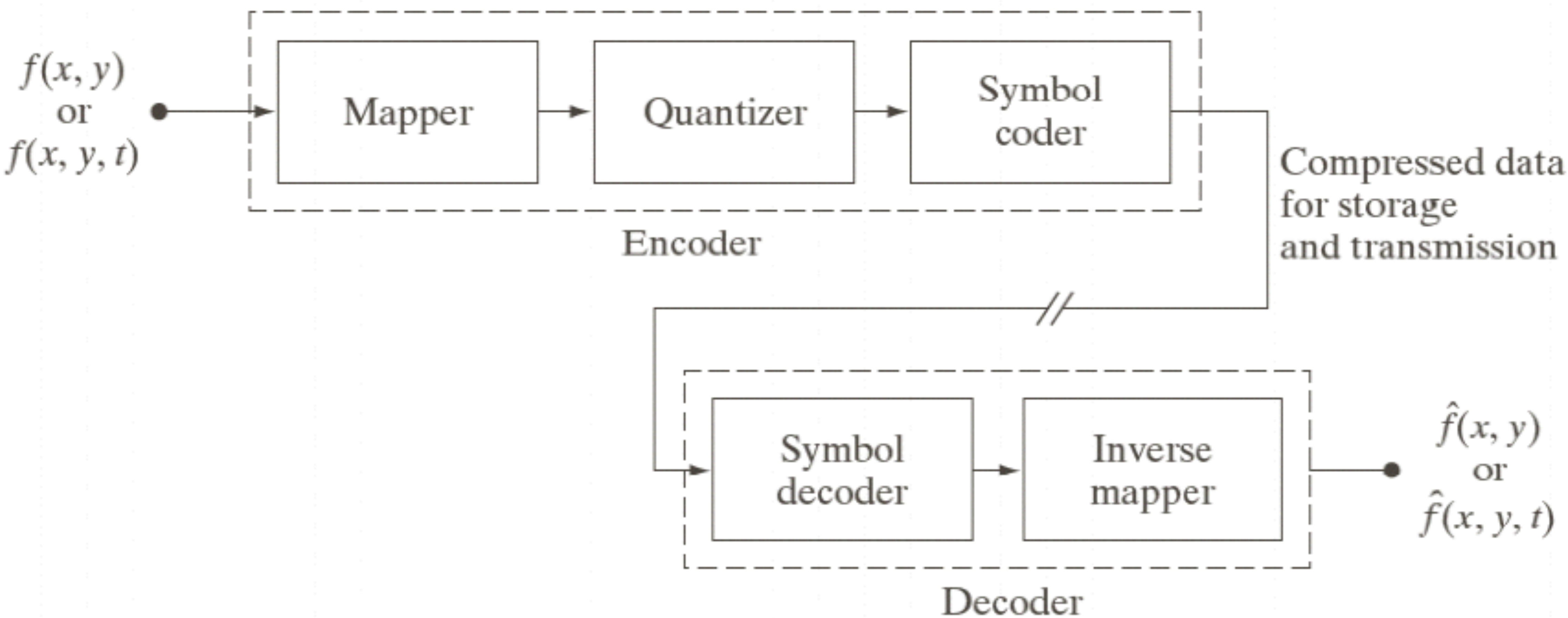
Image Compression

- One of the most successful applications of Image Processing
- Compression takes advantage of the redundancies
  - Coding redundancy
  - Interpixel redundancy
  - Psychovisual redundancy

Image Compression



Toy Problem

I =

21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243
21	21	21	95	169	243	243	243

Toy Problem

- If source is modeled as 256 symbol source with uniform prob distribution, H is maximum. This gives fixed-length code (8 bit/pixel).
- When source is modeled as 4-symbols with uniform probabilities, we have fixed length code (2bit/pixel)
- When source is modeled as 4-symbols with probabilities from the given source, H is lower (1.8bit/pixel).
- We can use variable coding to achieve better compression and reach as close as first order estimate as entropy.
- (See class notes for details)

Shannon's Source Coding Theorem

- **Statement:**

  In any (uniquely decodable) coding scheme, the average codeword length of a source (of symbols) can at best be equal to the source entropy, and can not be less than it

- If $\boldsymbol{L}$ is the shortest average codeword length (among different coding schemes) for a given source $\boldsymbol{z}$.

$$L \geq H(\mathbf{z})$$

- Source entropy is the **bound** on maximum compression that can be achieved using <u>entropy coding.</u>

- Coding efficiency: $\eta = \dfrac{H(\mathbf{z})}{L}$