8 - Texture and shape

Texture

Definition

- A definition from image processing: Texture is an region with spatial stationarity (same statistical properties everywhere in the region)
- A definition from computer graphics: Texture is a 2D surface applied to a 3D model

Types of texture

- Periodic texture - has a subregion that repeats in a regular pattern
- Stochastic (aperiodic) texture - generated by a random process

Texture models

- Parametric models: represent texture with a set of adjustable parameters
- Non parametric (stitching) models: represent texture as image patches

Why model texture

- Texture synthesis create more of a texture
  - Textures for computer graphics, video games, etc.
  - Image inpainting
- Texture transfer
  - Artistic effects
  - Online shopping

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Non-parametric texture synthesis

1. Randomly sample a small (e.g., 3 x 3 pixel) patch from the original image
2. Spiral outward, filling in missing pixels by finding similar neighborhoods in the original texture

- Neighbourhood size is a free parameter that specifies how stochastic the texture is L8.1 P17

Image quilting L8.1 P19

- Efficient patch based texture synthesis
- Use existing patches of texture to synthesis more texture; main problem is connecting them together without visible artefacts/seams (缝)
- “Corrupt Professor’s Algorithm"
  - Plagiarize as much of the source image as you can
  - Then try to cover up the evidence

- Algorithm:
  - Choose patch and overlap size
  - Initialize with a random patch
  - For each subsequent patch:
    - Find a patch in the original texture that is most similar to this region, considering only the pixels in the overlap region
    - Seamlessly paste in patch by cutting along a path with minimum overlap error

Graph cuts

- Represent neighbouring pixels as a graph
- Edge weight = overlap error
- Problem: Find path through graph with minimum total overlap error

Image inpainting

- Similar idea to fill in missing regions of an image:
  - Find a similar patch in another image
  - Paste in patch with an error-minimizing cut

Parametric texture synthesis

- Alternative to stitching approaches: represent texture with a number of parameters
- To synthesize texture, coerce (强制) a noise image to match the required parameters (usually through gradient descent)

Fourier texture synthesis

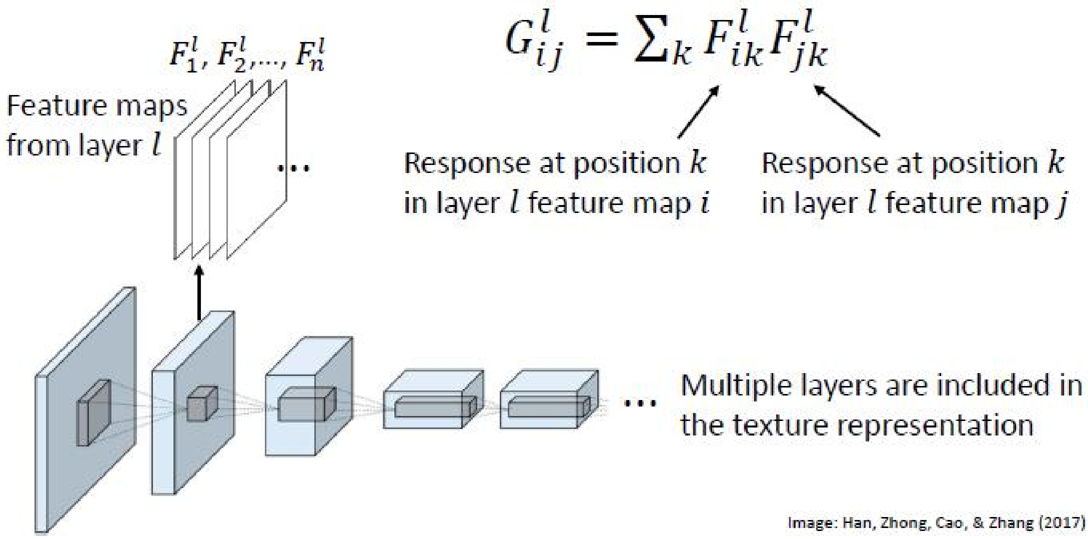
- Synthesize texture by matching Fourier magnitude
- Okay results for some simple textures, but doesn't work well in general

Colour and edges

- Textures could be defined as a distribution over simple features, like colour and edge orientation at various scales
- Synthesize texture by matching the distribution

More complex statistics

- Simple distributions of features are not sufficient
- Also need to represent feature co-occurrence
- The set of statistics needed to represent real images may be very complex
- Instead of modelling statistics by hand, represent texture as the feature response in the layers of a neural network trained on ImageNet classification
  - Feature correlations: Texture is represented as the correlations between feature maps at a layer of the neural network:



Summary - Texture synthesis

- Non parametric texture synthesis is based on copying texture patches
  - Works very well on periodic textures
  - Disadvantage: No model of texture parameters
- Parametric texture synthesis represents textures in terms of a set of parameters
  - Most methods work better on stochastic textures
  - Disadvantage: Even very complex models (e.g., based on neural networks) may be incomplete

Texture transfer

- **Render an image in the style of another image L8.1 P42**

Neural style transfer algorithm

- Both images (content, style) are run through a VGG network trained on ImageNet
- Content is represented as the responses from a layer of the neural network
- Style is represented as the correlations between feature maps at a layer of the neural network
- Use gradient descent to find an image that matches both content and style
- Style transfer parameters
  - Loss is sum of loss from content reconstruction and style reconstruction
  - Relative weight of content vs. style is a free parameter
  - Content and style can be matched at any combination of layers
  - Generally, match content at higher layers, and style across all layers

Summary - Texture

- Texture can be defined in different ways, but generally captures 2D/surface aspects of an image
- Texture representations are useful for texture synthesis and texture transfer
- Applications:
    - Image inpainting
    - Computer graphics
    - Art

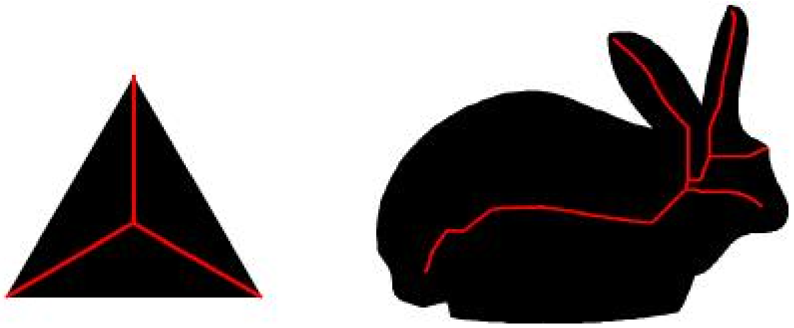
Shape

Models of 2D shape are usually based on either:

- The bounding contour of the shape (segments, angles)
- The internal structure of the shape (branches)

Shape skeletons L8.2 P7

Topological skeleton = thinnest possible version of a shape



- Formed of lines that are equidistant from the boundaries of the shape
- Geometrical description: L8.2 P9
    - The skeleton points are the centrepoints of the largest discs that can be fit inside the shape
    - If the shape was painted with a circular brush (of variable radius), the skeleton would be the path of the brush
- Skeletonisation algorithm L8.2 P10
    - Grassfire transform - algorithm for shrinking or thinning a shape
    - For each pixel within the shape, compute distance to closest boundary; peaks in the distance map are the skeleton
- Skeleton representation
    - Skeleton + distance to boundary at each skeleton pixel is a compact, invertible representation of shape
    - To "inflate" skeleton, place a disc at each skeleton pixel (radius = distance to boundary at that pixel)
- Application:
    - Shape recognition
        - Shape skeletons are easily converted to graphs

        - Graph representation can be used for shape matching, pose recognition
    - 2D -> 3D
        - Shape skeletons can also be used as the basis for a simple 3D model – just “inflate” with spheres instead of disks
- Drawbacks to skeletons   L8.2 P18
    - Shape must be segmented from background
    - Small changes in shape boundary produce large changes in skeleton

Summary - Shape skeletons

- Shape skeletons represent the internal structure of shapes
- Skeleton representations work well to model shapes that have a skeleton like structure
    - Human/animal figures
    - Written characters
    - Paths/networks (e.g., city roads, blood vessels (血管))

Contour representations

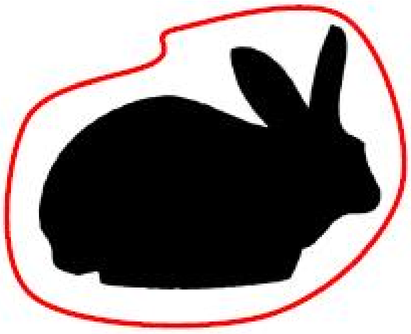
Active contours

- Parametric model that fits itself to object boundary
- “Shrink wraps” around object to capture shape
- Initialise contour outside object boundary
- On each step, allow each point on the contour to shift 1 pixel in any direction:
    - Shift to minimize a loss (or energy) function:

$$E_{total} = \alpha E_{elasticity} + \beta E_{stiffness} + E_{edge}$$

- $E_{elasticity}$ is based on contour length, penalises longer contours
- $E_{stiffness}$ is based on contour curvature, lowest for straight contour segments
- E_{edge} is based on image gradient at contour locations, lowest where image gradient is highest
- α, β are free parameters

- Repeat until loss does not change



- Active contours are used for segmentation and tracking, particularly in medical image analysis
- Drawbacks:
  - Requires initialisation (often from a human annotator)
  - May not fit shape correctly
    - Trade off between elasticity/smoothness and edge-matching - may fail to fit concavities in complex shapes
    - Difficult to detect shapes in clutter

Summary - Contour

- Active contours fit a shape boundary
- Tries to find an optimal shape which is both well fit to the edges and fairly simple (smooth, compact)
- Works well to segment objects with uniform appearance, moving objects

Face models L8.2 P31

- It's difficult to develop a general purpose model of shape that can represent all possible shapes well
- However, it is possible to develop parametric models for particular classes of shape
- One very widely studied class of shapes is the human face

Eigenfaces L8.2 P32

- If faces are aligned, pixel luminance values are sufficient to capture face shape
- Simple pixel based model: eigenfaces
- Each face is represented as a vector to the mean face image
- Parameters of face shape are obtained from PCA of face vectors
- Problem: Usually we can't assume faces appear in consistent alignment (or consistent lighting)
- To model faces under real world conditions, we need models that can consider shape/pose

Active appearance models L8.2 P36

- Label corresponding landmark points in each image
- Warp images onto the mean shape to get shape-free texture
- Obtain "shape," "texture," and "appearance" (shape+texture) parameters through PCA
- To fit the model to a new face, use gradient descent to minimize difference between model and image

- Applications: face synthesis, face segmentation
- Active appearance models separate shape and texture
    - Allows alignment of facial features, even when images are not aligned
- Problem: Shape is represented using 2D contours
    - Can’t separate face shape vs. pose
    - Can’t separate surface colour vs. lighting

3D face models L8.2 P40

- 3D version of active appearance model: morphable (形变) 3D mesh + texture map
- Parameters based on PCA of a large 3D dataset
- Gradient descent to match 3D shape, texture, and lighting to original image
- Application: Facial recognition
    - Most recognition algorithms use a shape model to align faces as a first step
    - Once faces are aligned, a standard CNN pipeline can be trained for face recognition
    - Alignment is critical for CNNs
        - Make it easier to design CNNs, no need to accommodate for different poses and only focus on texture
    -

Summary - Face models

- Face models are one of the main applications of shape representation in computer vision
- Current state-of-the-art algorithms are based on 3D face models
- Applications:
    - Facial recognition
    - Computer graphics (movie CGI, video games)
    - Zoom filters

Summary - Shape

- Although shape is not required for category level object recognition, shape is important for fine grained recognition and separating out effects of lighting and pose
- 2D shapes are typically represented in terms of skeleton structure or bounding contours
- 3D shape models have been developed for specific recognition problems (mainly faces and body pose)