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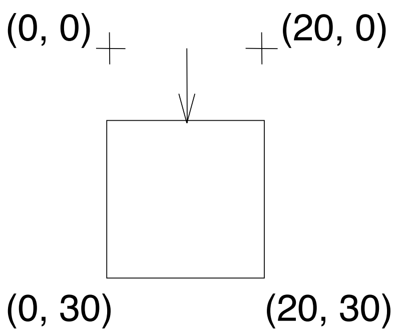
Chapter 4 - Image

Vector Graphics

- Raw data:
  - set (!)
    of lines and polygons
    with coordinates
    and attributes (line width, color)
- Registration data:
  - coordinate system (cartesian, polar)
  - definitions for colors, textures
- Description data:
  - grouping related lines and polygons into geometric, higher order objects: squares, rectangles, projections of 3D-objects

start point		end point		width
0	30	20	30	2
9	8	10	10	1
20	10	20	30	2
0	10	0	30	2
10	0	10	10	1
11	8	10	10	1
20	10	0	10	2

a) set of line definitions



b) resulting graphics

Vector Graphics (2)

- Operations:
  - focus on output
  - manipulation by special editors (not part of the repository)
  - "simple" manipulations in the repository without replacing the complete graphics
- Input: via file or interchange format
- Output:
  - to a file, on a device (display, plotter)
  - line by line (numberOfLines, getAllLines)
- Modification:
  - add/delete line
  - translate, rotate, resize
- Analysis, aggregation, extraction
  - extract rectangular section (clipping)
  - reconstruction of geometric objects

Search

- Comparison (for search)
  - using description data (-> text)
  - using raw data
    - similarity of geometric figures (for very simple graphics)
- Significant extensions required for
  - curves
  - surfaces
  - segments (collection of arbitrary related elements)
- Subtypes:
  - technical drawing (CAD)
  - bar charts, flow charts, pie charts
  - street maps
  - …

(Raster) Image

- Raw data
  - pixel matrix (pixel = picture element, or "pel")
- Registration data
  - # of bits/pixel (pixel depth, usually 1, 8, or 24)
  - # of pixels/line (picture width)
  - # of lines (picture height)
  - linearization: by line or column
  - pixel semantics: grayscale, color definition, index into colormap
  - (optional) colormap with specific number of entries, length of entries (e.g., 24 bit)
  - (optional) definition of color space (RGB, IHS, …)
  - and more
- Descriptive data
  - text, keywords, knowledge representation describing content
  - recognized lines, areas appearing in the image
  - resulting 2-D objects such as circles, elipses, polygons, …

Image Operations

- Input/Output
  - file (SUN Rasterfile, GIF, TIFF, JPEG, ...)
  - main memory data structure (matrix)
  - device (scanner, camera / display, printer)
- Modification:
  - set individual pixel(s)
  - change color map
    - for artificial colors (tomography)
    - for analysis (contrast)
  - bitmap operations
    - overlay with other images
- Analysis, aggregation, extraction
  - increasing contrast
  - line recognition
  - resize, zoom, crop (window)
  - convert to grayscale

Image Search

- Significant research efforts over the last 20 years
  - a number of techniques and systems available
- Alternative approaches:
  - attribute-based
  - text decription (annotation)
  - content-based image retrieval (CBIR)
    - elementary features (low-level)
    - semantic features, object recognition (high-level)

Text-based Image Retrieval

- Image description
  - unrestricted (free) text
- Queries
  - keyword or free text
  - with/without boolean operators
- Search
  - uses conventional IR techniques (see chapter 3)
- Differences to text search
  - manual annotation required (unless captions are already present in the image file)
    - needs to be efficient, complete, consistent
    - requires domain knowledge, thesaurus
- Advantages
  - abstractions, concepts can be used ("smile", "happiness")
    - hard to achieve with other techniques
- Disadvantages
  - visual appearance (e.g., texture) is hard to describe textually
  - query-by-example-image is not supported

CBIR: Color-based Search

- Main idea
  - given an image, find images with a similar color appearance
  - three primary colors, or color channels (e.g., RGB)
  - each channel is divided into *m* discrete intervals
  - results in m^3 different color combinations (bins)
- Color histogram
  - *H(M)* for image *M*
  - vector $(h_1, h_2, \ldots, h_j, \ldots, h_n)$ with
    - n = number of bins
    - h_j = number of pixels for image *M* that fall into bin *j*
- Query is mapped to a histogram as well
  - compute from example image, or "guess" from description
- Search
  - compute distance between histograms of stored images and query image
  - return images below a given threshold, or first k (sorted ascending by distance)

Color Histograms

- Distance metrics
  - numerous proposals
  - simplest: L-1

$$d(H_1, H_2) = \sum_{l=1}^{n} | h_{1,l} - h_{2,l} |$$

- Limitations of basic approach
  - similarity of colors (by human perception) and bins is ignored
  - assumption: all images have N pixels
    - if not, then perform a normalization step
  - maximum distance of two images: 2N
    - there is no bin in which both images have pixels
  - what if images do not have exactly the same colors, but colors perceived to be similar?
    - queries only give an approximation of the desired colors
    - colors may be slightly different due to noise, lighting conditions, etc.
  - problem is made worse by the exact definition of bins

Accounting For Color Similarity

- Account for color perception in distance computation
  - method by Niblack et. al. (used in QBIC)
  - query histogram X, database image histogram Y
    - normalized: $0 \le x_i, y_i \le 1; \Sigma x_i = \Sigma y_i = 1$
  - bin-by-bin distance histogram Z = X – Y
    - $-1 \le z_i \le 1; \Sigma z_i = 0$
  - distance between X and Y

$$d^2_{hist}(X,Y) = (X-Y)^t A(X-Y) = \sum_i^k \sum_j^k a_{ij}(x_i - y_i)(x_j - y_j)$$

  - A is the symmetric color similarity matrix with
    $a(i, j) = 1 - d(c_i, c_j) / d_{max}$
    - c_i and c_j are the colors of bin i and j in the histogram,
    - $d(c_i, c_j)$ is the distance of colors,
    - d_{max} is the maximum distance of all colors
  - for similar colors, $d(c_i, c_j)$ is small, so a(i, j) is close to 1
    - presence of similar colors will result in reducing the distance

Example: bins for red, orange, blue

R = [1.0, 0.0, 0.0]
O = [0.0, 1.0, 0.0]
B = [0.0, 0.0, 1.0]

$A_{red,orange,blue} =$

$$\begin{bmatrix} 1.0 & 0.9 & 0.0 \\ 0.9 & 1.0 & 0.0 \\ 0.0 & 0.0 & 1.0 \end{bmatrix}$$

$$d^2_{hist}(R,O) = 0.2$$
$$d^2_{hist}(R,B) = 2.0$$

Perceptually Weighted Histograms

- Determine representative colors of a color space
- For each color, create a color bin
  - equal distribution across color space
- Histogram computation:
  - for each pixel, determine the ten most similar representative colors
  - determine the color distance
  - assign a weight proportional to the inverse distance and add to the corresponding color bin
    - pixel counts (fractionally) in multiple bins
- Most important difference to previous approaches:
  - histogram computation already considers color similarity
- Apparently results in performance advantage

Image Regions

- Consider position of colors within the image's spatial dimensions
- Partition the image into regions and compute histograms for each region
  - raster-based (e.g., 4 x 4 regions of fixed size)
  - separation of foreground and background
    - background often dominate regarding image area
    - foreground usually more important for search
    - separate histograms should be computed
    - segmentation does not need to be precise
      - minimum bounding rectangle, can be determined automatically based on horizontal and vertical pixel variations, or can be manually assigned
- Search may exploit the presence of regions (or foreground/background) in different ways
  - global search, considering region-specific similarity measures
  - focused search, referring to a specific region (e.g., foreground only)
  - weighting regions differently
- Experiments show significant improvements

Color Histograms – Additional Aspects

- Color distribution
  - so far, we partitioned the color space into bins in an equi-distant manner, without considering which colors are actually used
  - alternative approaches: use finer-grained partitioning for color intervals that receive more pixels
- Color variability
  - which color spaces are best suited for distance computation?
  - when should pixels in different pictures be considered "equivalent"?
  - color spaces
    - RGB is device-dependent, requires White and three primary colors for reference, is very sensitive regarding lighting conditions, surface reflections, etc.
    - Munsell or Lab spaces achieve a better perceptual uniformity
    - HSV (hue, saturation, value) – hue is invariant regarding illumination

Shape-based Search

- Requires segmentation
  - semi-automatic methods exist
- Shape representation and similarity
  - every shape should have a *unique* representation, invariant to translation, rotation, scaling
  - similar shapes should have similar representations to allow for search based on distance measures
- Query
  - query-by-example, sketch
- Terminology
  - **major axis**: straight line between the two most distant points on the boundary of the shape
  - **minor axis**: straight line perpendicular to the major axis such that a minimum bounding rectangle can be constructed which is parallel to the major and minor axis and width/ height correspond to the lengths of the major/minor axis
  - **base rectangle**: the minimum bounding rectangle described above
  - **excentricity**: ratio of major to minor axis (≥ 1)

Shape Representation

- Simple shape representation
  - based on the four measures defined above
  - may be used for representation, search
  - is only a "weak" characterization of the shape
  - usually combined with additional characteristics
    - example (QBIC system by IBM): area, circularity, major axis orientation, …
- Region-based shape representation
  - closer to perceived shape by including regions
  - promises better retrieval quality

Shape Regions - Idea

- Raster definition
  - quadratic cells of equal size
  - raster is just large enough to cover the shape
- Cells
  - may be completely or partially "filled" by the form, or may be "empty"
  - are labeled with "1" when filled at least 15%, otherwise 0
  - ordered left to right, top to bottom within the raster: bitstring for the shape
  - compact, easy to compute, invariant to translations
- Raster size
  - smaller cells result in more accurate shape representation, but require more resources
  - compromise: cell size from 10x10 up to 20x20 pixels

Region Normalization

- Achieves uniform shape orientation and scale
- Rotation
  - major axis parallel to x-axis
  - still two possible positions
  - results in two bitstrings
    - not for stored objects (would double storage space requirements)
    - but for queries
- Scale
  - proportionally scale the shape to a fixed length of the major axis (e.g., 192 pixels)
- Results in unique shape representation
  - provided that the major axis is unique
- Bitstring length
  - raster is just large enough for normalized shape: #cells along x-axis is always the same
    - example: 8 cells with cell size 24x24, major axis length 192 pixels
  - number of cells along the y-axis may vary (difference in excentricity), but is always smaller than along the x-axis
  - has to be accounted for by the similarity measure

Similarity Measure

- Idea: distance = number of unequal cells
- Excentricity needs to be accounted for
  - equal raster size: bitwise comparison
  - significant difference in #cells along y-axis:
    - shapes are regarded as different
    - threshold depends on cell size and application
      - typical example: 3
  - small difference for y-axis: fill with zeroes, do bitwise comparison
- Reflections (horizontal/vertical)
  - should be considered similar
  - two additional bitstrings for each query
- Multiple possible major axis
  - need to store all possible major axes, determine all possible major axes for query
  - pairwise distance comparison, keep minimum

Indexing and Retrieval

- For every shape in the database
  - determine major/minor axis, excentricity
  - normalize regarding rotation and scale
  - apply raster, determine bitstring
  - store bitstring, length of minor axis
- For every query
  - determine bitstring in the same manner
    - but include bitstrings for 180 rotation, reflections
  - search for bitstrings in the database with (almost) equal minor axis length (similar excentricity)
  - compute distance for all matches
  - return sorted ascending by distance

Texture-based Search

- Texture is hard to characterize
- Approach by Tamura et.al: six different features
  - coarseness
    - most important feature
    - size of distinguishable picture elements
  - contrast
    - grayscale levels, edge sharpness, periodicity of repeated elements
  - directionality
    - shape and position of elements
  - line-likeness
    - shape of elements
  - regularity
    - variation in placement of elements
  - roughness

Systems

- Have to support combinations of different kind of search
  - especially for elementary features *and* text
- QBIC
  - query image (color, shape, texture) plus keywords
  - partly included in DB2
  - wwwqbic.almaden.ibm.com
- Virage
  - Features: color, shape, texture
  - www.virage.com
- WebSEEK
  - www.ctr.columbia.edu/webseek

Summary

- Vector graphics
  - media object – raw/registration/description data, operations
  - search
- Raster image
  - media object – raw/registration/description data, operations
  - text-based image retrieval
- Content-based image retrieval (CBIR)
  - mostly based on elementary (low-level) features:
  - color-based
    - histograms, color similarity matrix, perceptually weighted histograms, regions
  - shape-based
    - representation – raster, normalization, similarity
  - texture-based