Shape and Matching

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Topics

- Approaches Involving New Descriptors
  - Shape Contexts
  - Matching Local Self-Similarities
- Novel Matching Techniques
  - Pyramid Match Kernel
  - Spatial Pyramid Matching

Shape Contexts (2002)

- Shape Matching and Object Recognition Using Shape Contexts
  - Serge Belongie
  - Jitendra Malik
  - Jan Puzicha

Shape Contexts (2002)

- As vectors of pixel brightness values, very different
- As shapes to human perception, very similar

Three steps to shape matching with shape contexts

1. Find the correspondence between sets of points from the two shapes
2. Use the matches to compute an alignment transform
3. Compute the “distance” between the shapes

Three steps to shape matching with shape contexts

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2. Use the matches to compute an alignment transform
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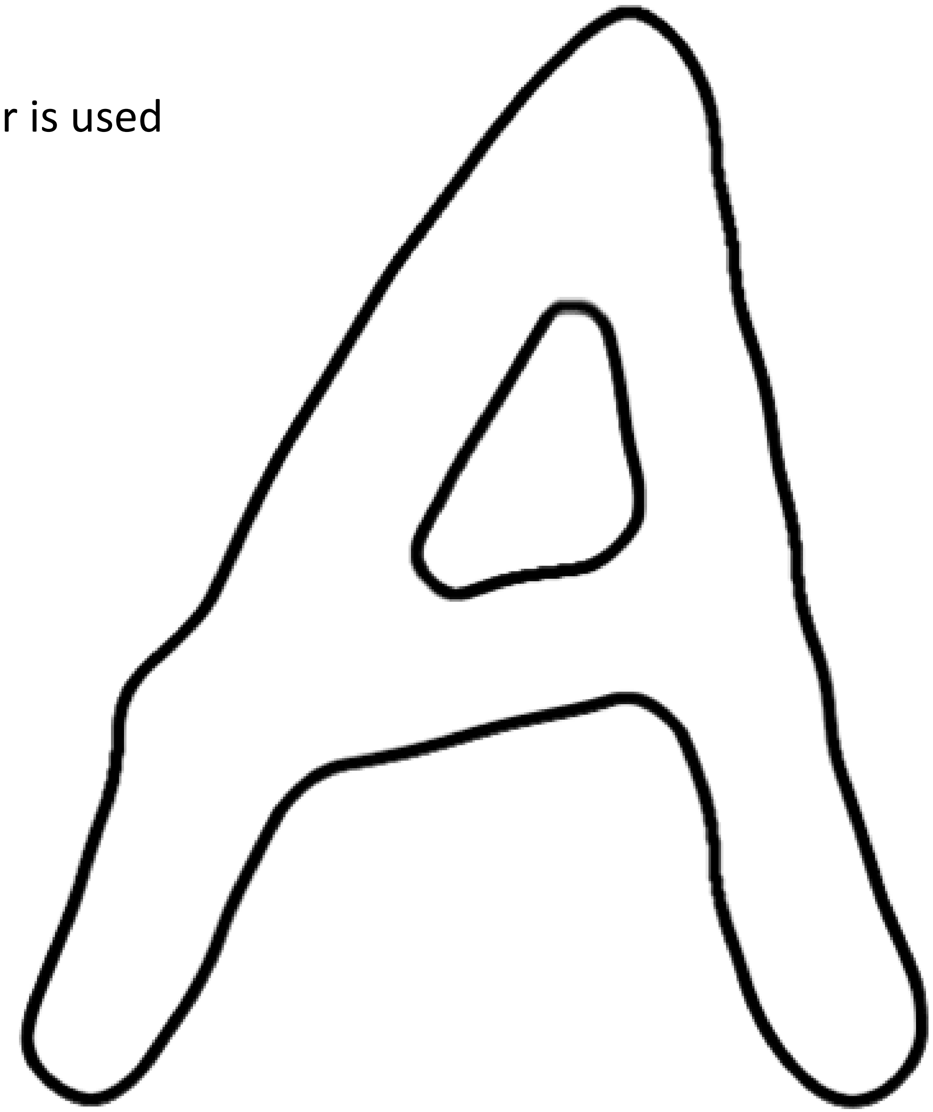
Shape contexts are a point descriptor used in step 1

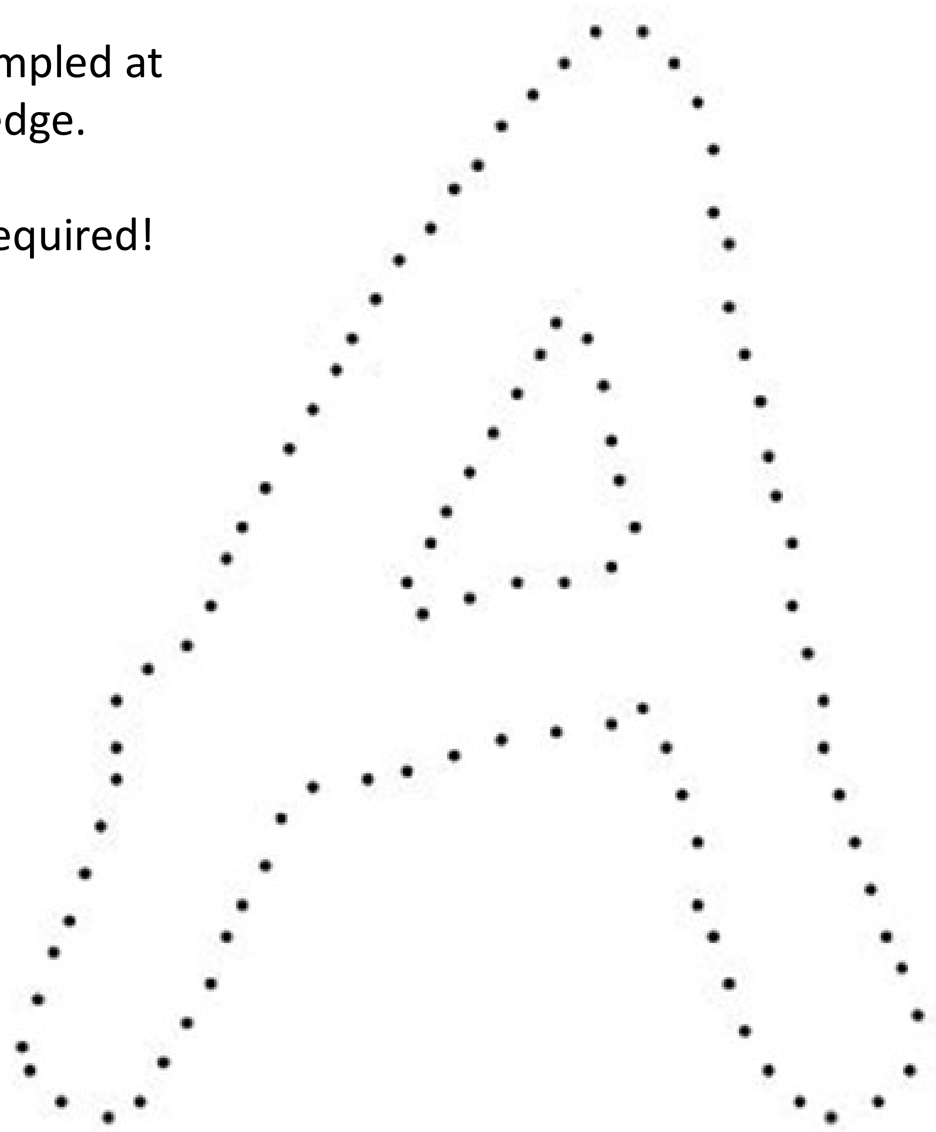
A

An edge detector is used

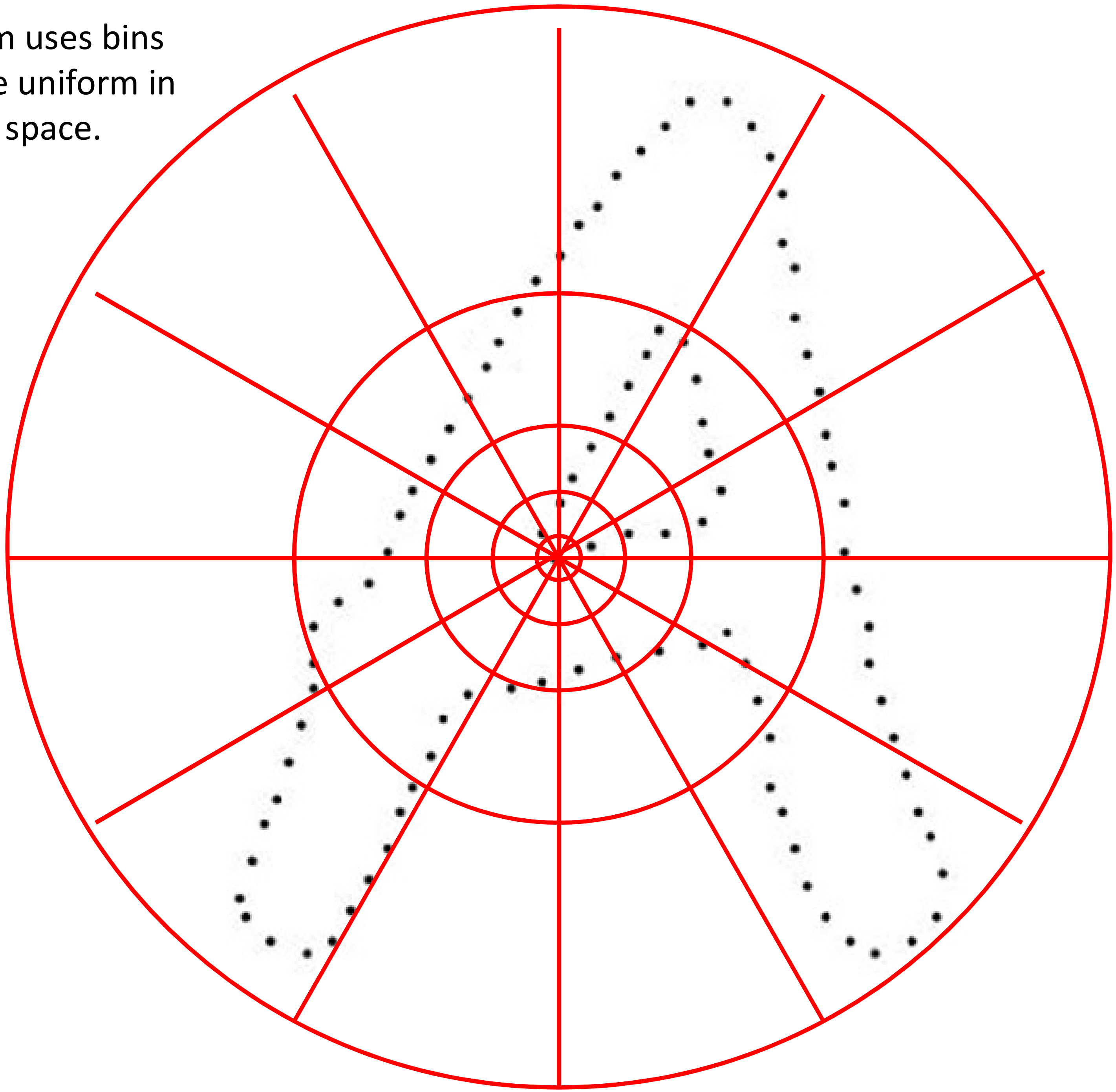


~100 points are sampled at random from the edge.

Uniformity is not required!

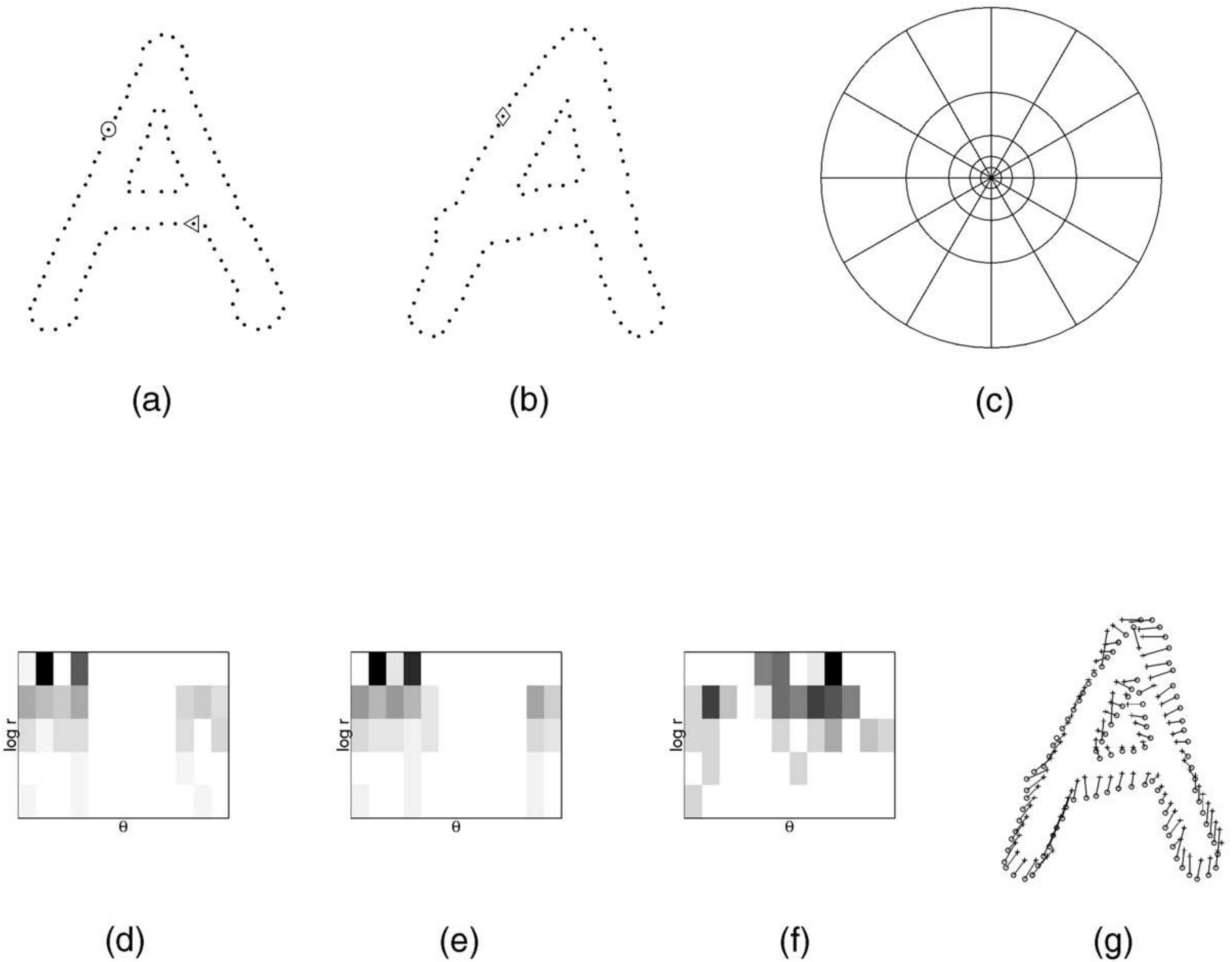


Histogram uses bins
which are uniform in
log-polar space.



Rotation invariance

- If rotation invariance is desired for a domain, the shape context can be calculated with the tangent vector as the x-axis.
- For many domains this is undesirable.

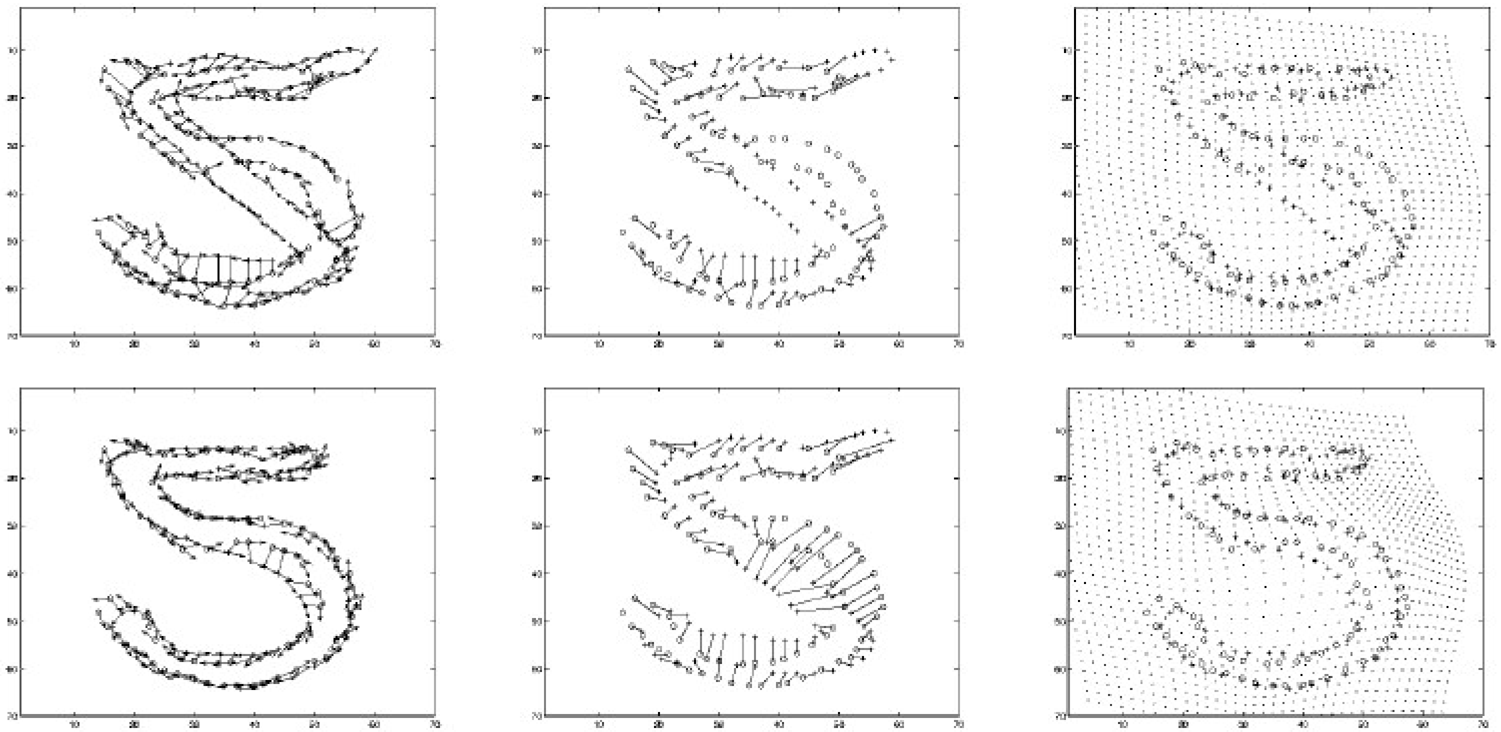

(a)
(b)
(c)
log r
θ
(d)
(e)
(f)
(g)

Matching points

- Must find the distance from every point in one image to every point in the other
- Dummy points with a constant ε distance from every other point are added to both sets
- For non-dummy points, the cost of matching is the L_2 norm

Shape Distance

- The authors use an iterative method to measure the magnitude of the transformation required to align the points



Categorization of Images

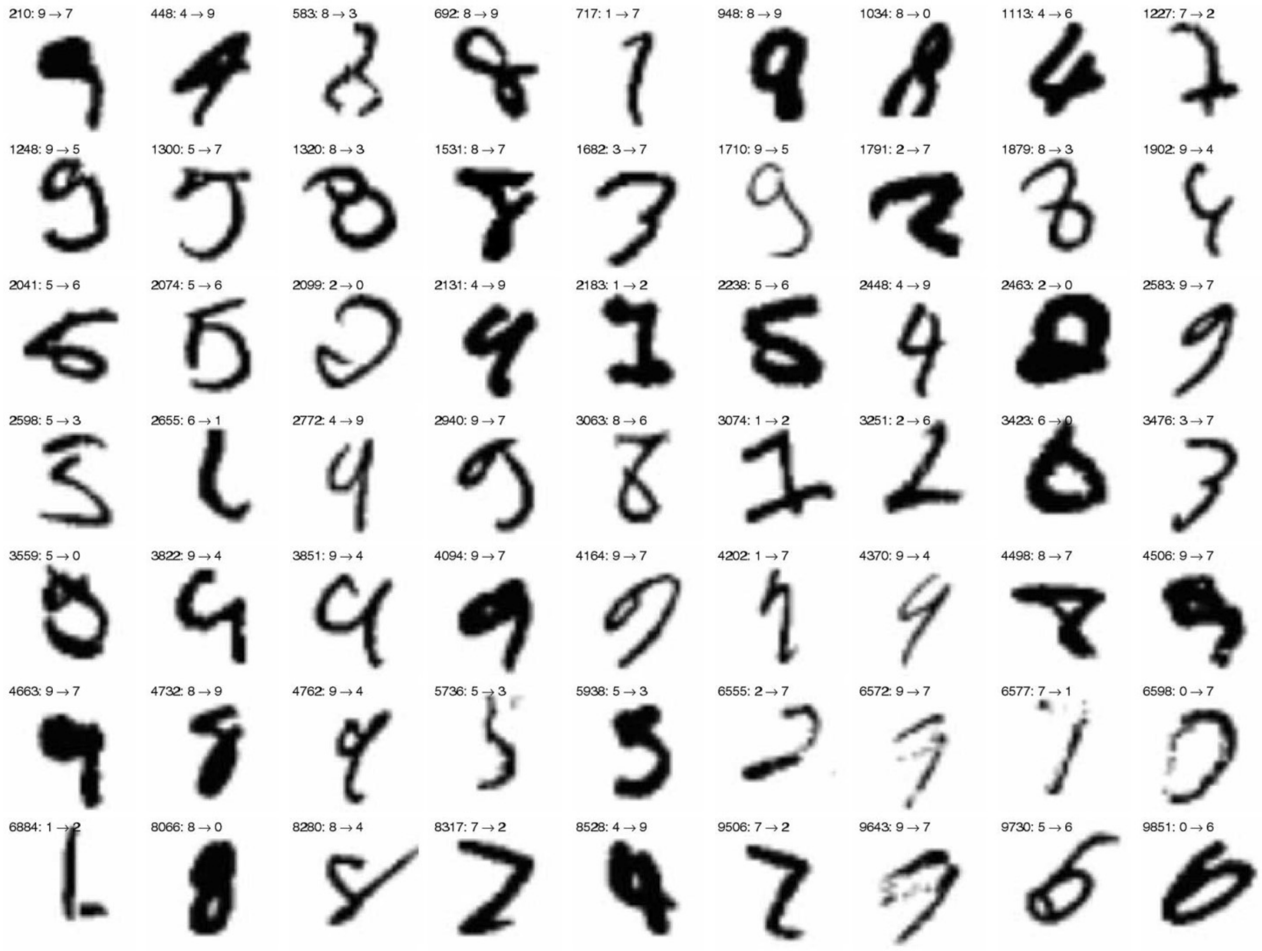
- Prototype-based approach (with k-NN)
- Prototypes are chosen using *k-medoids*
- k is initialized to the number of categories
- Worst category is split until training classification error drops below a criterion level

Application: Digit Recognition

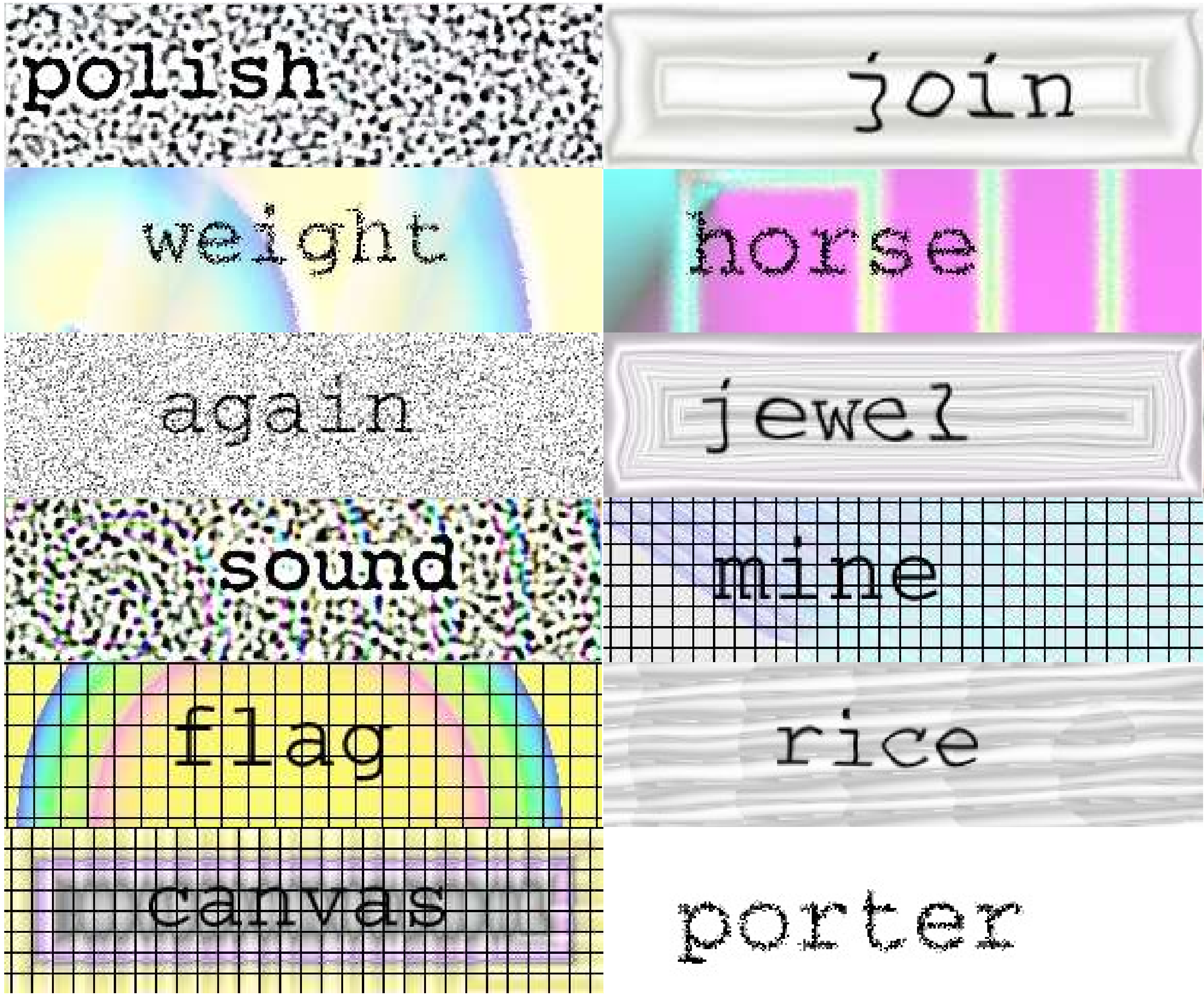
Training set size:
20,000

Test set size:
10,000

Error:
0.63%



Application: Breaking CAPTCHA



92% success rate on EZ-Gimpy

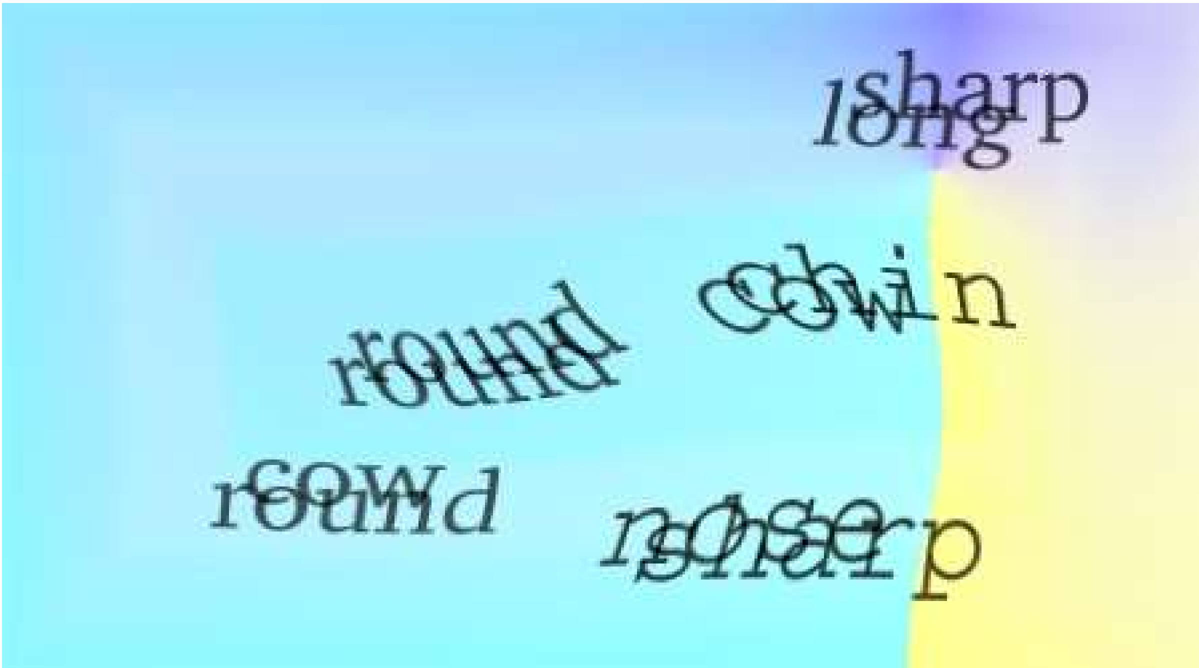
space

sock

Application: Breaking CAPTCHA

Must identify three words.

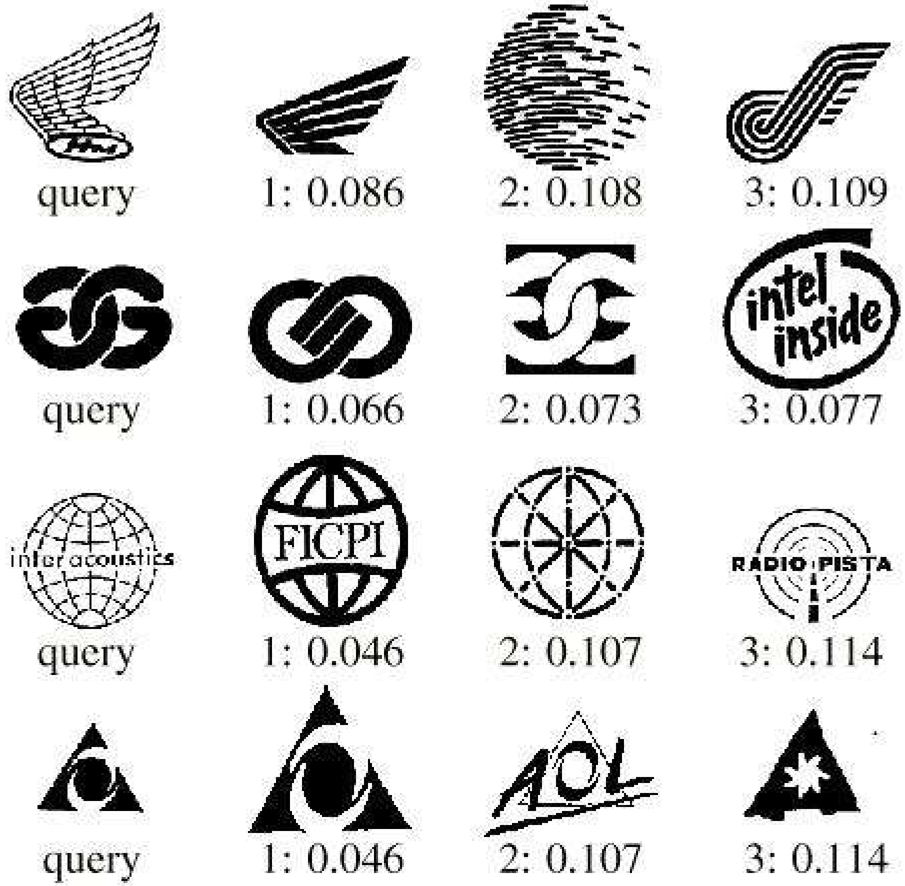
33% success rate on Gimpy.



Application: Trademark Retrieval

- Can be used to find different shapes with similar elements.

- Useful to determine cases of trademark infringement.



Application: 3D Object Recognition

Not the most natural application of shape contexts.

Test examples can only be matched to an image taken from a very similar angle.

Shape context conclusions

- Shape context is a local descriptor that describes a point's location relative to its neighbors
- Good at character recognition, comparison of isolated 2D structures
- Not well suited to classification of objects with significant variance

Matching Images/Video Using Local Self-Similarities (2007)

- Matching Local Self-Similarities across Images and Videos
  - Eli Shechtman
  - Michal Irani

Matching Images/Video Using Local Self-Similarities (2007)

- All of these images contain the same object.

- The images do *not* share colors, textures, or edges.

Problem:

- Previous Descriptors for Image Matching:
  - Pixel intensity or color values of the entire image
  - Pixel intensity or color values of parts of the image
  - Texture filters
  - Distribution-based descriptors (e.g., SIFT)
  - Shape context

- All of these assume that there exists a visual property that is shared by the two images.

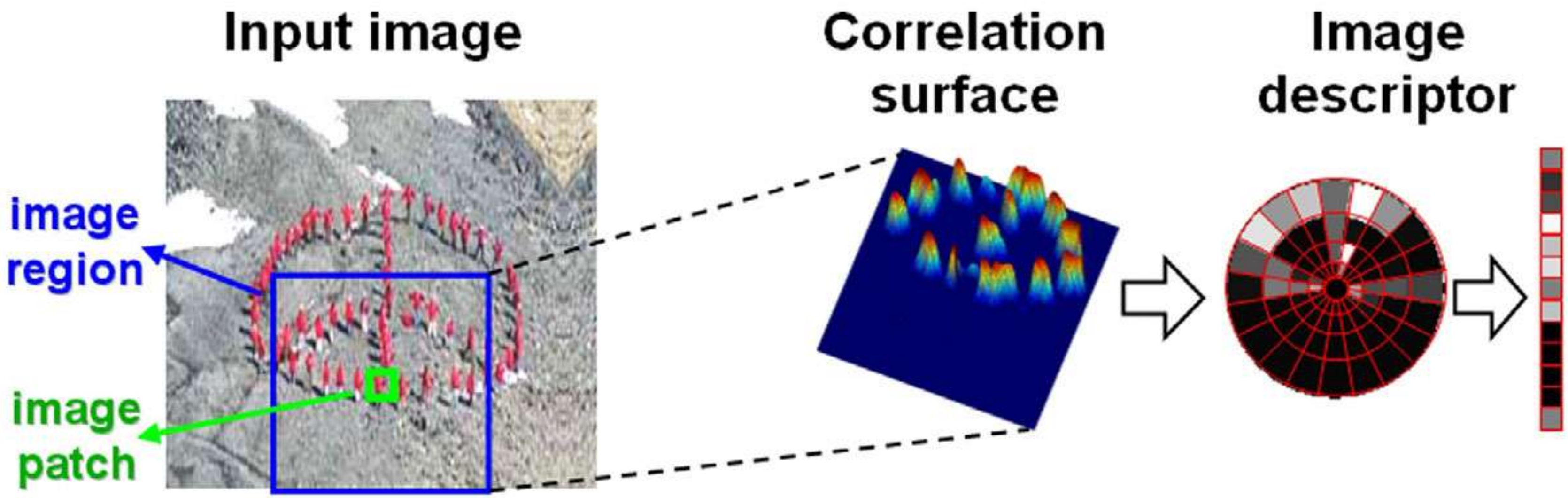
Solution: A “Self-Similarity” Descriptor

- The four heart images are similar only in that the local internal layouts of their self-similarities are shared.

- Video data (seen as a cube of pixels) is rife with self-similarity.

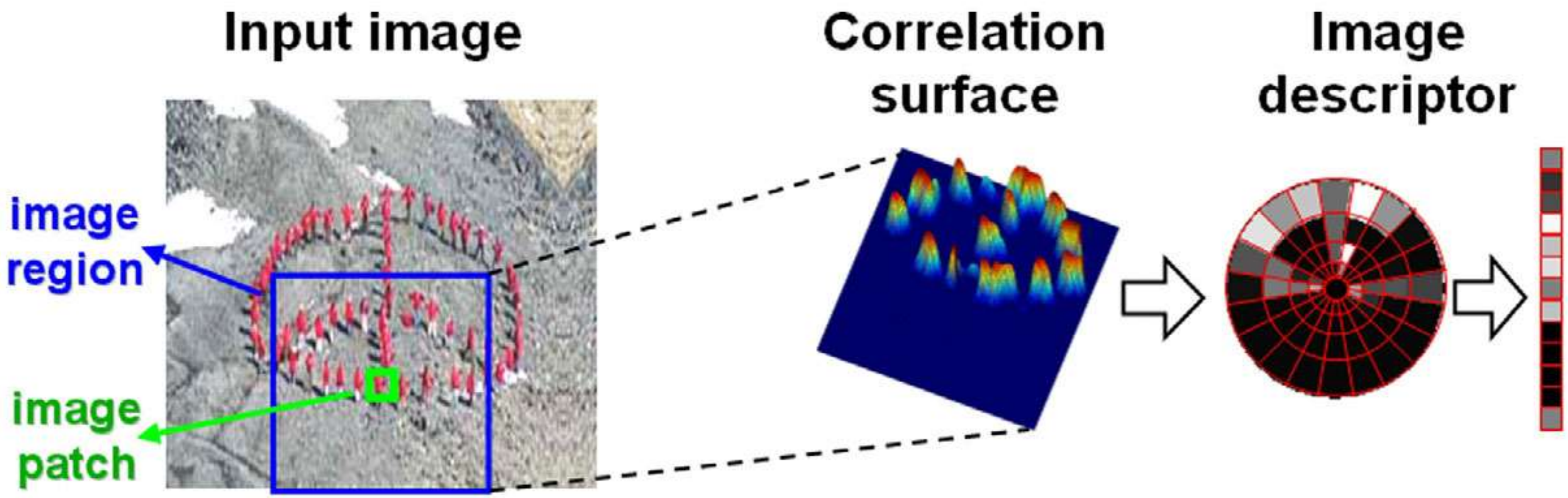
General Approach

- Our smallest unit of comparison is the “patch” rather than the pixel.
- Patches are compared to a larger, encompassing image region.



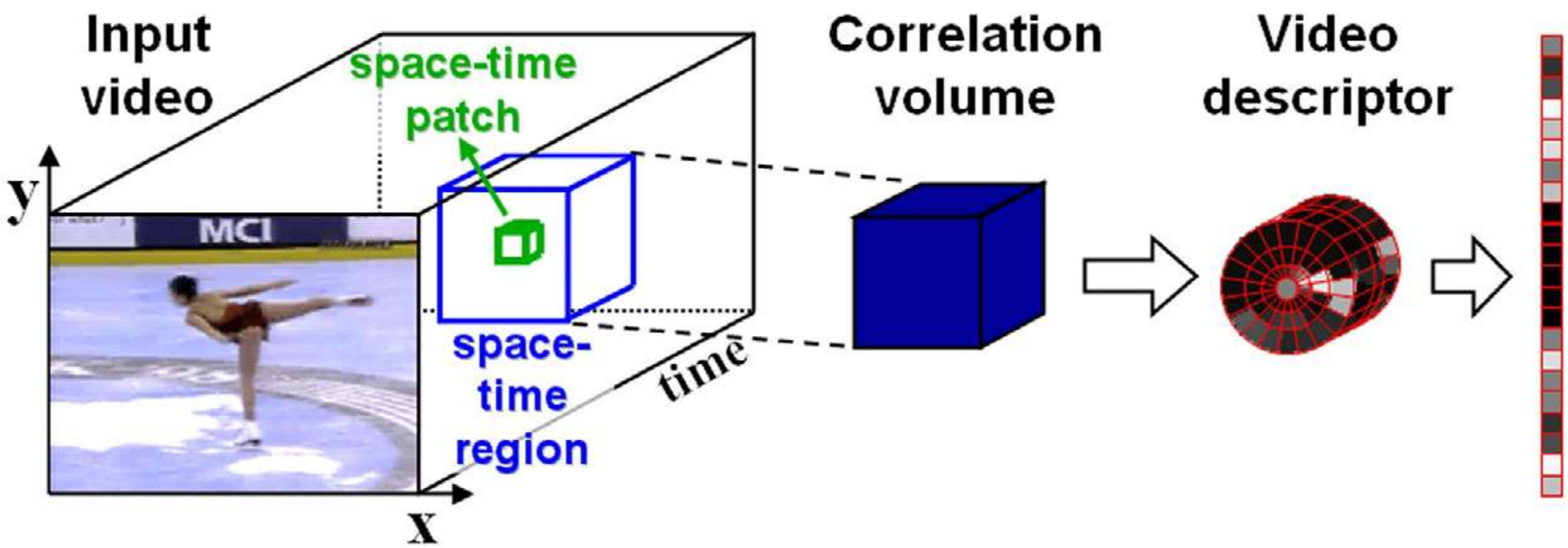
General Approach

- The comparison results in a correlation surface which determines nearby areas of the image which are similar to the current patch.
- The correlation surface is used to produce a self-similarity image descriptor for the patch.



General Approach

- For video data, the patch and region are cubes, as time is the depth dimension.
- The resulting video descriptor is cylindrical.



Descriptor Generation Process

- For every image patch q (e.g., 5x5 pixel area)
  - For every patch-sized area contained in the enclosing image region (e.g., 50x50 pixel area)
    - Calculate SSD and determine correlation surface

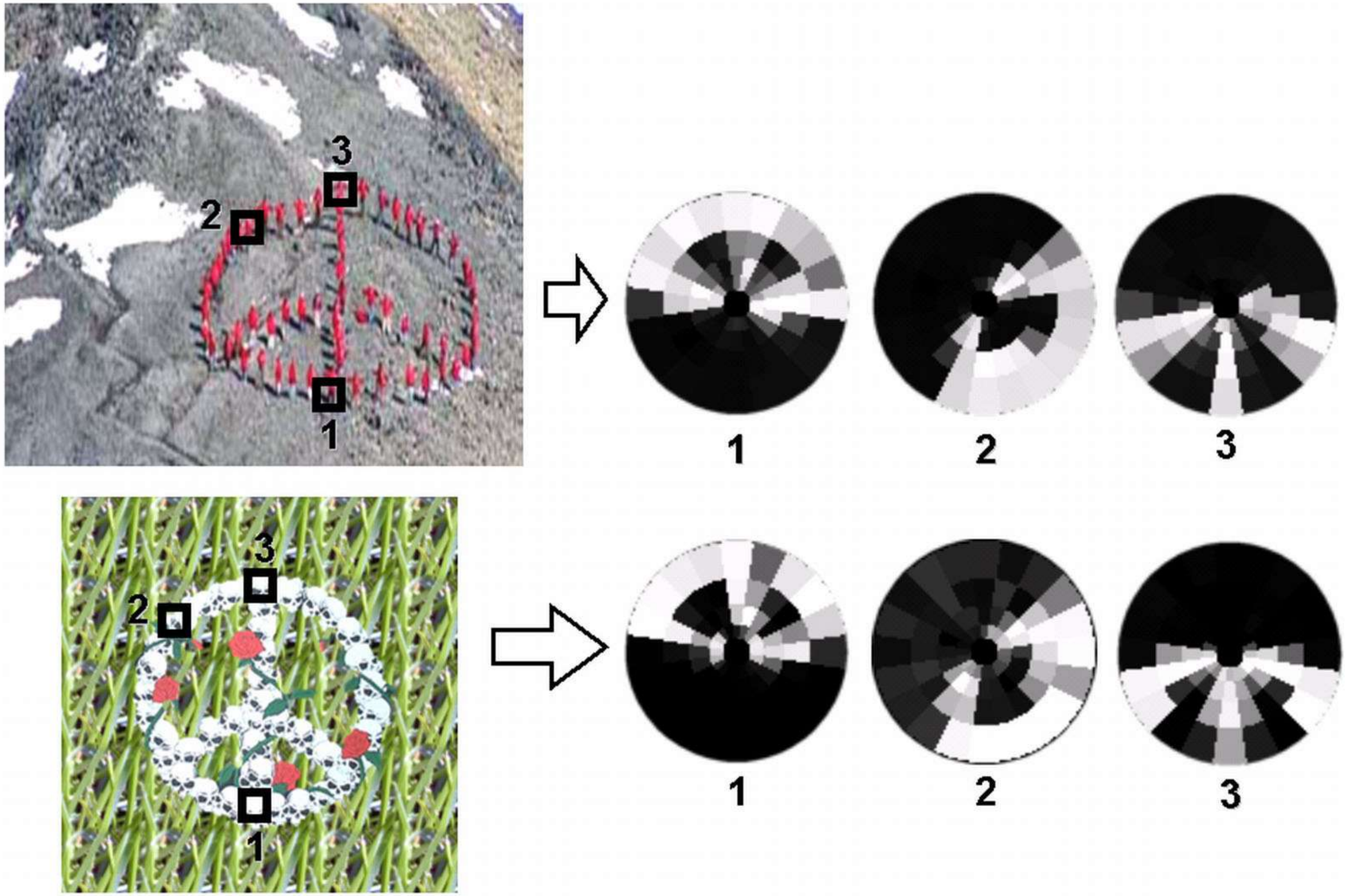
$$S_q(x, y) = \exp\left(-\frac{SSD_q(x, y)}{\max(var_{noise}, var_{auto}(q))}\right)$$

- var_{noise} is a constant which specifies the level of acceptable photometric variation
- $var_{auto}(q)$ is the maximal variance of the difference of all patches near q

Descriptor Generation Process

- Transform each correlation surface to log-polar coordinates with 80 bins (20 angles, 4 radial intervals)
- The largest value in each bin determines the entry in the descriptor.

Descriptor Generation Process



Descriptor Generation Process

- Video data adaptations:
  - Image patch exists in three dimensions, but is usually chosen to have 1 frame depth (e.g., 5x5x1)
  - Image region encompasses several frames (e.g., 60x60x5)
  - This creates a cuboid correlation volume, from which we generate a cylindrical descriptor by binning it in log log polar coordinates

Properties of the Self-Similarity Descriptor

- Self-similarity descriptors are *local* features
- The log-polar representation allows for small affine deformations (like for shape contexts)
- The nature of binning allows for non-rigid deformations
- Using patches instead of pixels captures more meaningful patterns

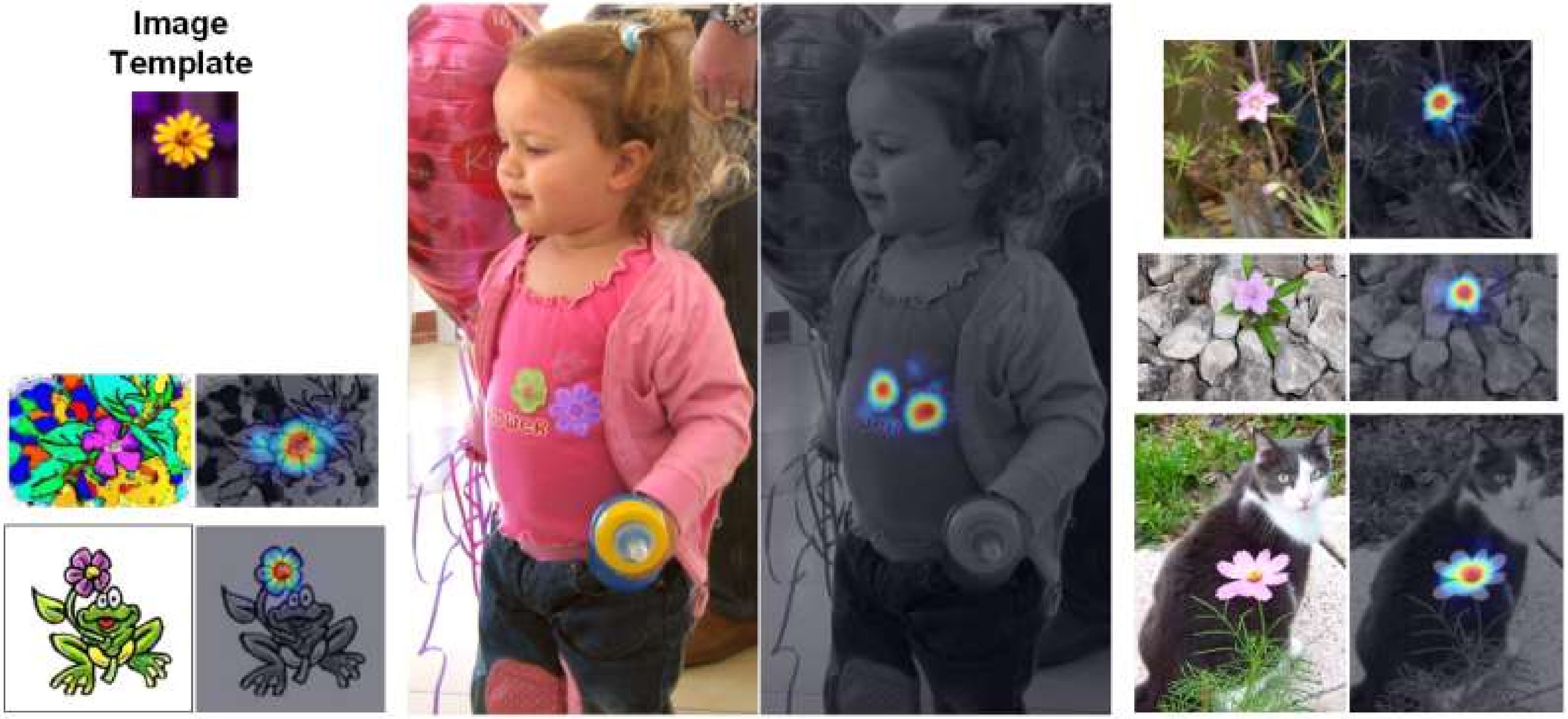
Performing Shape Matching

1. Calculate self-similarity descriptors for the image at a variety of scales (gives us invariance to scale)
2. Filter out the uninformative descriptors for each scale
3. Employ probabilistic star graph model to find the probability of a pattern match at each site for each scale
4. Normalize and combine the probability maps using a weighted average

Results

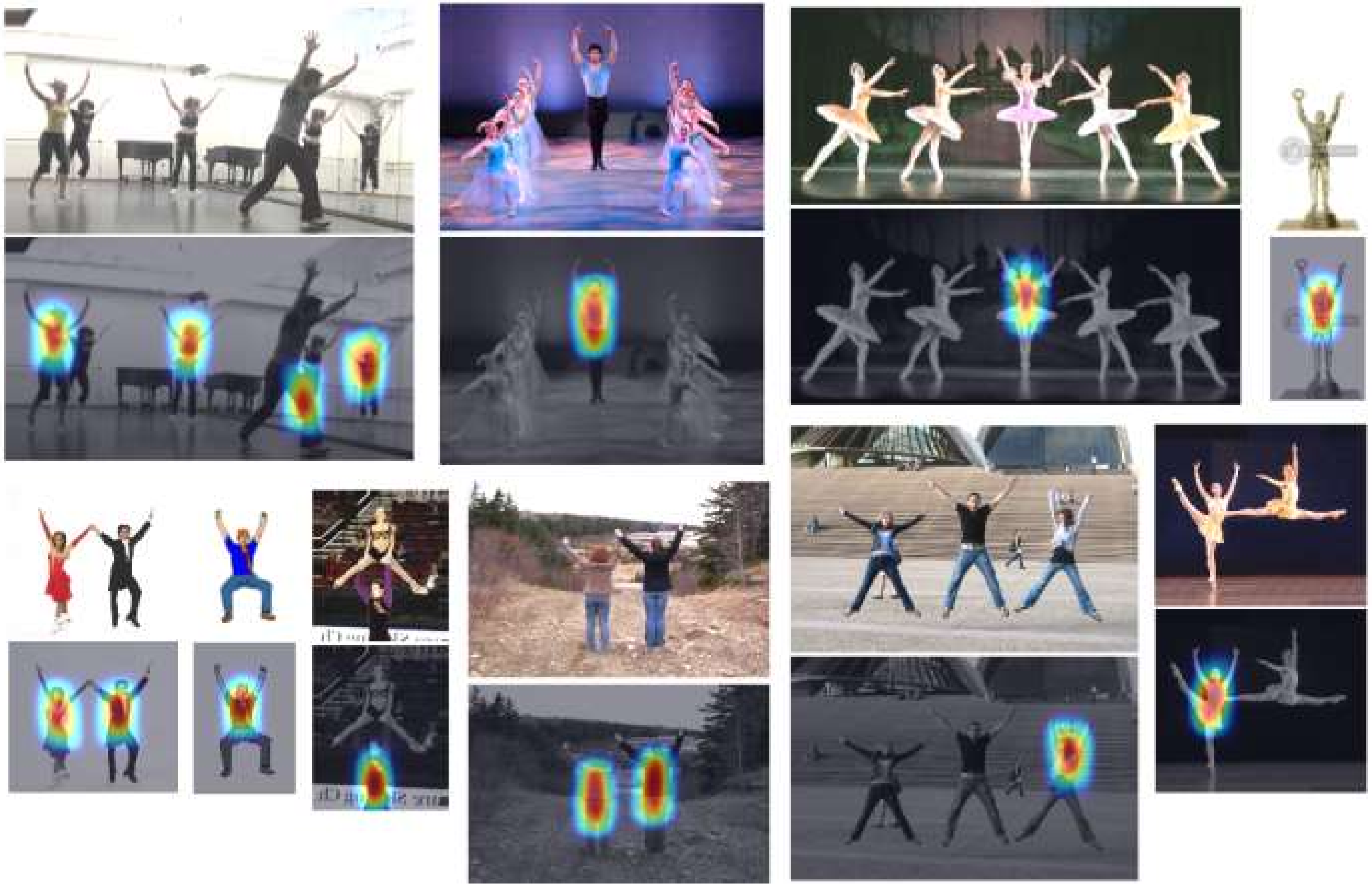
- Results require only one query image which can be much smaller than the target images
- Process even works when one of the images is hand-drawn

Results



Results

Sketch Template




Input video
[Shechtman-Irani CVPR'05]
[Shechtman-Irani CVPR'07]


Turn 1
Turn 2


Input
video
Our
result

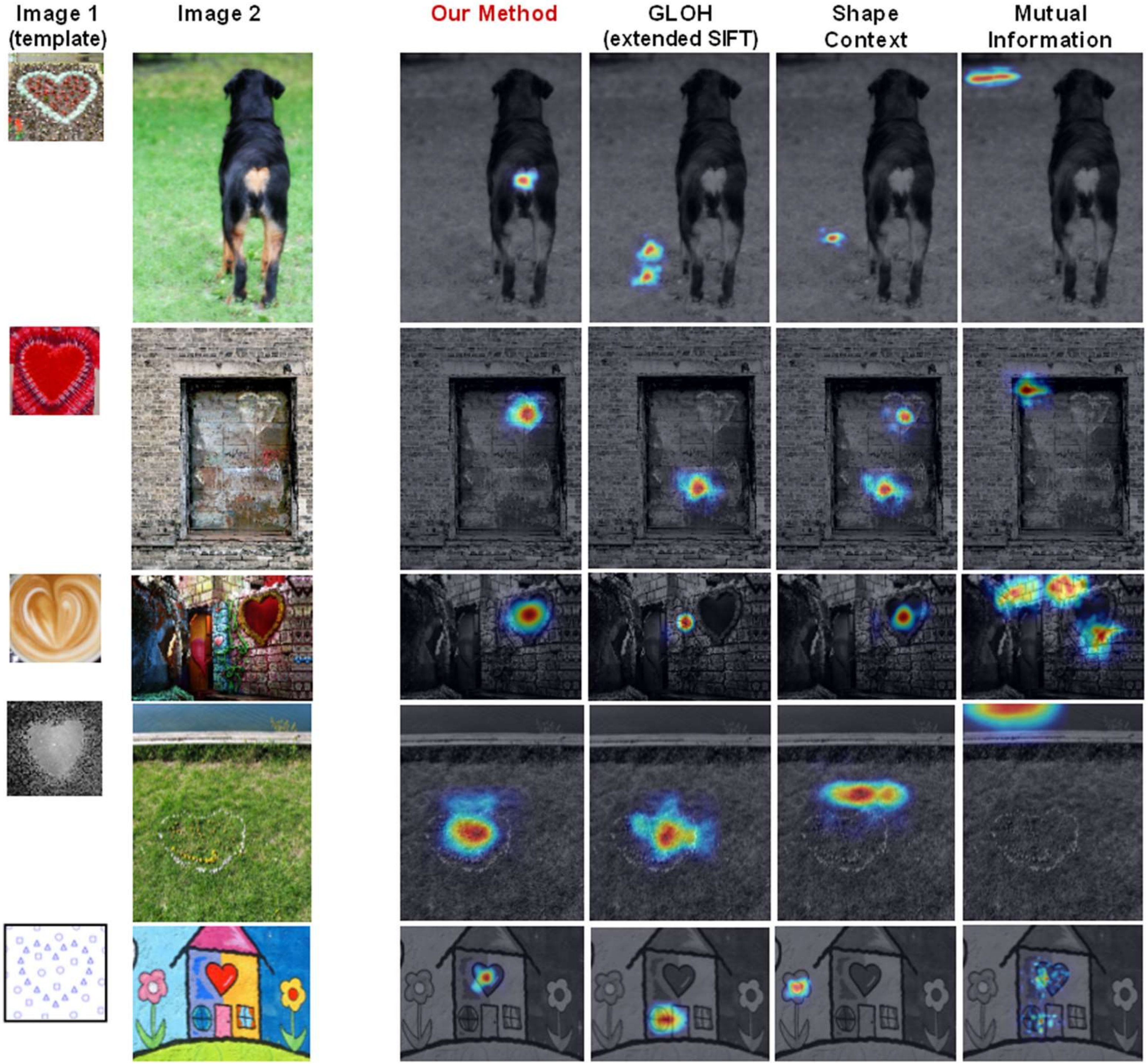
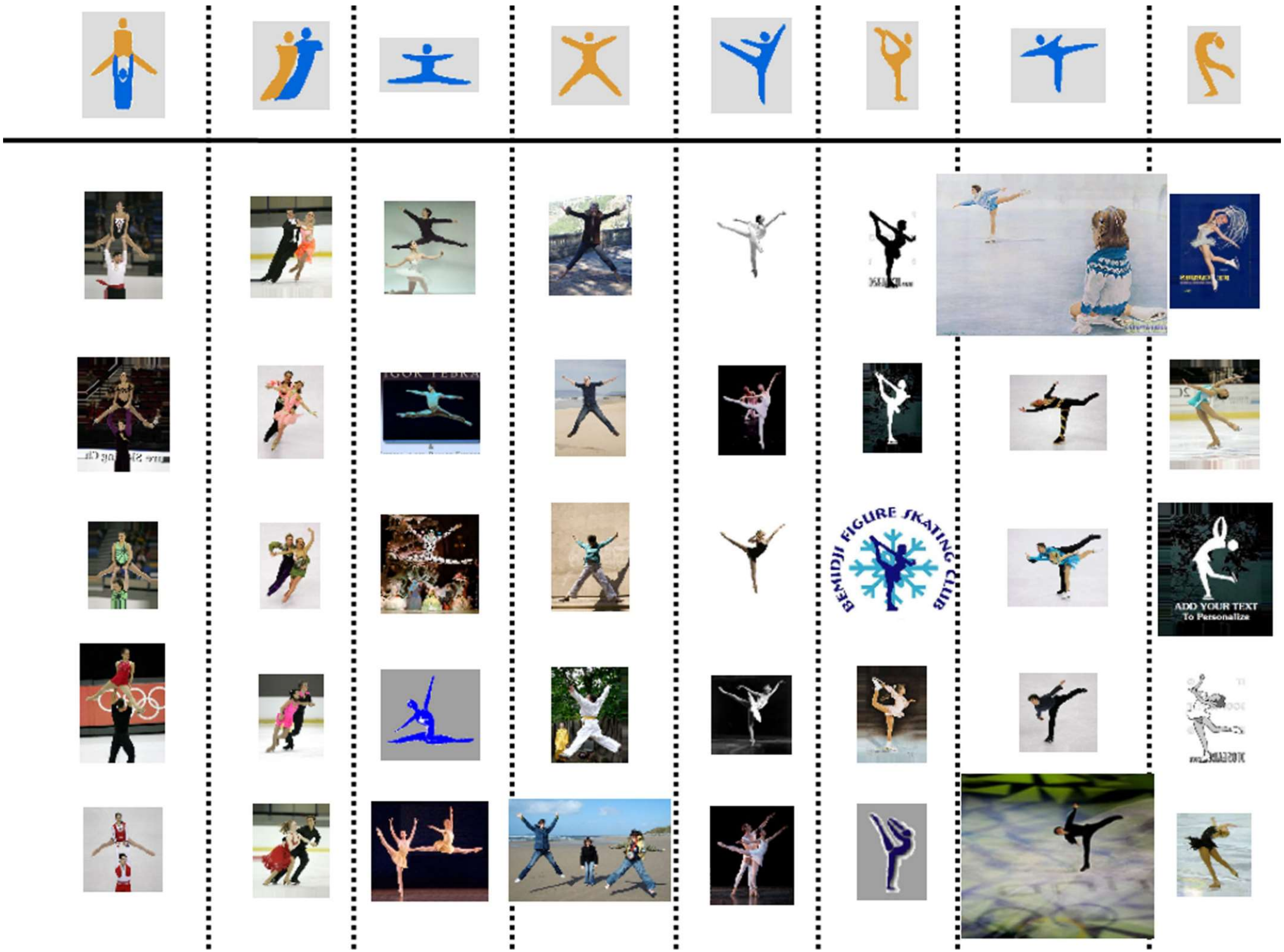
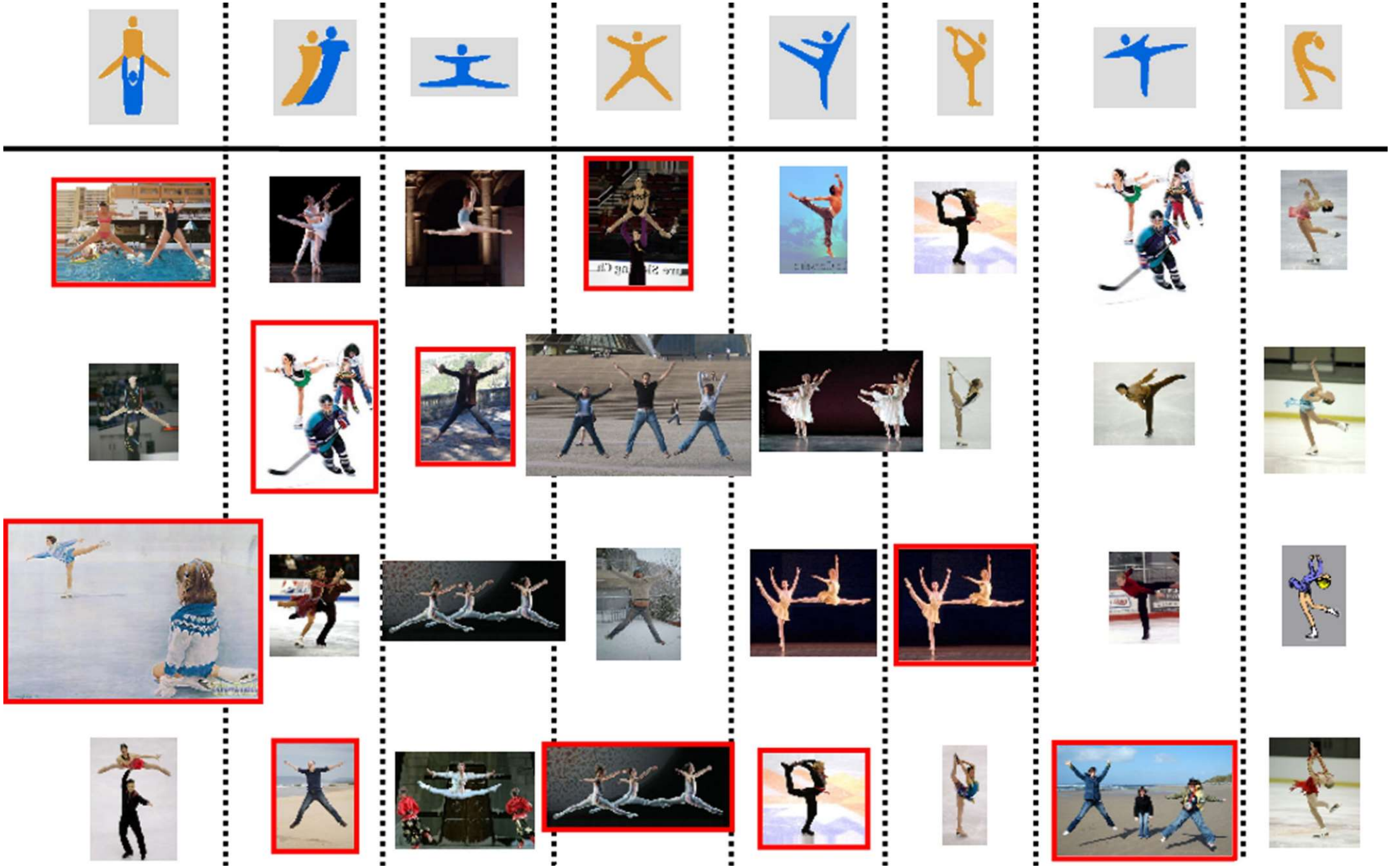


Image 1
(template)
Image 2
Our Method
GLOH
(extended SIFT)
Shape
Context
Mutual
Information


BEMIDJI FIGURE SKATING CLUB
ADD YOUR TEXT
To Personalize



Self-Similarity Conclusions

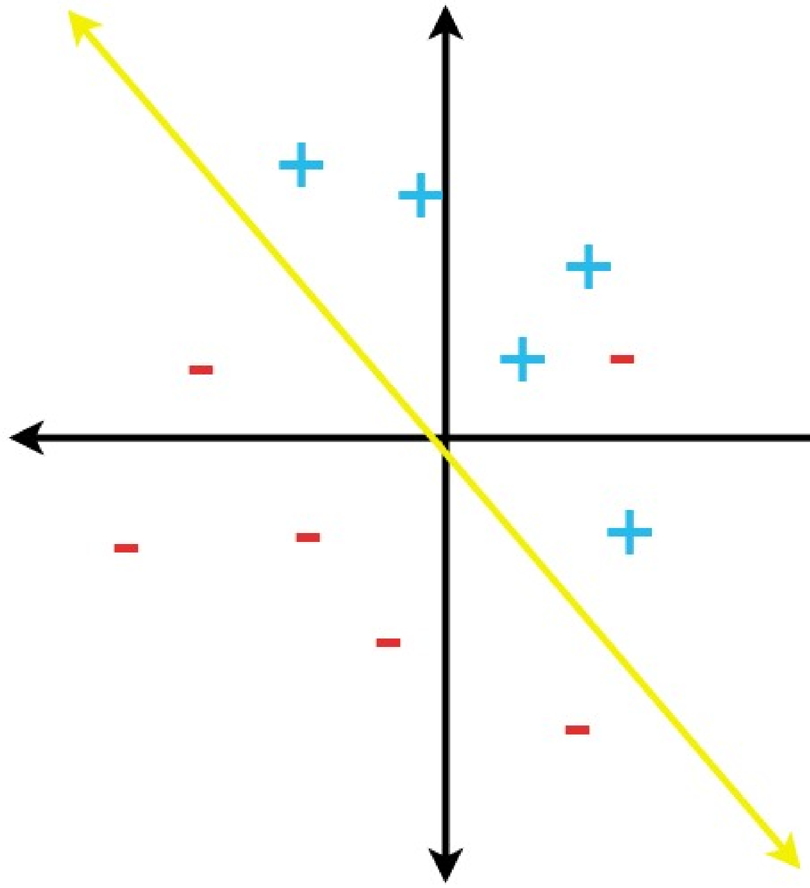
- Can discover similar shapes in images that share no common image properties
- Requires only a single query image to perform complex shape detection
- Hand-drawn sketches are sufficient to find matches
- Video is a natural extension

The Pyramid Match Kernel (2005)

- The Pyramid Match Kernel: Discriminative Classification with Sets of Image Features
  - Kristen Grauman
  - Trevor Darrell

The Pyramid Match Kernel (2005)

- Support Vector Machines
  - Widely used approach to discriminative classification
  - Finds the optimal separating hyperplane between two classes



The Pyramid Match Kernel (2005)

- Kernels can be used to transform the feature space (e.g. XOR)

- Kernels are typically similarity measures between points in the original feature space

The Pyramid Match Kernel (2005)

- Most kernels are used on fixed-length feature vectors where ordering is meaningful
- In image matching, the number of image features differ, and the ordering is arbitrary
- Furthermore, most kernels take polynomial time, which is prohibitive for image matching

Desirable characteristics in an image matching kernel

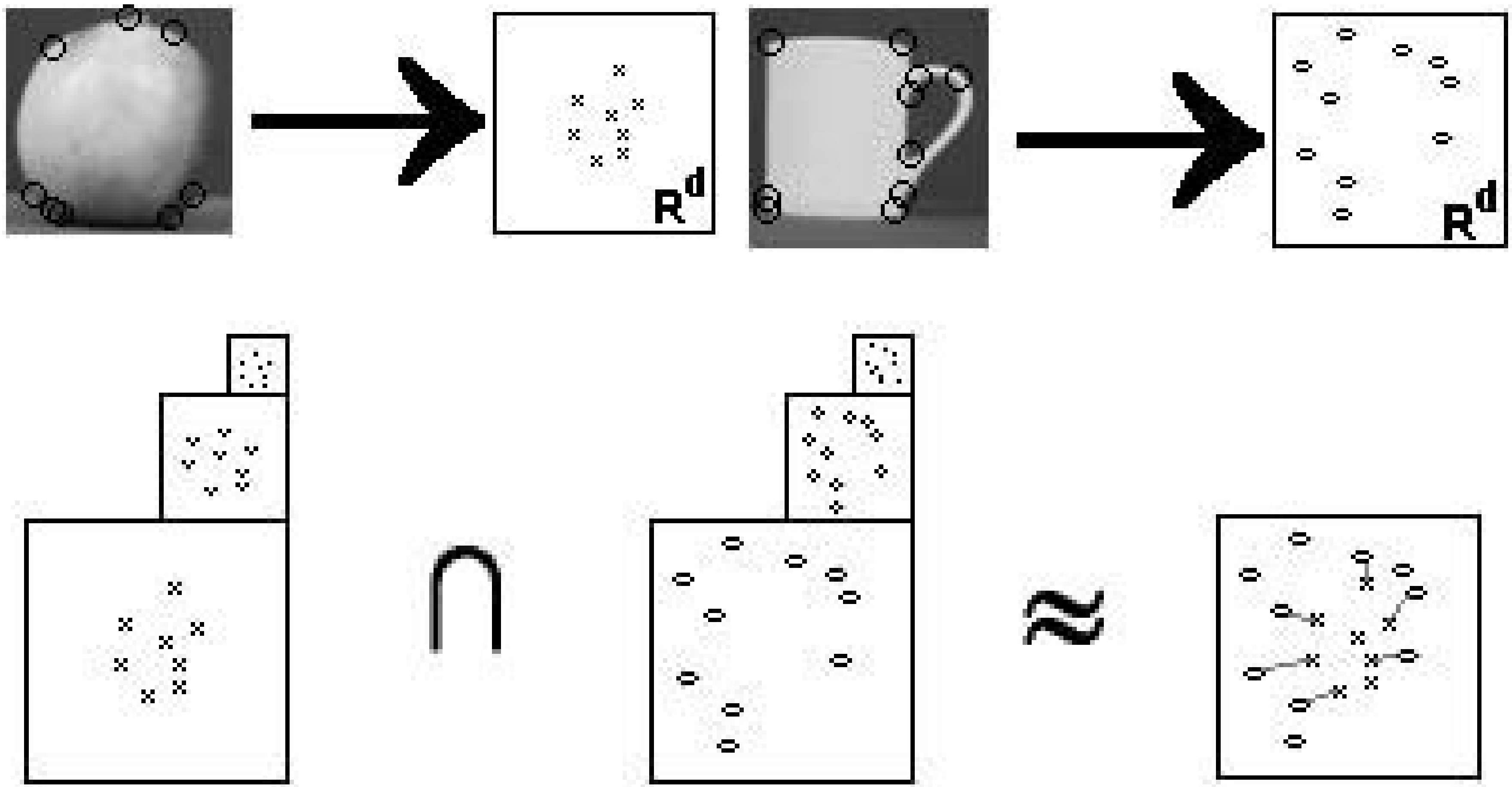
- Captures co-occurrences
- Is positive-definite
- Does not assume a parametric model
- Can handle sets of unequal cardinality
- Runs in sub-polynomial time

- No previous image matching kernels had all four of the first characteristics, and all ran in polynomial time

General Approach

- Divide the feature space into bins of equal size
- Repeat
  - Count the features which fall into each bin for both images
  - Min the two counts to find the overlap in each bin
  - Calculate new match score based on new overlaps and ease of overlapping at this resolution
  - Create a new set of bins with side length double that of the current side length

General Approach



Process

- Input space X
- d-dimensional feature vectors that
  - are bounded by a sphere of diameter D
  - have a minimum inter-vector distance of $\frac{\sqrt{d}}{2}$

Process

- Feature Extraction Algorithm:

$$\psi(x) = [H_{-1}(x), H_0(x), \dots, H_L(x)]$$

- H are histograms
- L is the number of levels in the pyramid

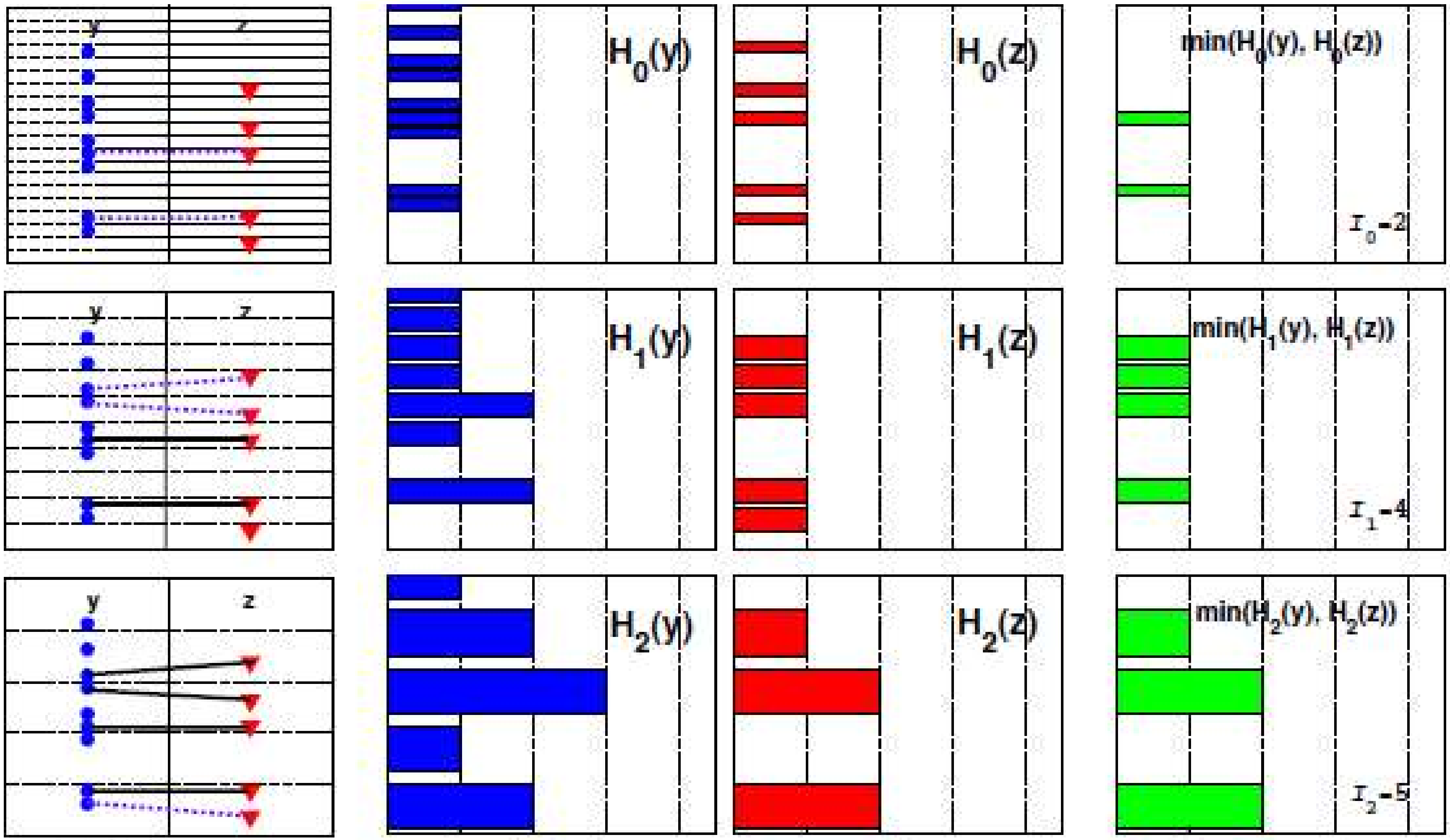
Process

- Similarity between two feature sets is defined as:

$$K_\Delta\big(\psi(y), \psi(z)\big) = \sum_{i=0}^{L} w_i N_i \qquad w_i = \frac{1}{2^i}$$

- N_i is the number of *new* matches across all bins
- w_i is the maximum distance that could exist between points that matched at this level

Process



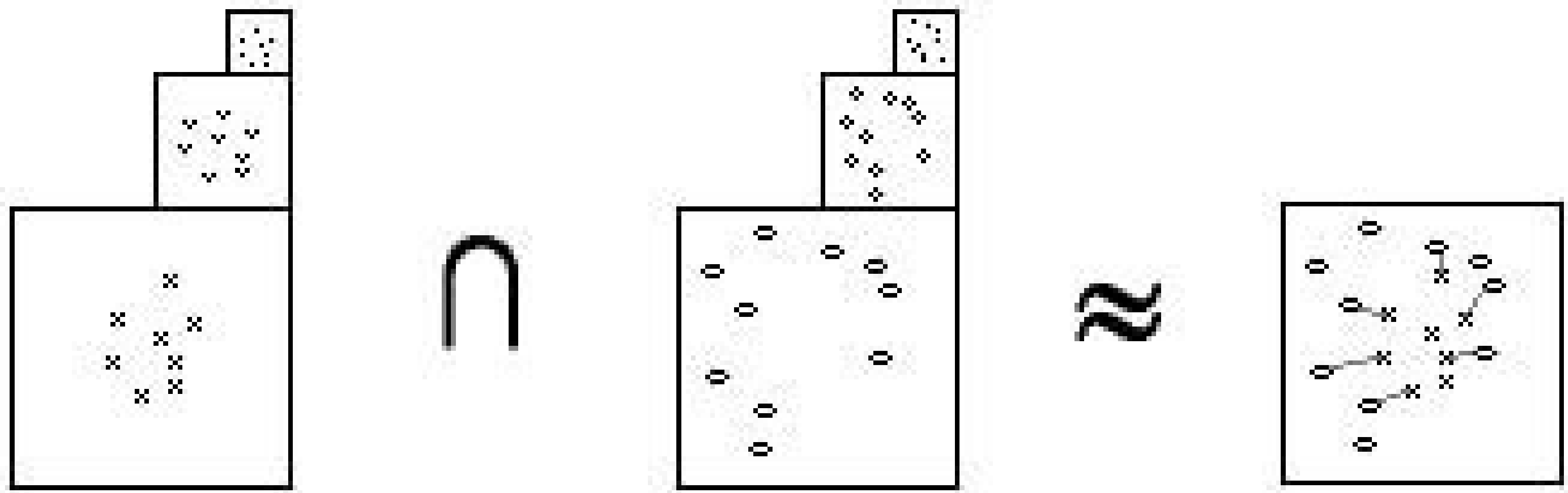
(a) Point sets (b) Histogram pyramids (c) Intersections

Process

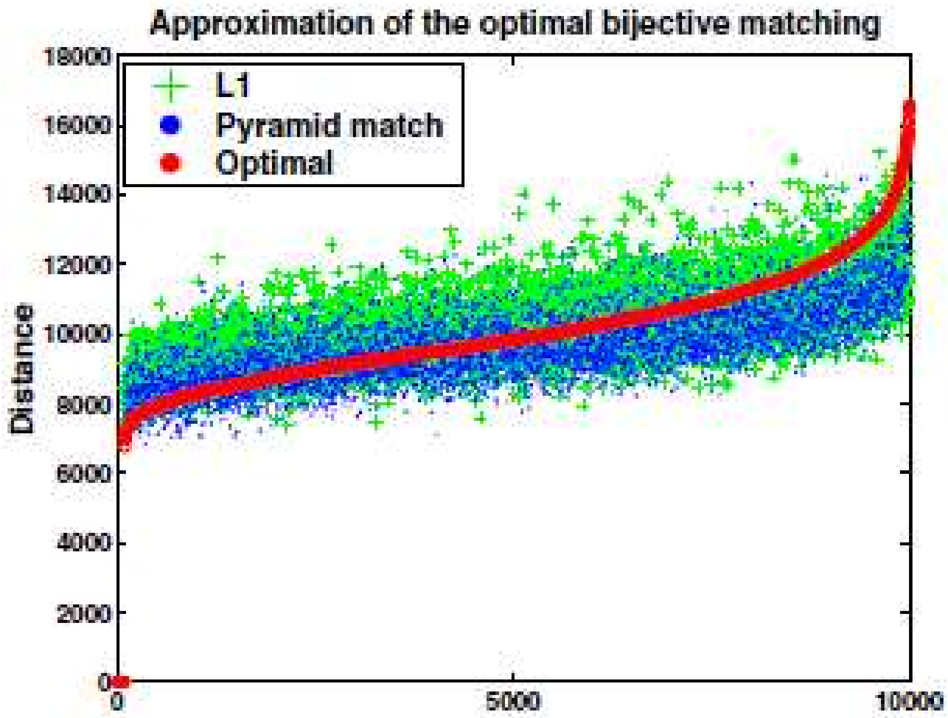
- To counteract the arbitrary nature of the bin borders, the entire process is repeated several times with the origin randomly shifted.

Partial Match Correspondences

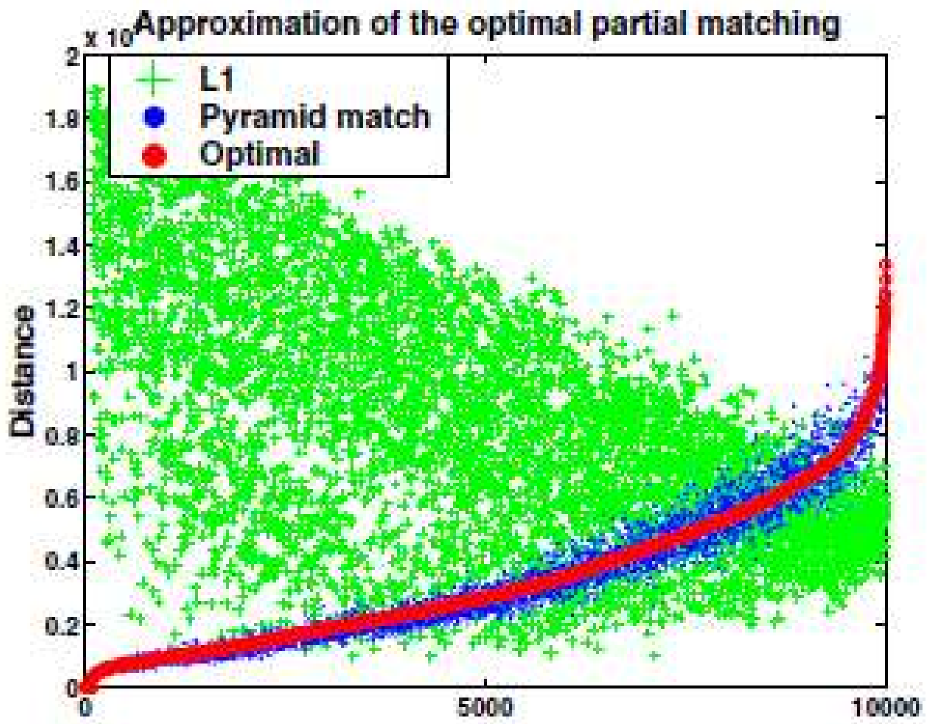
- Unequal cardinalities are not an issue
- Algorithm matches the most similar pairs first; only the least similar features will be unmatched



Results: Synthetic Data

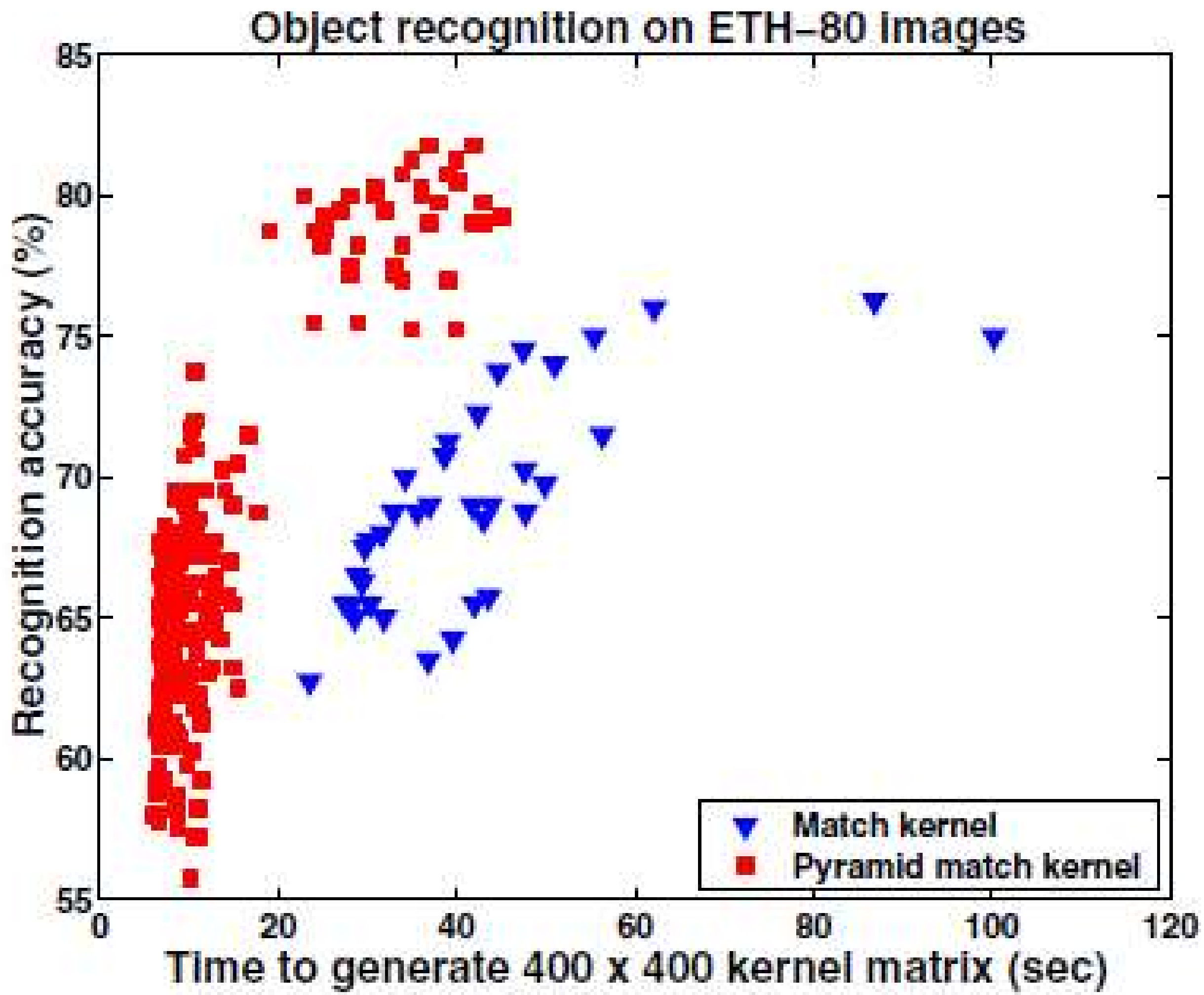


Equal Cardinalities



Unequal Cardinalities

Results: Object Recognition



Pyramid Kernel Conclusions

- By not searching for specific feature correspondences, the kernel can run in less than polynomial time
- Accuracy is generally higher than other kernels on both artificial and real-world data
- Can handle arbitrary-length feature sets

Spatial Pyramid Matching (2006)

- Beyond Bags of Features: Spatial Pyramid Matching for Recognizing Nature Scene Categories
  - Svetlana Lazebnik
  - Cordelia Schmid
  - Jean Ponce

Spatial Pyramid Matching (2006)

- Task: Whole image classification
  - Bag of features methods (like pyramid kernel) are somewhat effective, but ignore feature location

- Alternate solution: Kernel-based recognition method that calculates a global rough geometric correspondence using a pyramid matching scheme

General Approach

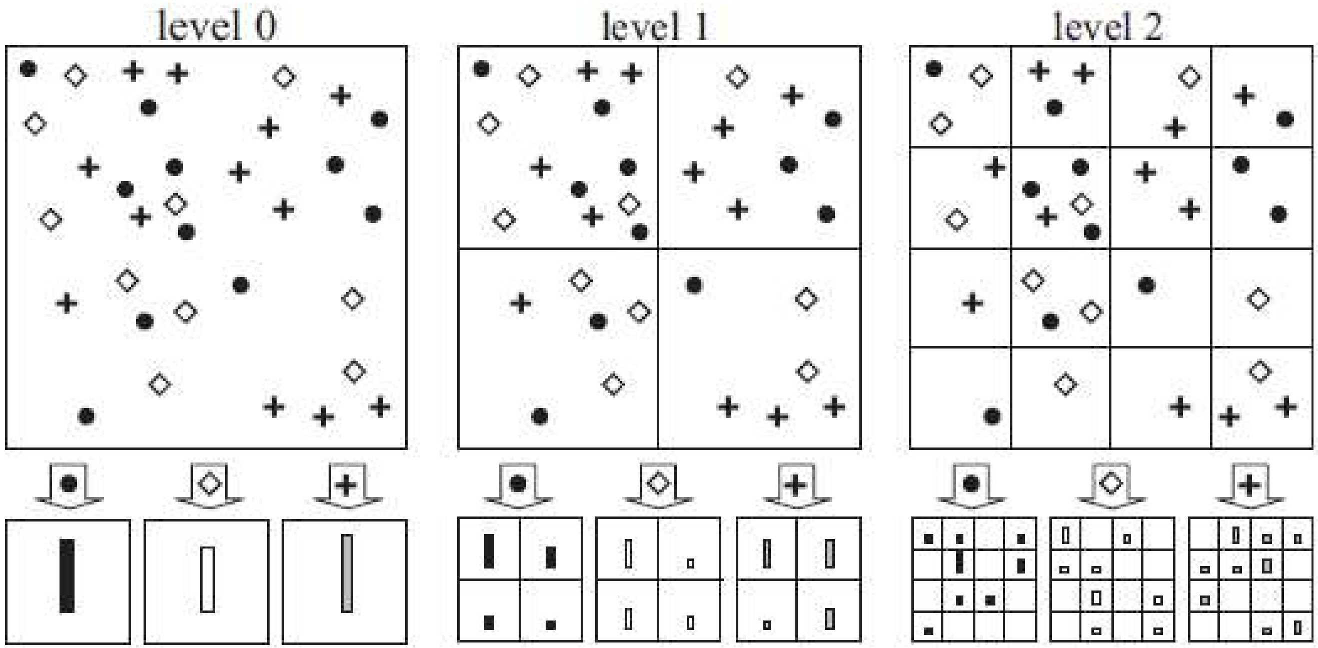
- Similar pyramid matching scheme to previous approach, but
  - pyramid matching in *image* space
  - clustering in feature space
- Use training data to cluster features into M types
- Within image-space bins, count occurrences of each feature type

Process

- Algorithm parameters
  - M = number of feature types to learn (200)
  - L = levels in the pyramid (2)
- Learn M feature prototypes via k-means clustering
- Assign one of the M types to every feature value in both images

Process

- Beginning at the deepest level of the pyramid and moving to coarser levels:
  - Count the number of feature values of each type in each bin for each image
  - Determine how many new matches there are in each bin



Results

- To classify scenes into one of N categories, we use N SVMs
  - Each SVM is trained to recognize a particular type of scene
  - Test images are classified based on which SVM returns the highest confidence that the test image is a member

(a) kitchen
living room
living room
living room
office
living room
living room
living room
living room
(b) kitchen
office
inside city
(c) store
mountain
forest
(d) tall bldg
inside city
inside city
(e) tall bldg
inside city
mountain
mountain
mountain
(f) inside city
tall bldg
(g) street

Results

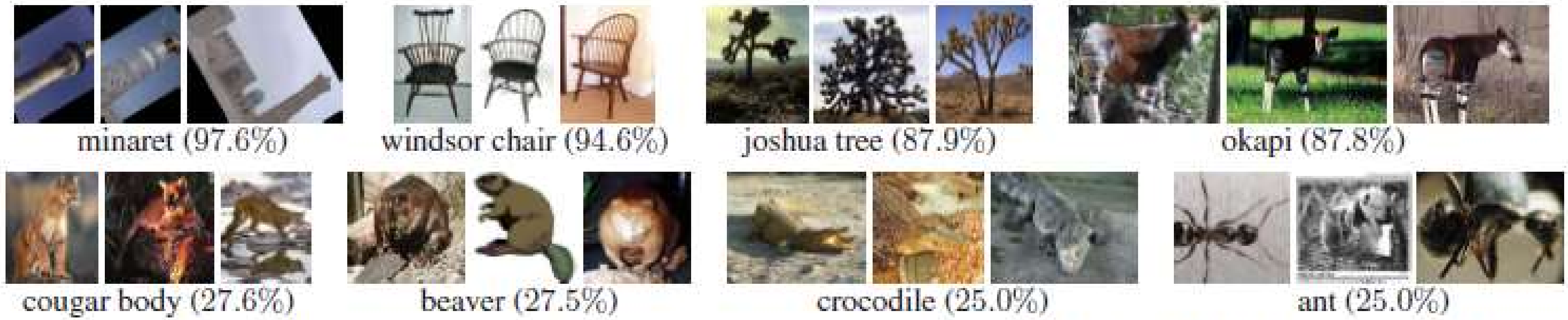


Figure 5. Caltech-101 results. Top: some classes on which our method ($L = 2, M = 200$) achieved high performance. Bottom: some classes on which our method performed poorly.

- Method performs well on similar-looking subjects, poorly on subjects with different poses/textures

Spatial Pyramid Matching Conclusions

- Makes use of positional information in addition to extracted feature values
- Has the form of an extended bag-of-features method
- Has ~80% accuracy categorizing images into 15 different classes

Images taken from

- http://www.cs.sfu.ca/~mori/research/gimpy/
- http://www.eecs.berkeley.edu/Research/Projects/CS/vision/shape/belongie-iccv01.ppt
- http://www.wisdom.weizmann.ac.il/~vision/SelfSimilarities.html
- The four papers