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Robust Synthetic Basis Feature Descriptor

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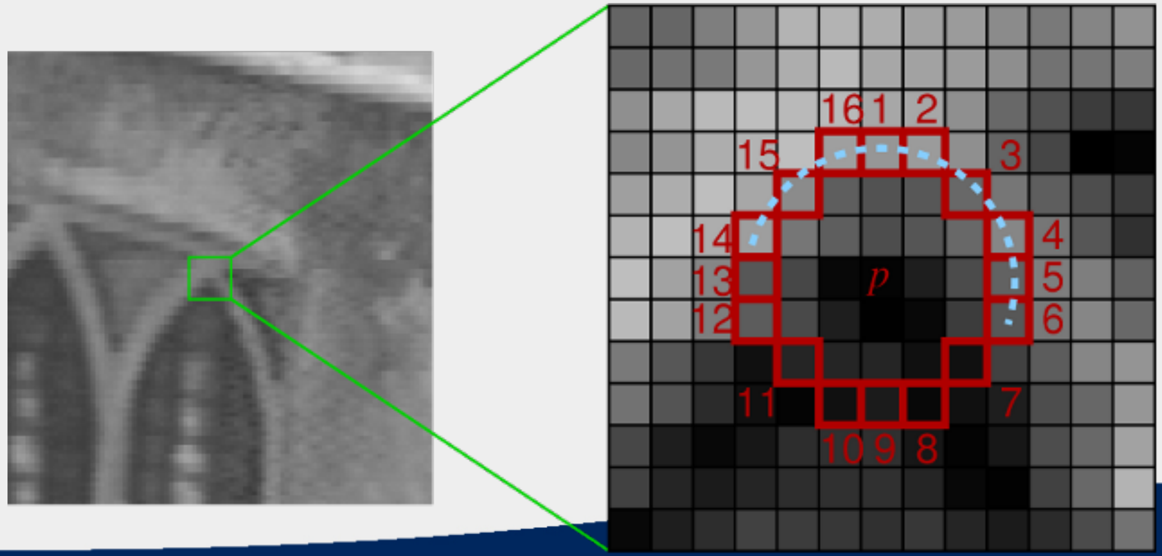
Feature Detection

- Image Features:
  - Individually distinguishable regions of an image that can easily be tracked between subsequent images
    - Corners, Blobs, or T-Sections – Good Features
    - White Walls, Straight Lines – Bad Features



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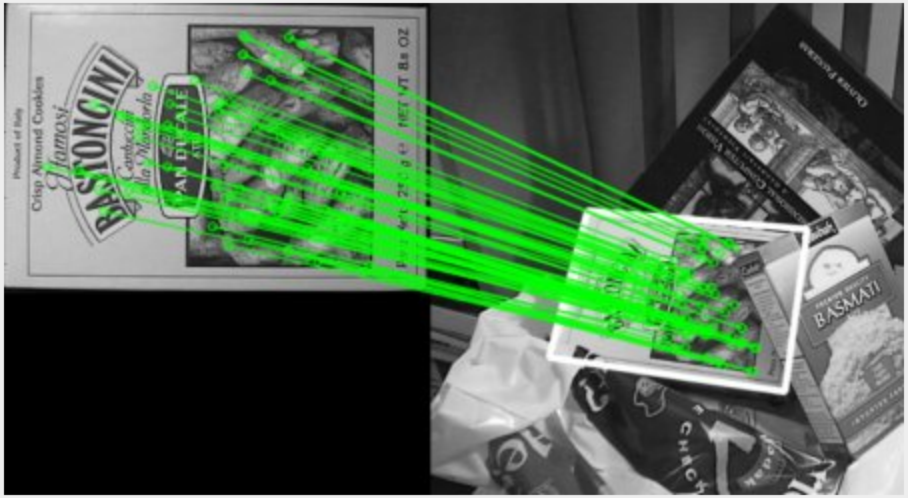

Crisp Almond Cookies
BASTONCINI
BASMATI

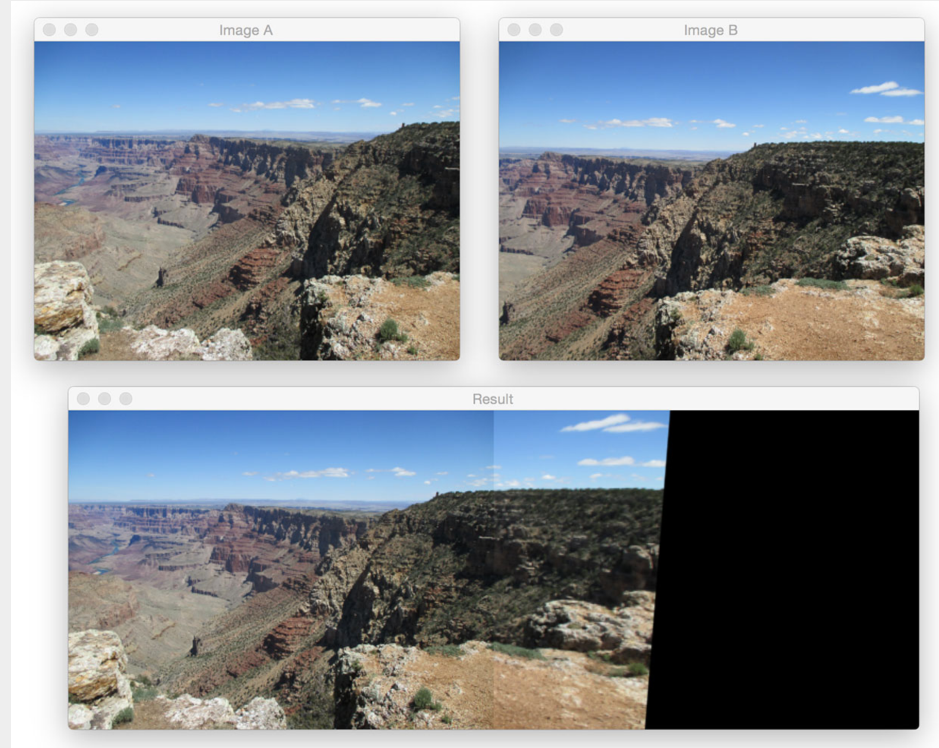
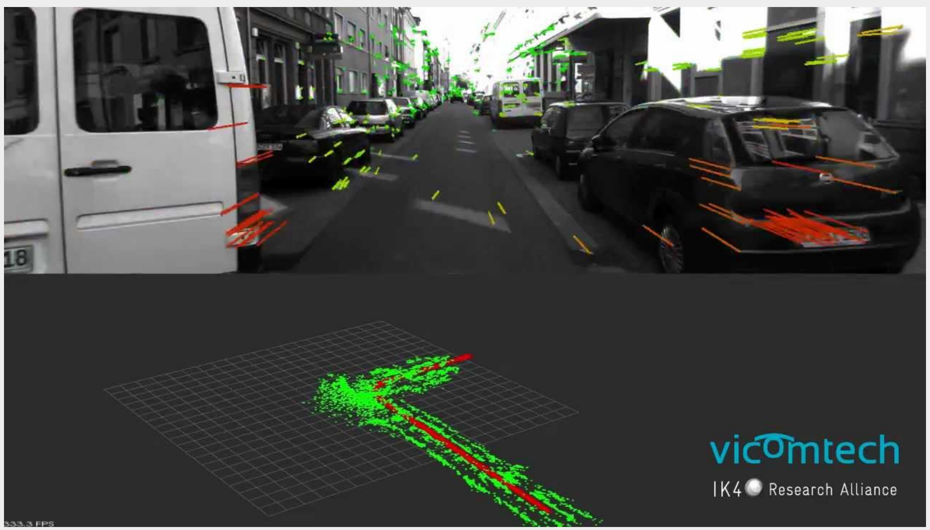


Image A
Image B
Result

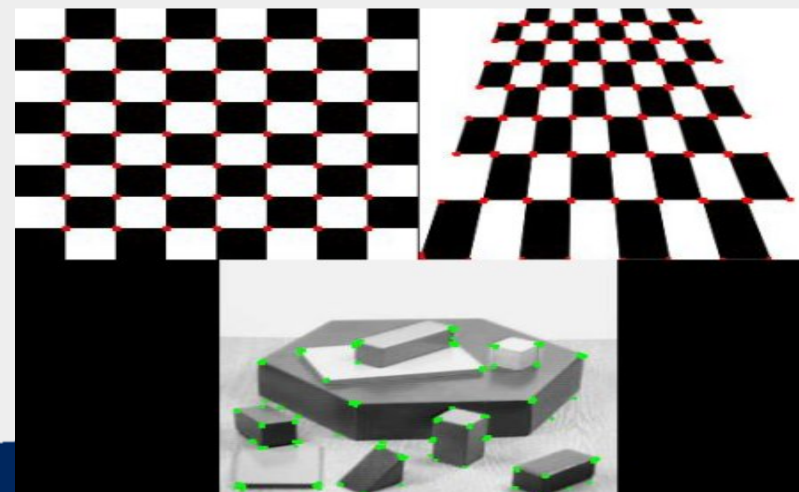

vicomtech
IK4 Research Alliance

Feature Detection

- Usually image features can be detected and quantified using geometric or statistical properties of an image

- Common method for feature detection: Harris Corner Detection

$$
\begin{aligned}
E(u,v) &= \sum_{(x,y)\in W} [I(x+u, y+v) - I(x,y)]^2 \\
&\approx \sum_{(x,y)\in W} [I(x,y) + \begin{bmatrix} I_x & I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} - I(x,y)]^2 \\
&= \sum_{(x,y)\in W} \left(\begin{bmatrix} I_x & I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} \right)^2 \\
&= \sum_{(x,y)\in W} \begin{bmatrix} u & v \end{bmatrix} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix}
\end{aligned}
$$



Feature Description

- Feature Descriptions:
  - Need to be accurate and unique
  - Compressed for embedded applications
  - Invariant to image deformations:
    - Lighting
    - Rotation
    - Scaling
    - Blurring
    - Perspective

Oxford Affine Image Dataset

Common Feature Description and Matching Algorithms

- SIFT: Scale Invariant Feature Transform
  - DoG (Difference of Guassians) to detect scale invariant features
  - Harris Corner and Maxima suppression to filter points
  - Generate a normalized orientation vector as a descriptor (rotation Invariant)
- SURF: Speeded Up Robust Features
  - Similar to SIFT but uses integral images and Gaussian pyramids to speed algorithm

Compressed Descriptor Algorithms

- SIFT + SURF costly in terms of space consumption
- Compressed Description Algorithms:
  - BRIEF (Binary Robust Independent Elementary Features)
  - BRISK (Binary Robust Invariant Scalable Key-points)
    - Both algorithms use random sampling to generate a compressed feature description
- Compressed sensing feature descriptor algorithms usually suffer in matching accuracy due to image variations

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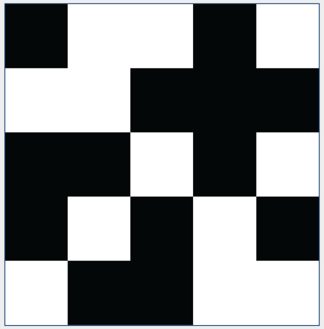
SYnthetic BAsis Feature Description Algorithm (SYBA)

Motivation

- A compressed sensing theory reported recently seems to be a good approach for improving feature description performance.
- Until now, no feature descriptor algorithm has used the compressed sensing theory.
- The compressed sensing theory uses synthetic basis functions to encode and decode a signal efficiently and reduce the bandwidth and storage requirements.
- An algorithm that is suitable for hardware implementation.

SYBA Algorithm

- Compressed Sensing theory:
  - Can accurately reconstruct a signal using minimal sampling
  - Sampling can be dictated by synthetic basis functions

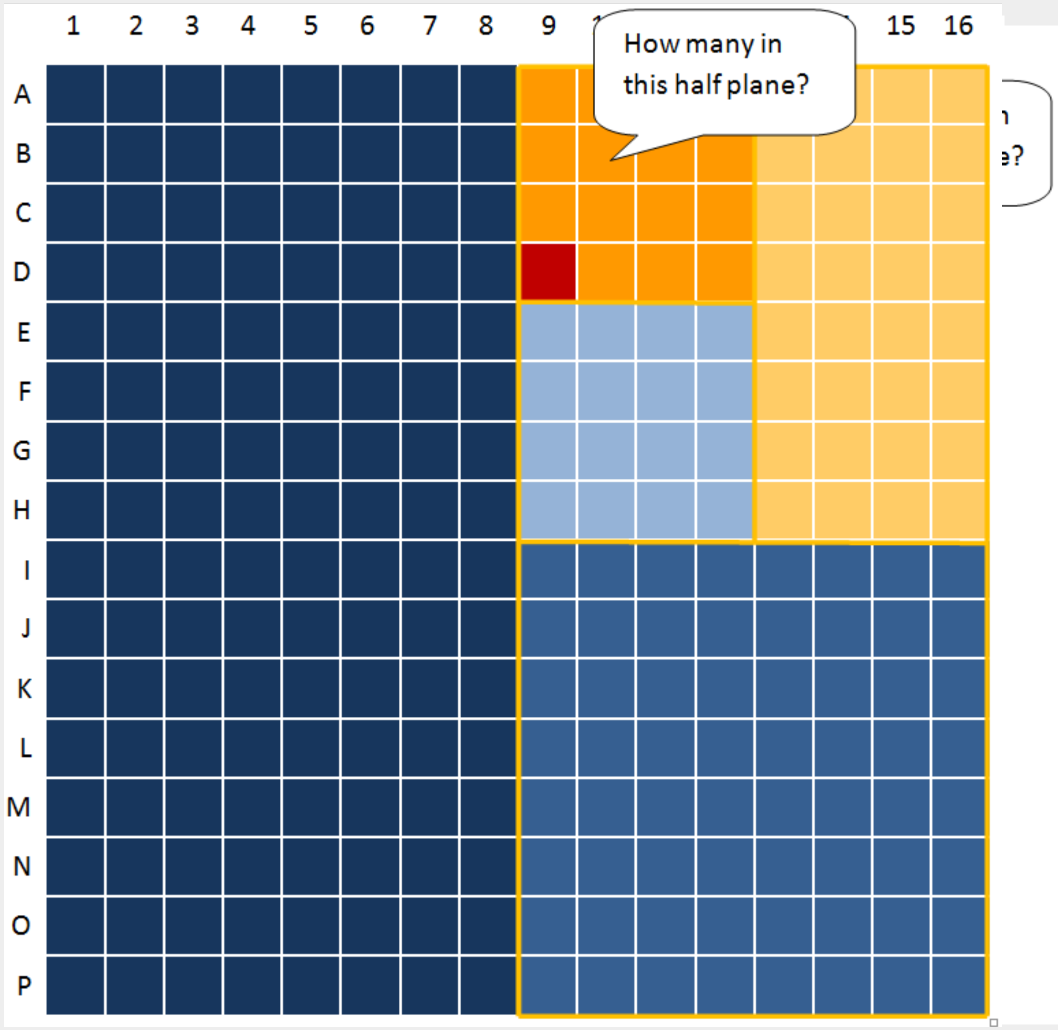


- SYBA: apply Synthetic Basis Images to accurately describe an image region:
  - $M = C\left(K \ln \frac{N}{K}\right)$ number of SBI images needed to accurately describe an image region

Battleship Game – Adaptive Strategy

- Count the number of hits in recursively subdividing half-planes

- Drawback:
  - Next query depends on answer from previous guess (requires memory)



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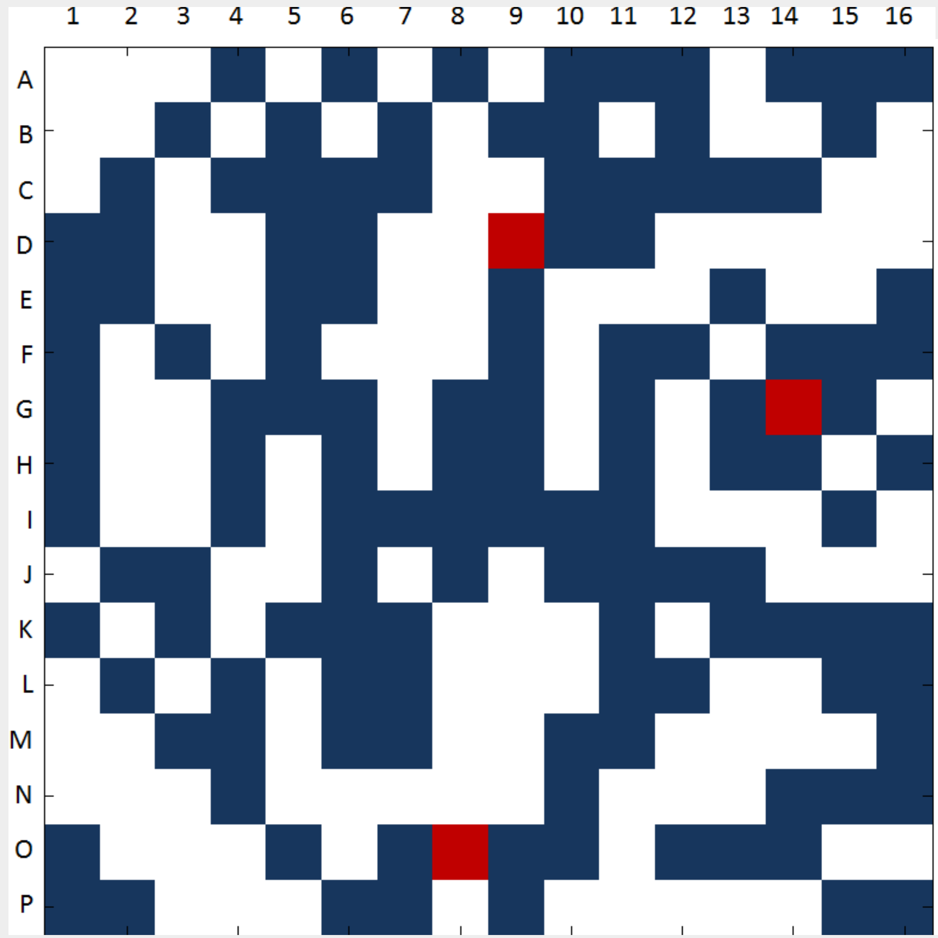
Battleship Game - Synthetic Basis Functions

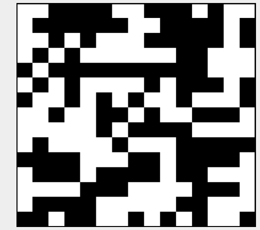
- Count number of ships showing through the mask.

- Total number of ships (red squares) is 8
  - Random Pattern A1 => 7
  - Random Pattern A2 => 5
  - Random Pattern A3 => 3



Battleship Game - Synthetic Basis Functions

$$M = C\left(K \ ln \frac{N}{K}\right)$$



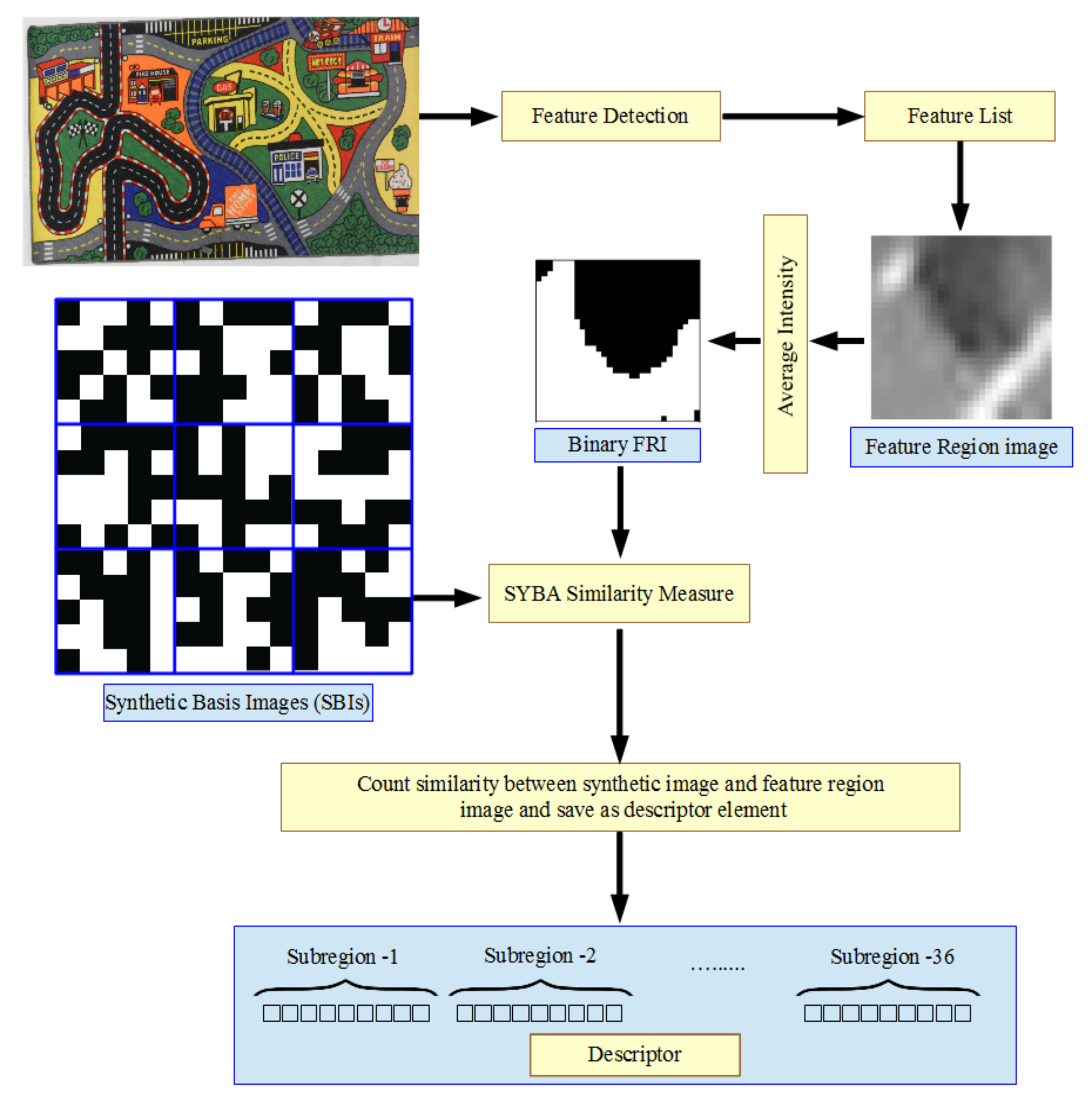
where,

N represents the $n \times n$ square area

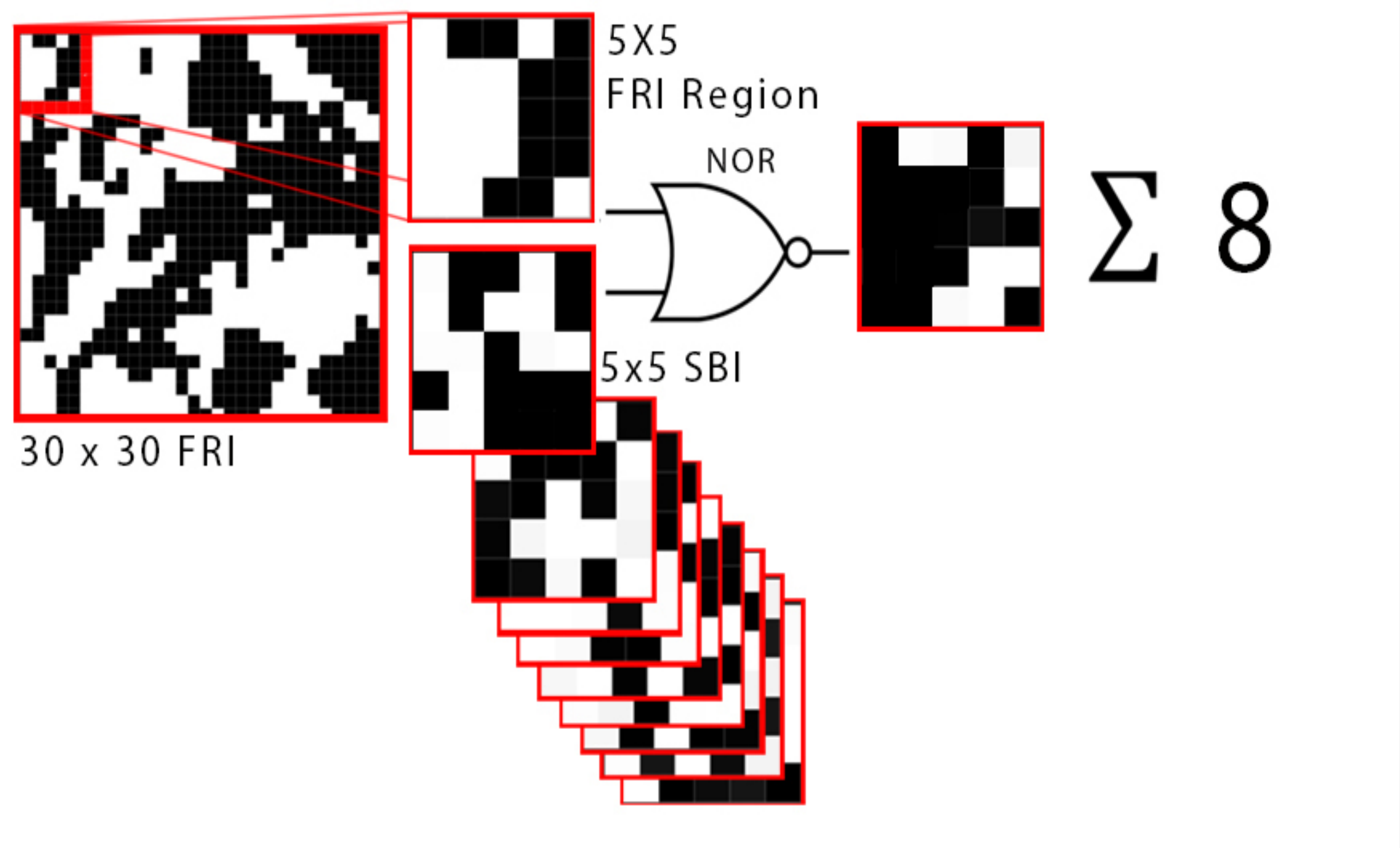
K is the number of black squares where the battleships might locate

M represents the maximum number of random patterns (guesses) required to locate all ships when K is equal to the rounded up integer of $N/2$.

SYBA Algorithm Flow



SYBA Algorithm: Generating a Descriptor Value



SYBA Algorithm: Feature Matching

- Use L1 norm comparison to compare descriptor values
  - $d = \sum_{i=1,j=1}^{n} |x_i - y_j|$
- Descriptor similarity measure computation:

$$\begin{array}{r} 5\ 4\ 6\ 6\ 6\ 4\ 5\ 6\ 7 \ldots 2\ 5\ 0\ 0\ 0\ 0\ 0\ 1\ 1 \\ 5\ 3\ 7\ 6\ 6\ 4\ 5\ 5\ 7 \ldots 1\ 5\ 0\ 0\ 1\ 0\ 0\ 1\ 1 \\ \hline \sum(0\ 1\ 1\ 0\ 0\ 0\ 0\ 1\ 0 \ldots 1\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 0) = 5 \end{array}$$

- Between two features: similarity measure must indicate features are mutually the best match for a feature match to be made

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SYBA Algorithm

- Benefits of SYBA:
  - Compressed description
  - Simple operations
  - Accurate Feature matches

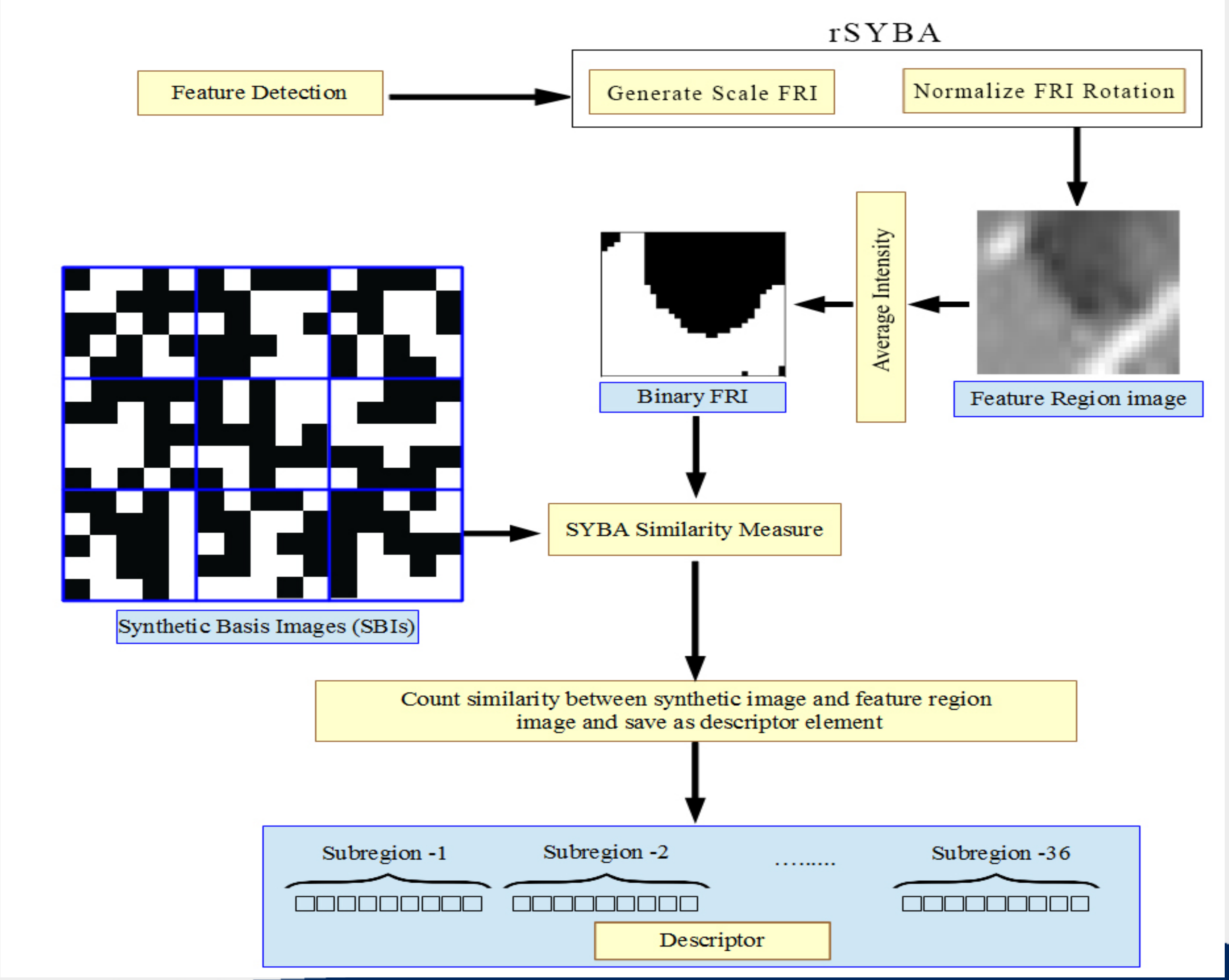
- Limitations of SYBA:
  - Feature match count and accuracy suffers under large image variations specifically for:
    - scale
    - orientation
    - perspective

Robust Synthetic Basis Descriptor Algorithm (rSYBA)

rSYBA Algorithm

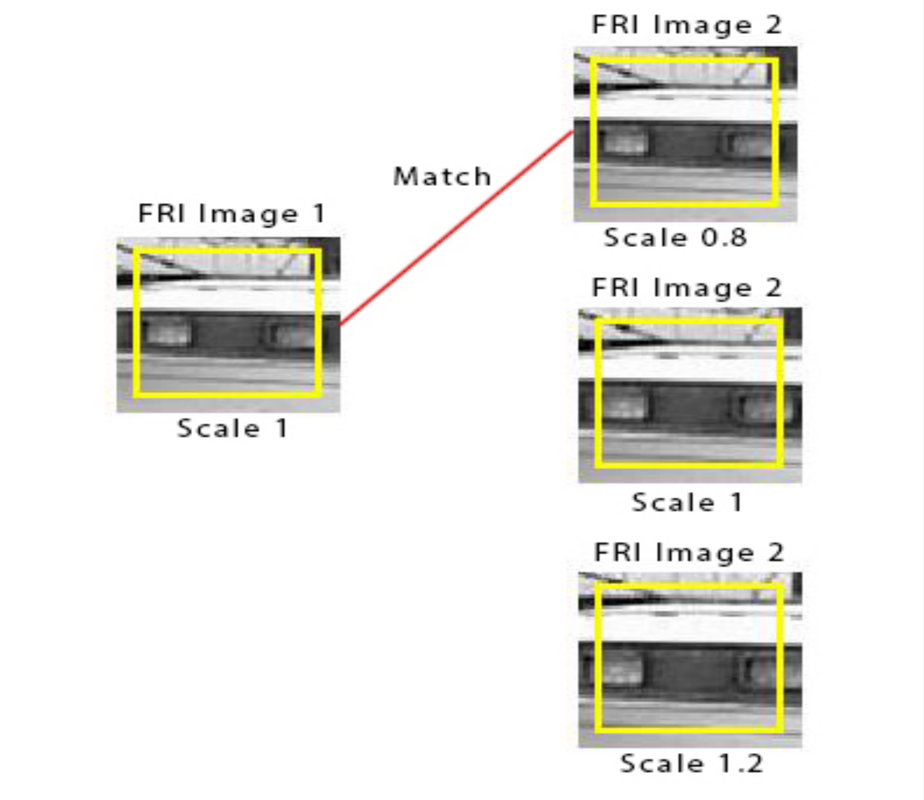
- Goal: make the SYBA algorithm invariant to scale and rotation image variation
  - Generate binarized image regions that are normalized to image scaling and rotation
  - Maintain benefits of SYBA

rSYBA Algorithm Flow



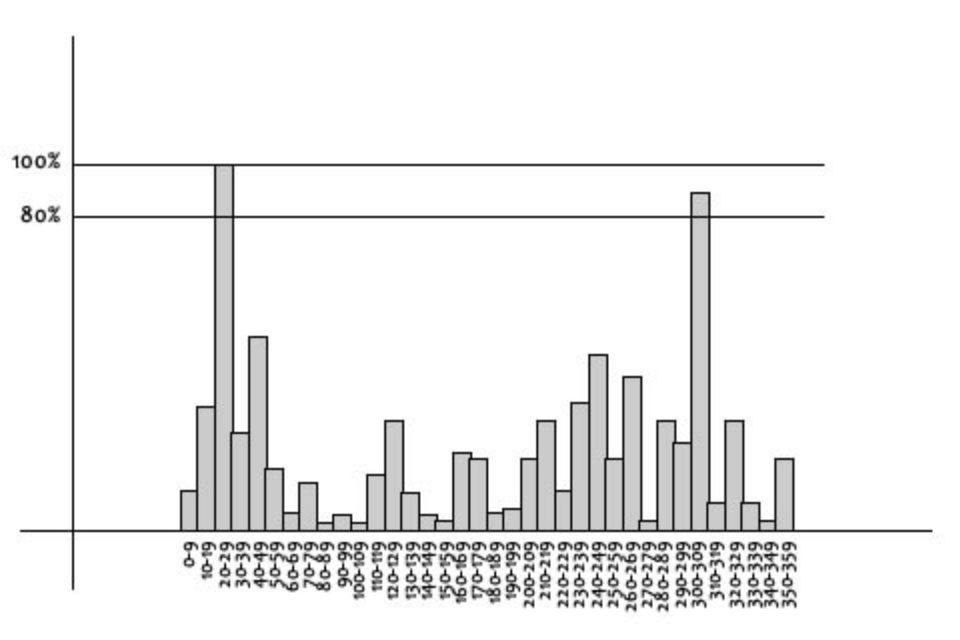
rSYBA Algorithm: Scale Invariance

- Generate multiple FRI's for the same feature at different scales



rSYBA Algorithm: Rotation Invariance

- Calculate the dominant gradient of the image region and rotate it
  - follow similar methodology to SIFT by using a gradient histogram



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Results

Datasets

- Oxford Affine Image Dataset

- BYU Rotation and Scaling Dataset

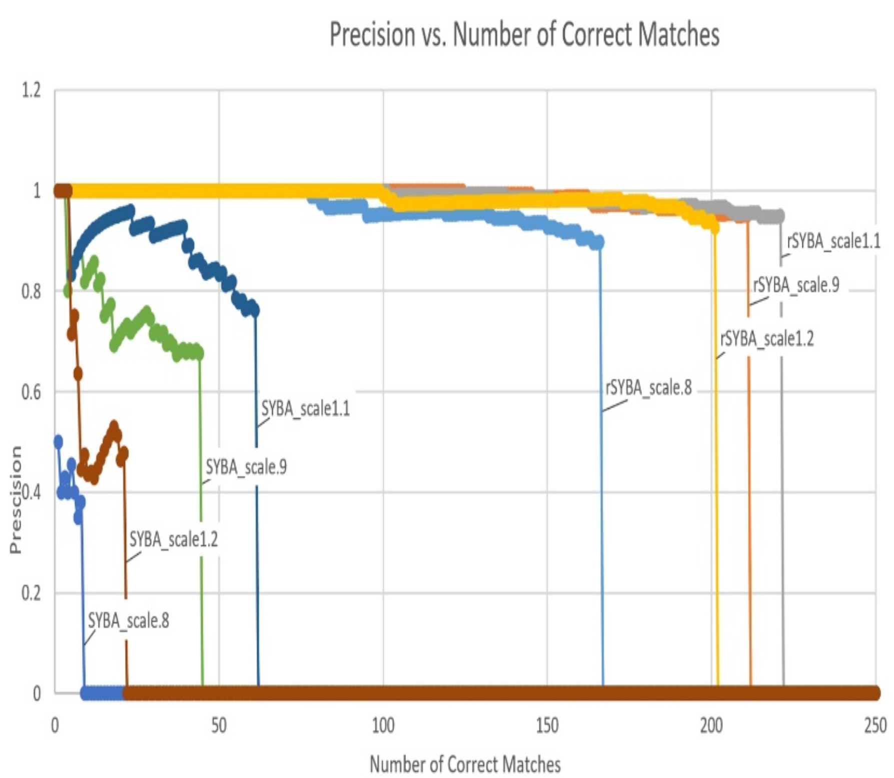
Metrics

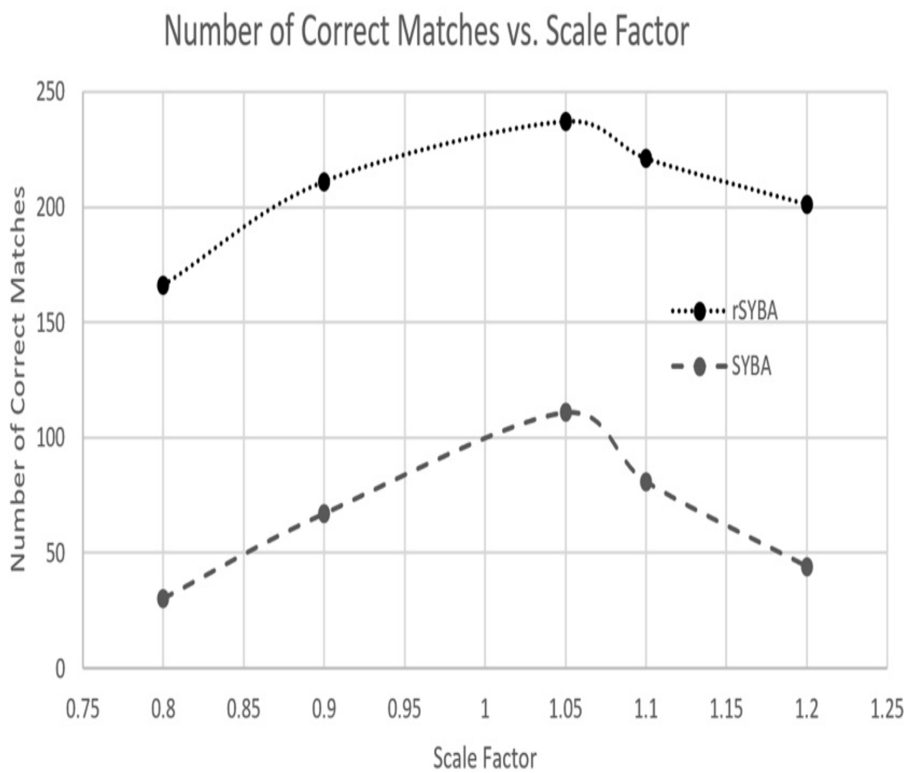
- Correct feature matches were determined using the Homography matrix:
  - $p_2 = H * p_1$

- $precision = \frac{The\ Total\ Number\ of\ Correct\ Feature\ Matches}{The\ Total\ Number\ of\ Matches\ Found}$

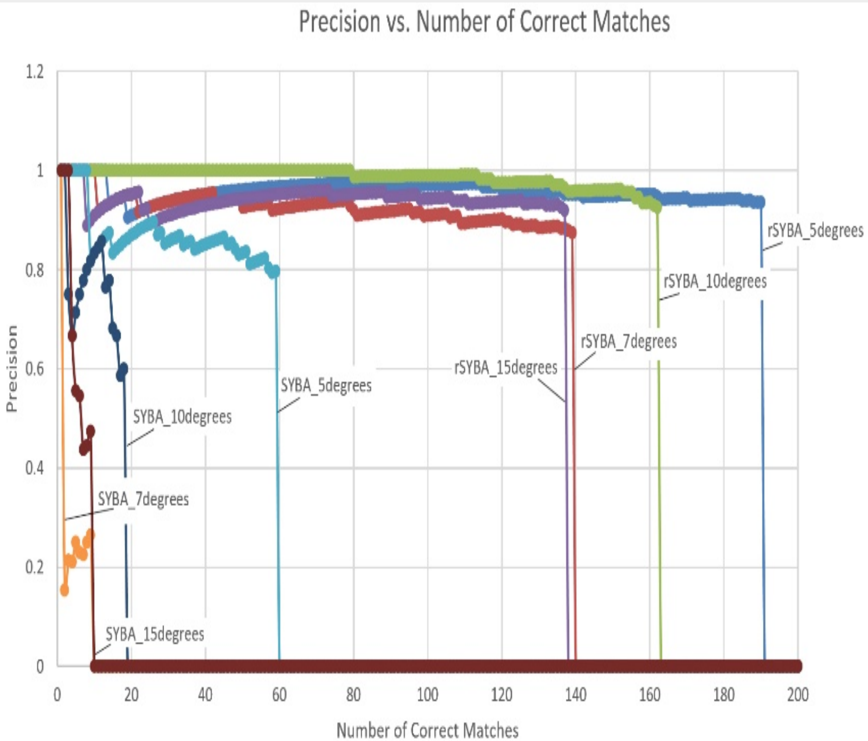
- $recall = \frac{The\ Total\ Number\ of\ Correct\ Feature\ Matches}{The\ Total\ Number\ of\ Possible\ Matches}$

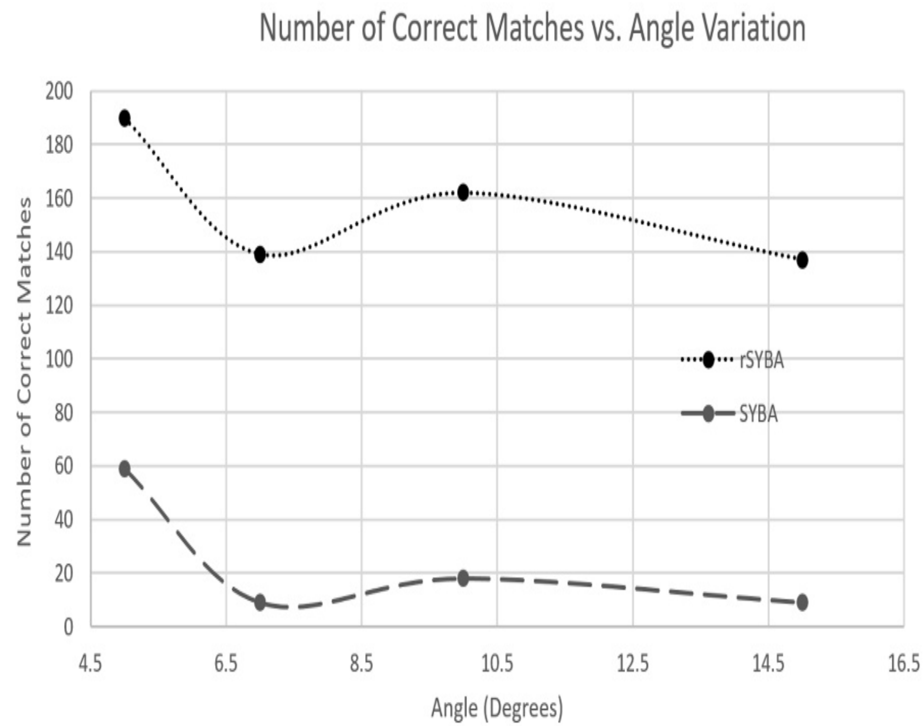
BYU Scale Dataset



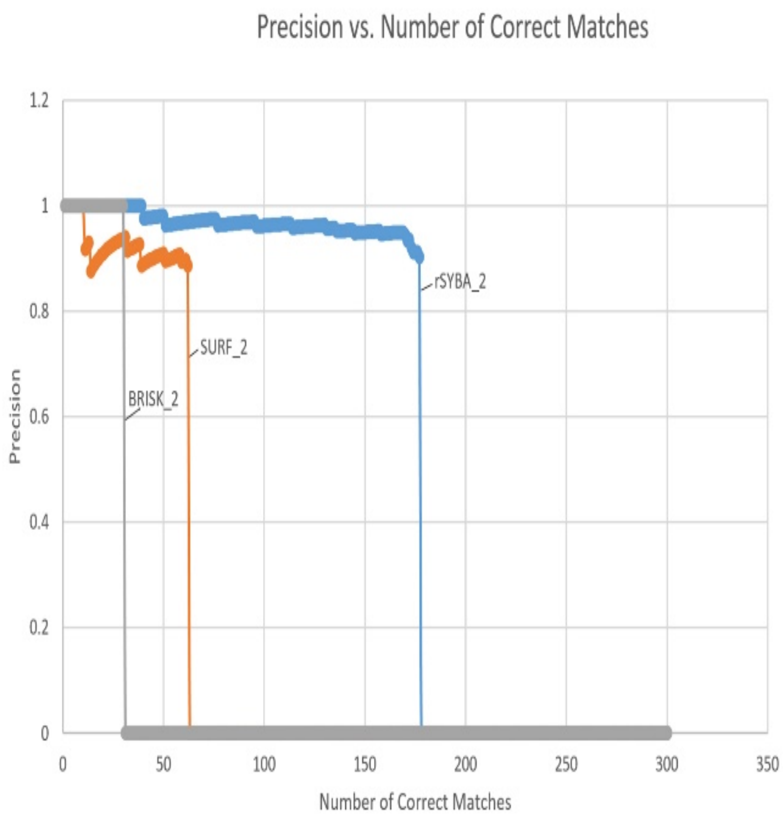


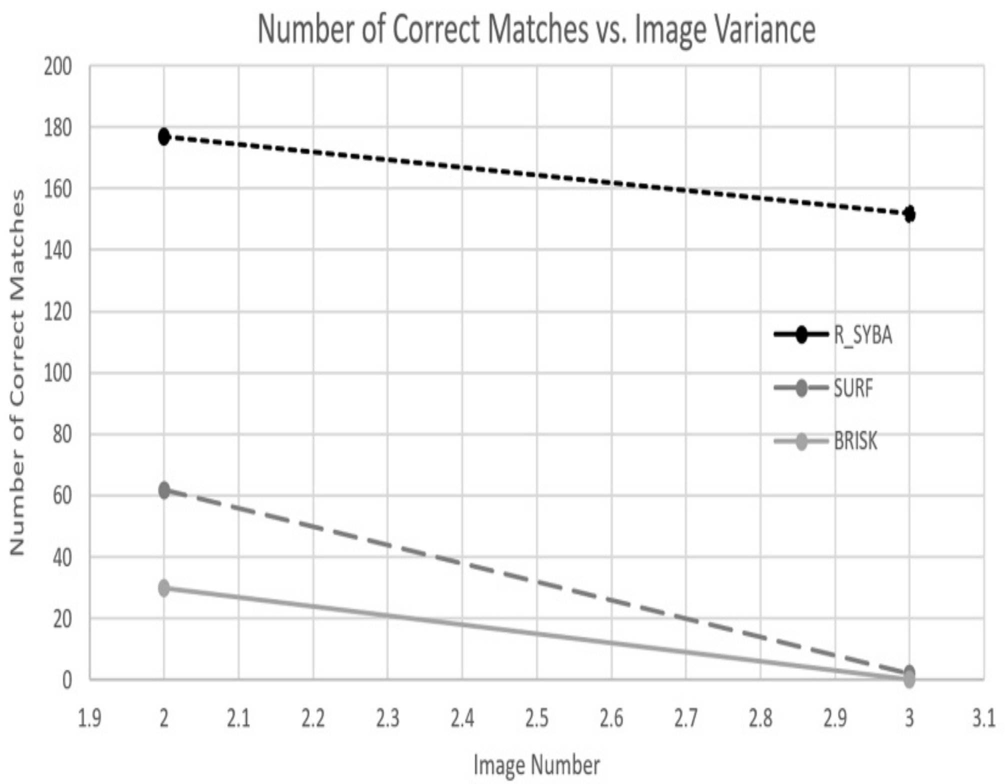
BYU Rotation Dataset





Oxford Affine Dataset





Questions?