



Artificial Landmark Recognition for Robot Navigation

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To operate successfully in indoor and outdoor environments, mobile robots must be able to localize themselves. The proposed approach detects and recognizes text in the surrounding environment from a vision sensor.

A support vector machine algorithm is responsible for classification of different raw text fonts and evaluation of text embedded in images and video sequences acquired from a typical camera mounted on a robot.

To aim text discrimination from the background, text can be framed with simple coloured geometrical shapes. Our system is able to calculate relative position and distance from detected landmarks.



To navigate successfully in a large-scale environment, mobile robot should know where it is within this environment

landmarks, are distinct features that a robot can recognize easily from sensory data

Artificial landmarks are objects purposefully placed in the environment, such as visual patterns or road signs

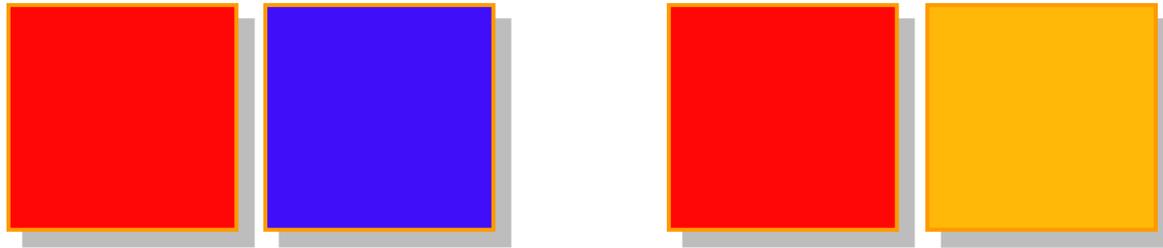
Why text?

More expressive, simple task programming for the end user



Color Spaces

Which pair is more similar?

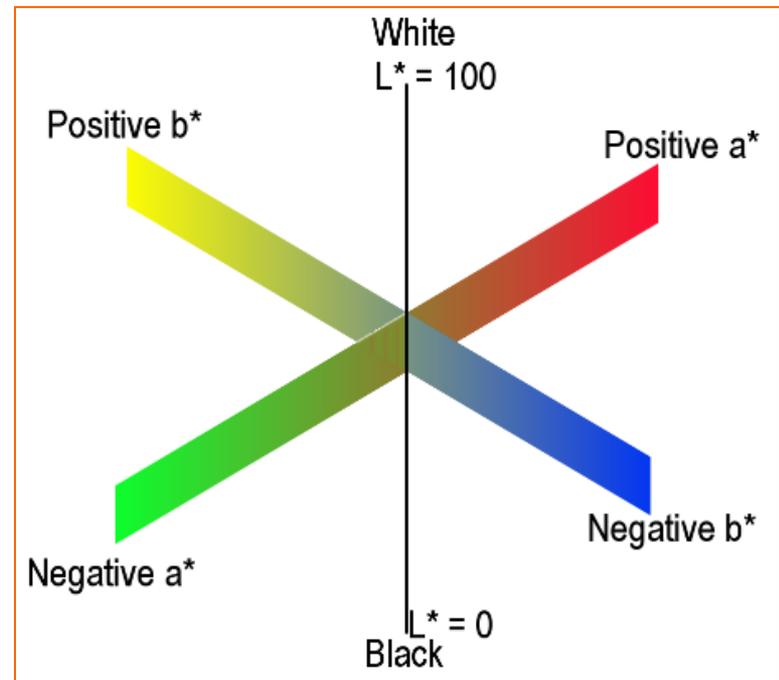


$L^*a^*b^*$ was designed to be uniform in that perceptual "closeness" corresponds to Euclidean distance in the space.



$L^*a^*b^*$ Color Space

- L** - lightness (white to black)
- a** - red to greeness
- b** - yellowness to blueness





Applying Kmeans in L^*a^*b Color Space

- Separate groups of similar coloured pixels
- K-means treats each object as having a location in space
 - objects are pixels with ' a^* ' and ' b^* ' values
- K-means requires to specify the number of clusters

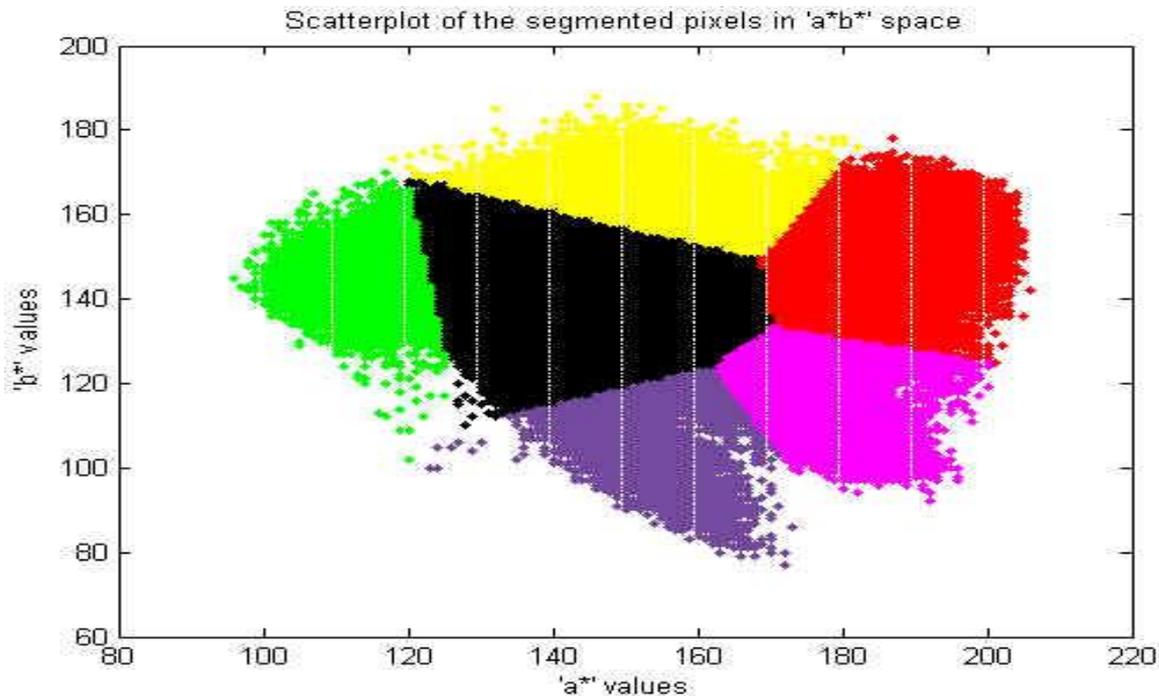


Image pixels clustered into six clusters using the Euclidean distance metric.



Automated Color Segmentation



Target Images



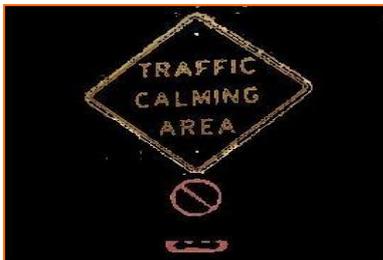
Cluster 1



Cluster 2



Cluster 3



Cluster 1



Cluster 2

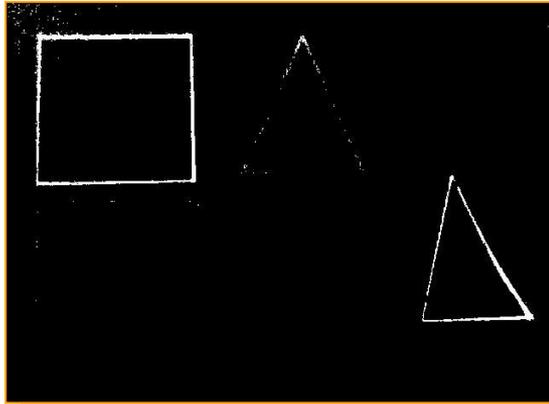


Cluster 3

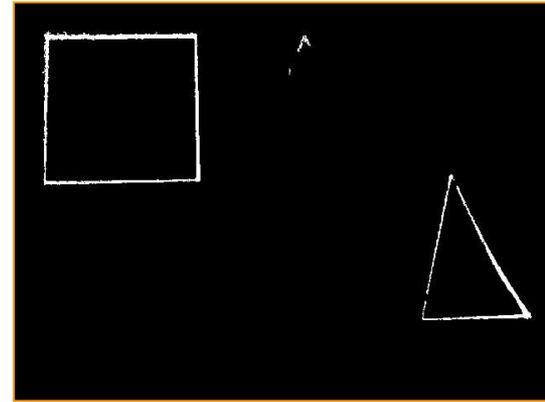


Shape Detection

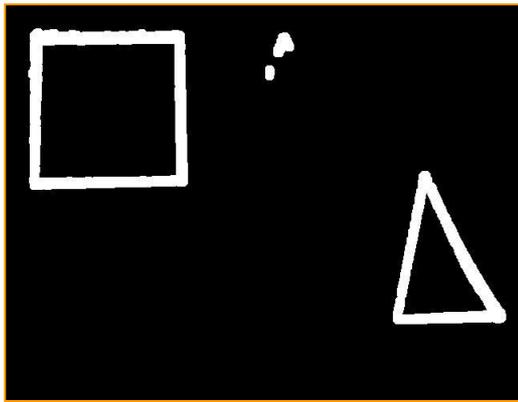
Morphological techniques application



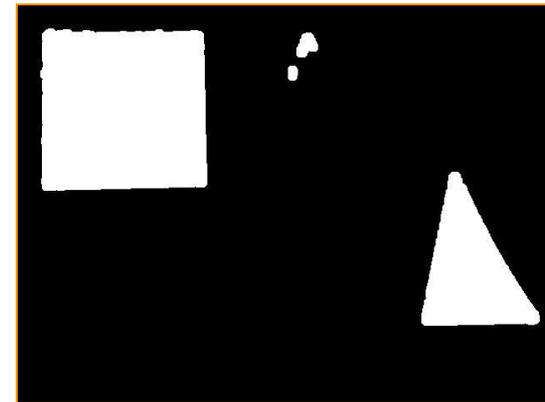
(1) Convert the image to black and white in order to prepare for boundary tracing



(2) Remove salt and pepper noise



(3) Dilate image to fill closed shapes

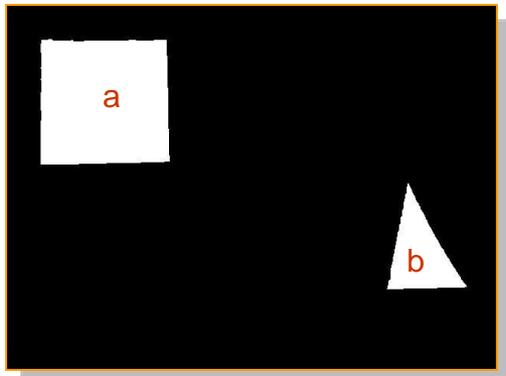


(4) Fill all closed shapes



Find object of interest

- ❑ Remove all objects smaller than a predefined number of pixels
- ❑ Index all objects in image
- ❑ Through some metric, calculate the shape of every object
- ❑ Delete all unwanted shapes



Indexed objects



Filtered object

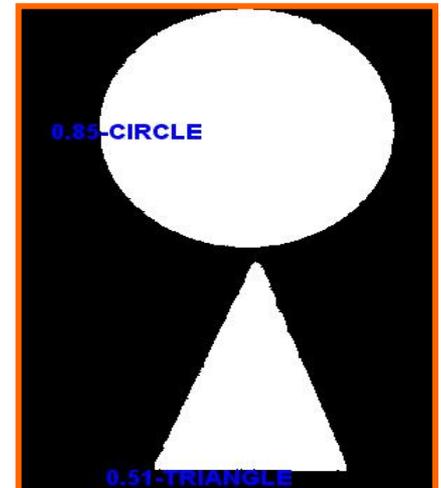
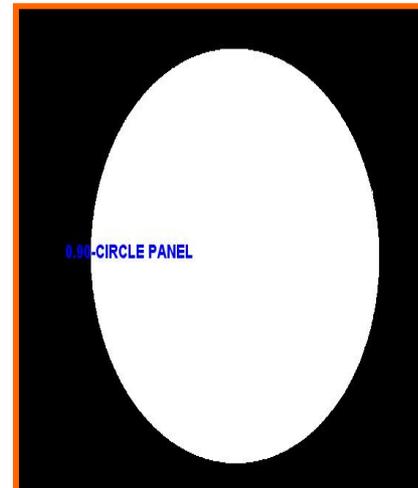
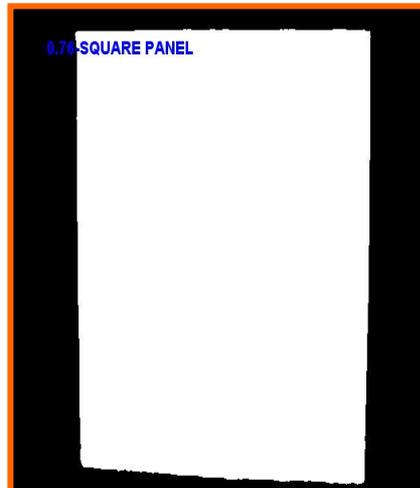
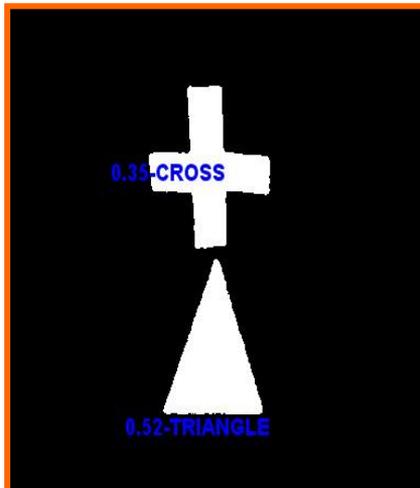


Determine the panel type

Estimate each object's area and perimeter.
Use these results to form a simple metric
indicating simple shapes

$$4\pi * \text{Area} / \text{Perimeter}^2$$

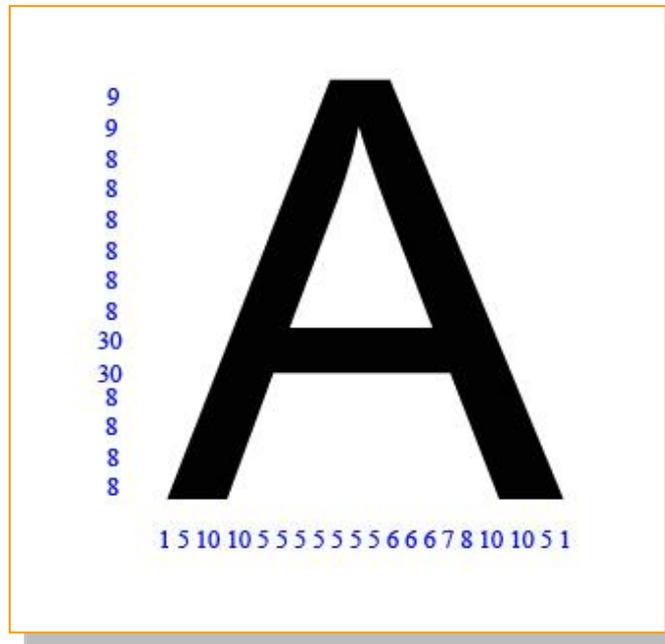
Shape	Metric
Circle	0.85 → 1
Square	0.65 → 0.85
Triangle	0.45 → 0.65
Cross	0.30 → 0.45





Building Character Signature

1. Transform $L*a*b$ image to binary
2. Calculate sum of pixels line by line and column by column
3. Concatenation of both histograms

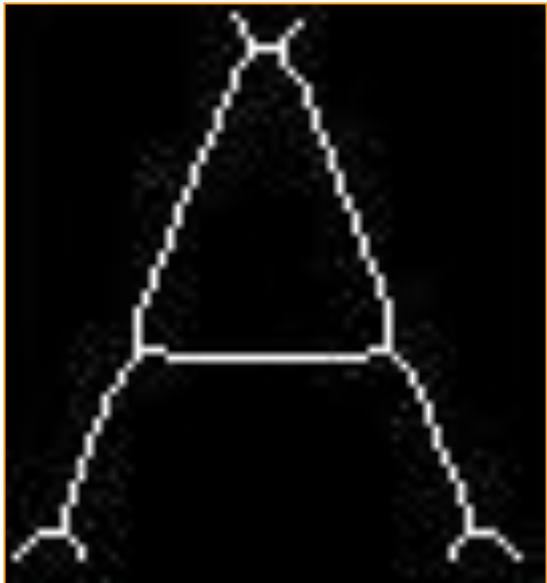


[1,5,10,10,5,5,5,5,5,5,6,6,6,7,8,10,10,5,1,9,9,8,8,8,8,8,8,30,30,8,8,8,8]

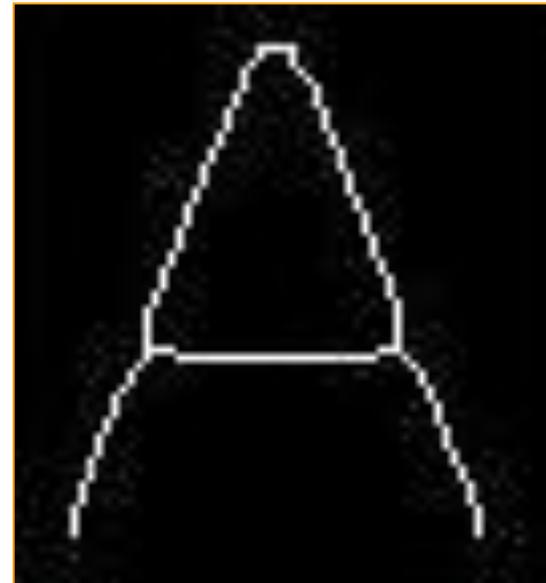


Skeletons & Spurs

- Reduce structural shape of a region to a graph
- Retain important information about the shape of original object
 - Offset pruning means, identify and remove endpoints



Skeleton version of the letter with parasitic components.

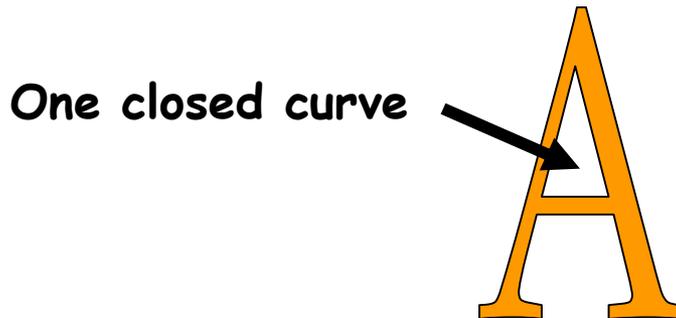


Skeleton after 6 applications of spur removal algorithm.



Complex Signatures (1/3)

- ❑ Upgrade quality of recognition
- ❑ These characteristics add to histogram signature:
 - Number of holes on the letter
 - Number of straight lines for every letter
 - The area of the letter shape



1 hole : A, D, O, P, Q, R

2 holes : B

0 holes : C, E, F, G, H, I, J, K, L, M, N, R, S, T, U, V, W, X, Y, Z

So, for example, if we have found 1 hole, we can check for next characteristics only on A,D,O,P,Q,R letters.

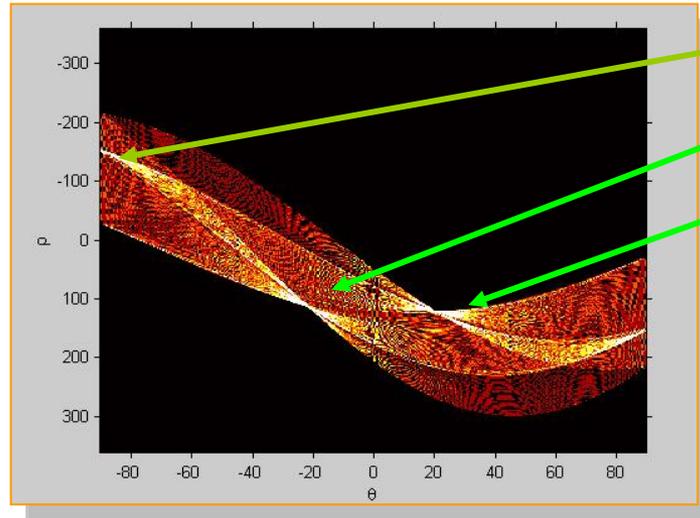


Complex Signatures (2/3)

Hough Transform: In the simplest form can locate straight lines if any

Every line is a vector of parametric coordinates

- ρ : the standard of the vector
- θ : the angle



Hough transform for letter A (Skeletonized)
 Left and right luminous points are part of the same line

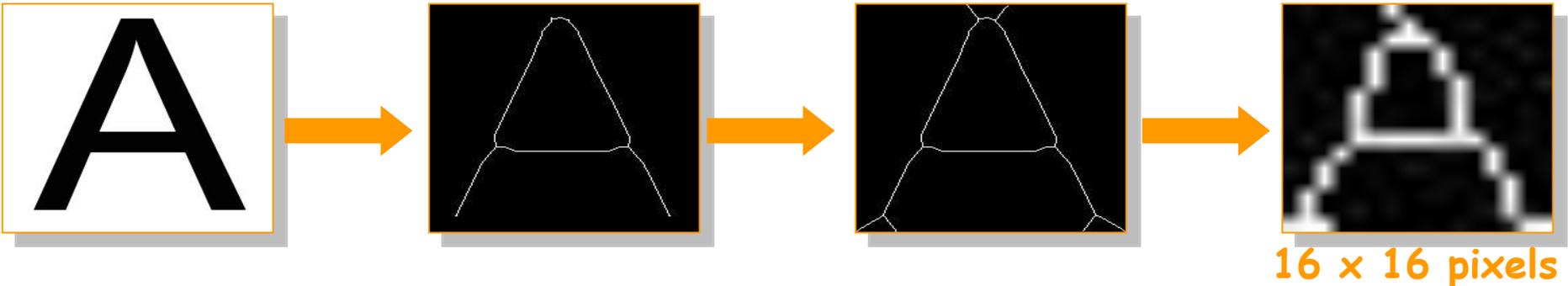


Complex Signatures (3/3)

Area of letter shape

In order to have a coherent value the size must be the same for every letter. A good idea is to resize to a fixed height and width

The letter must be in skeleton form
Smaller image means less parasitic information
increased performance and reduced time processing





Matching by Correlation

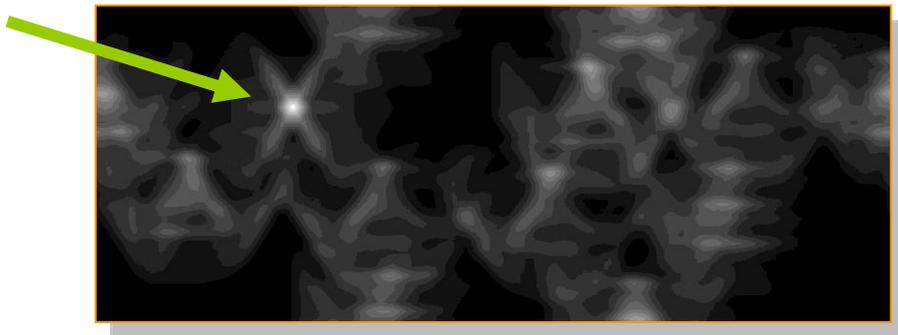
Scan target object with a mask, here the mask is the letter with which we want to compare or find on the source image. Typically the mask is much smaller than the source image



1. Source Image

2. Mask

X:318 Y:257
Index: 1
RGB: 1,1,1



Letter A is found where luminosity is greater than anywhere else



SVM Training

- Additional attributes from rotated images (30° and 60°)
 - All rotated characters have the same size
- Build signature from original & slightly rotated characters



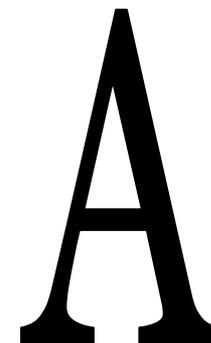
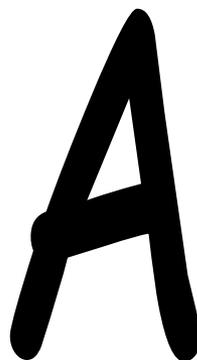
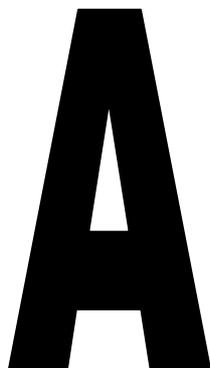
Original Image



Rotated:30°



Rotated 60°

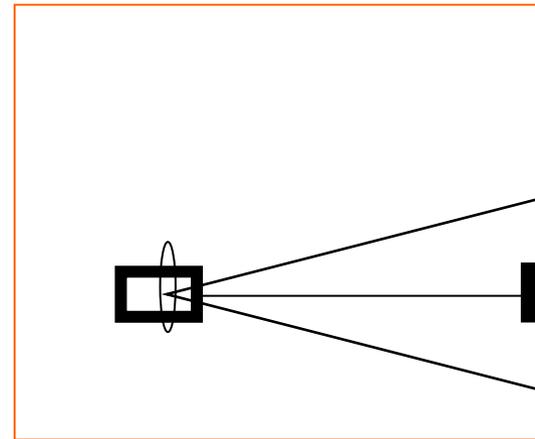
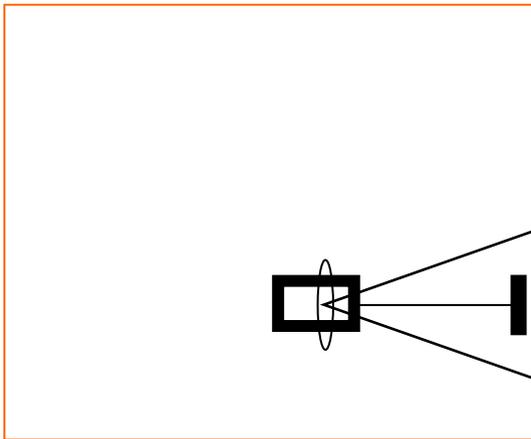


Train SVM with different fonts...

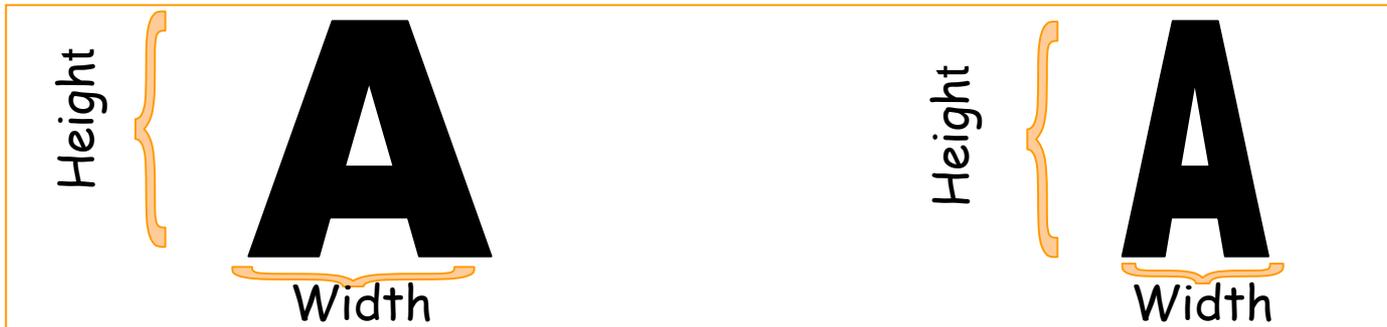
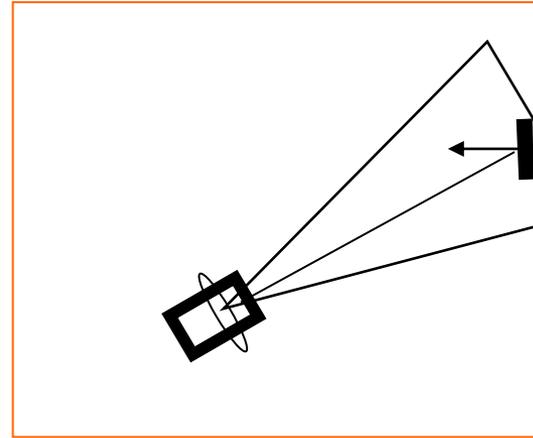
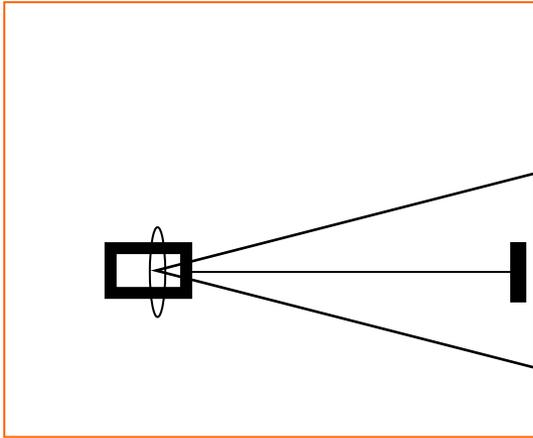


Distance & Angle from a Character

Text size and deformation can be used for accurate robot localization only after camera calibration



128px128p=3 meters from camera 512px512p=1.8 meters from camera



512px512p=1.8m angle: 0°

512px256p=1.8m, angle:30°



Conclusions

These preliminary results show that the method performs well for distinct coloured shapes and angles not exceeding 30°

Support Vector Machines appears to be a good approach but the performance depends on the learning database

The experiments have been performed in varying lighting conditions
During experimental testing, illuminations occasionally caused misclassification of text