

# Recognition of Unistroke Gesture Sequences

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Presented by

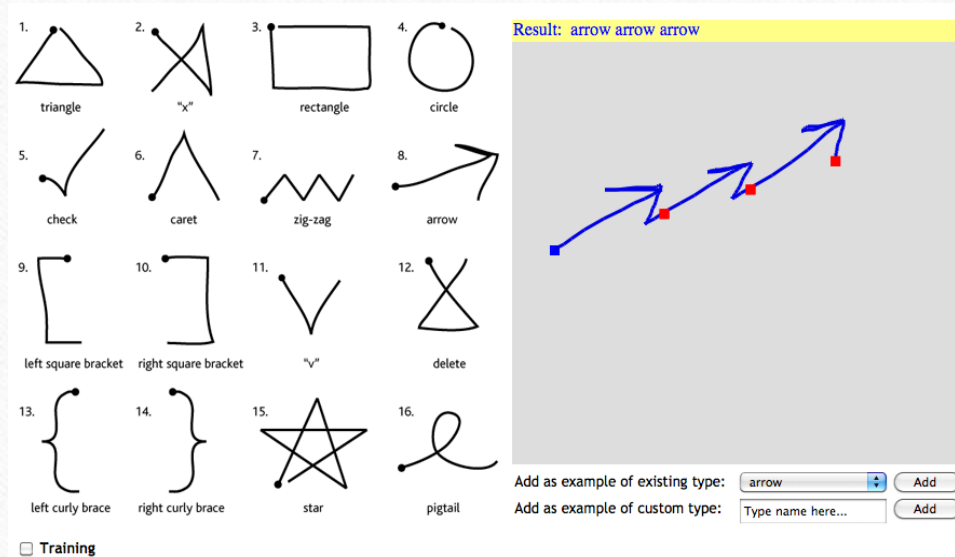
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# Problem Statement



Unistroke gesture image and original S1 Recognizer source code Copyright (C) 2007-2012, Jacob O. Wobbrock, Andrew D. Wilson and Yang Li. All rights reserved.

To develop a gesture recognition system, which will segment the input sequence consisting of multiple gestures, drawn in one stroke, into the constituent.

Our primary objective in solving this problem is to have a minimal set of training data in order to quickly build a prototype system.

# Related Work

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- Recognition of individual gestures in unistroke and multistroke sequences of digits – Yang et al: Training HMMs for continuous sequences
- Individual gesture recognition : Extracting several features from an input and constructing Hidden Markov Models for each gesture – Tanguay
- Recognizing an individual unistroke gesture sequence, using a distance measure from existing templates - \$1 Recognizer - Wobbrock et al



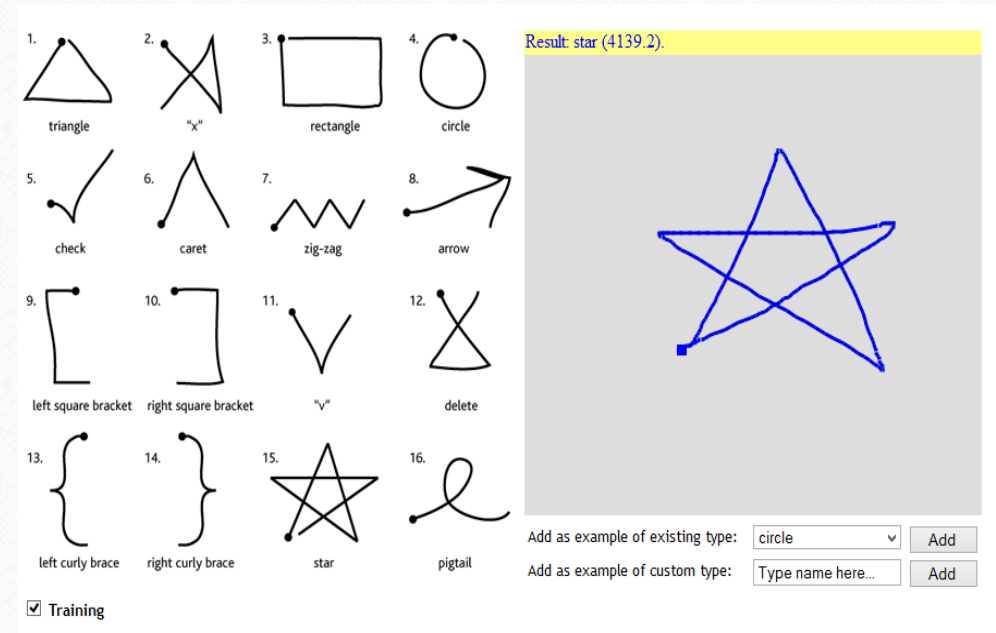
# Our Approach – Salient Features

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- Extend \$1 recognizer to identify multiple gestures in a gesture sequence.
- Hardest problem is that of segmentation – Classified in literature as “Inverse Perception Problem”.
- Based on a “Visual Affinity” approach – a type of geometric match.
- Employs Dynamic Time Warping to decide the distance from a given template.
- No restriction on gestures in the input sequence –
  - Arbitrarily long
  - Can contain any pre-defined gesture. New gestures can also be added to the system.

# Approach – Training mode

- In training mode, the user draws a template of either an existing or new gesture.
- Only individual gestures are drawn – no need to train the system with gesture sequences.
- If misclassification occurs during training, user can indicate the intended gesture.
- Score next to the shape (“star”) is based upon a distance measure between the input and the indicated gesture.





# Approach – Match using Dynamic Time Warping

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- Euclidean distance used as the distance metric between the neighboring points of input sequence and each template.

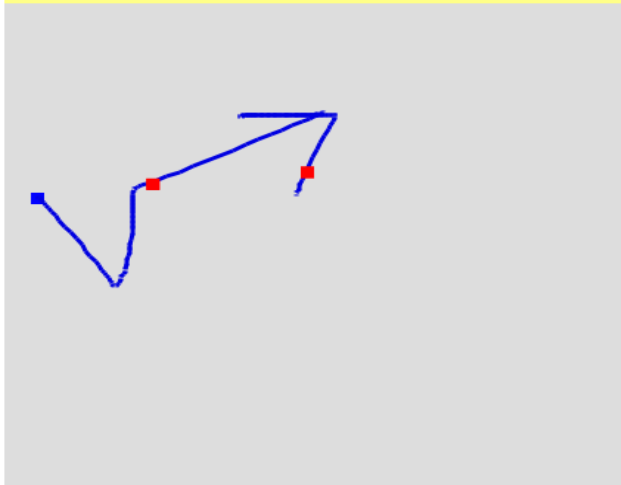
$$d = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2}$$

where  $(x_k, y_k)$  correspond to the points on the template under consideration  
and  $(x_i, y_i)$  correspond to the points on the input sequence.

- For a given set of input points, if there is a template which gives a score lower than a fixed threshold, then that gesture is recorded as being part of the input.
- The identified portion of the input is “spliced off” and the matching procedure is repeated for the remaining input.

# Approach – Segmentation and Recognition

Result: v arrow



Input Gesture Sequence  
Blue Dot – Start of the Sequence  
Red Dots – Points at which  
sequence is segmented



Candidate input points  
No Match

Slide the input set of points  
Match with “v” (First dot)

Remaining input after splicing  
off the matched template



Next set of candidate points  
from remaining input – No Match



Sliding the set of points  
Match with “Arrow” (Final dot)



# Results and Interpretation

Sequence Length	Accuracy Rate (%)
1	57.5
2	32.16
3	25.72

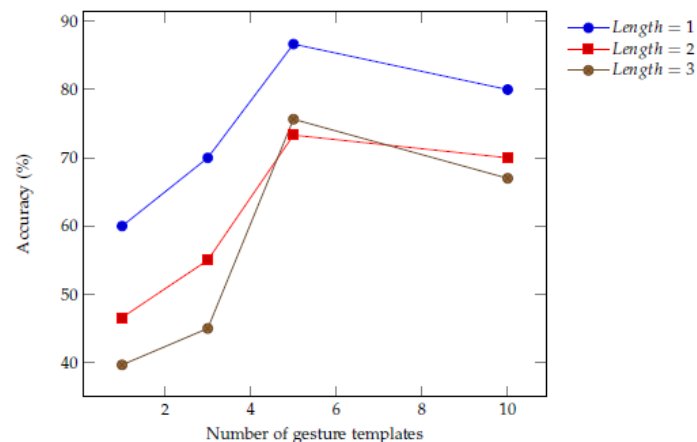
Table:1 Overall Accuracy – Exact Match

Sequence Length	Segmentation Accuracy(%)
1	71.5
2	71.5
3	52.27

Table:2 Segmentation Accuracy

Sequence Length	Relaxed Accuracy (%)
2	56.19
3	56.37

Table:3 Relaxed Accuracy



$$\text{Relaxed Accuracy} = \frac{\text{Reported Gestures in input}}{\text{Total Gestures in input sequence}}$$

Training Size Vs. Accuracy Rate graph, indicates the following:

1. Even for relatively low training samples ( $n = 3$ ) fairly good accuracy rates are reported.
2. An optimum recognition rate is achieved at ( $n = 5$ )
3. Too many templates, cause incorrect recognition due to “confusion” caused by many variations of an individual gesture.



# Discussion

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- Training only on individual gestures → lose features indicating a transition from one gesture to another (such as a pause)
- Construct HMMs for each individual gesture in the “gesture library” and then chain HMMs to construct arbitrarily long sequences of gestures.
- Compromise training time and computation for improved accuracy.

# References

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