Hybrid Learning Using Genetic Algorithms and Decision Trees for Pattern Classification

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Outline

- Hybrid Approaches
- Genetic Algorithms
- Decision Trees
- Feature selection
- Facial image data and Satellite images
- Results

Pattern Classification

- Difficult but fundamental task
- Depends heavily on the particular choice of features used by classifier

  Rank features according to some statistic

  Eliminate low-ranked features

$\leadsto$ Ranking is not enough:

  Non-linear interactions between features

  Does not measure effectiveness on the complete task

Feature Selection

- First step in any classification task
- Feature Selection is crucial for classification performance
- Reduces amount of data
- Increases classification accuracy
- Very difficult: Number of features is very large, space of possible subsets is exponential in number of features ($100\text{features} \rightarrow 2^{100}\text{subsets}$).

Optimal Feature Selection

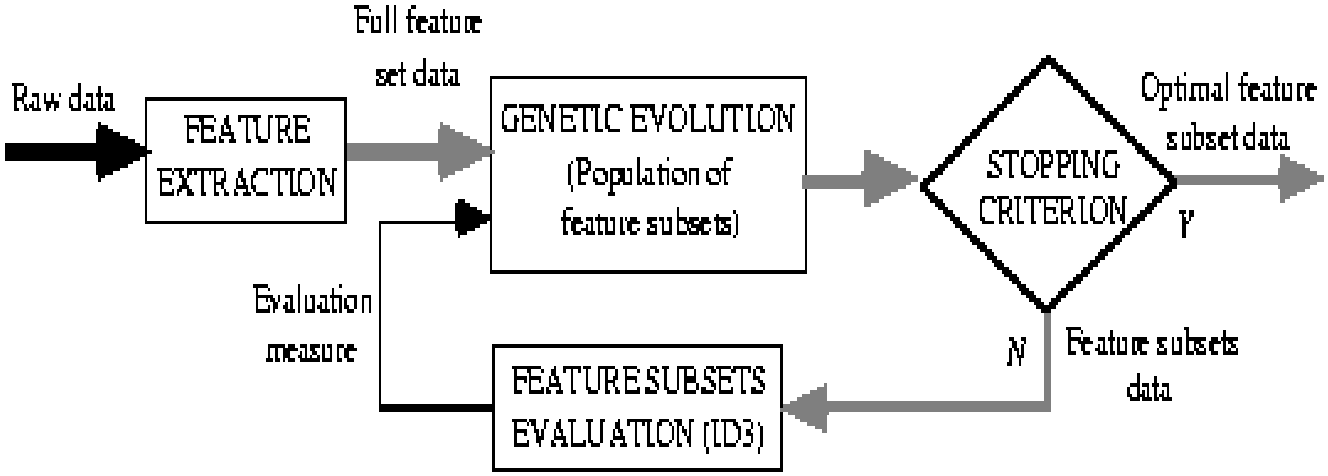
- Minimize number of features
- Improve classification rates

- GA + DT system: GA searches the space of all possible subsets of a large set of candidate discrimination features for an optimal feature subset
  1. For a given subset, ID3 produces a DT
  2. Accuracy on unseen data $\rightarrow$ fitness to GA
  3. GA evolves better subsets

  Stop when performance passes a threshold

System Architecture

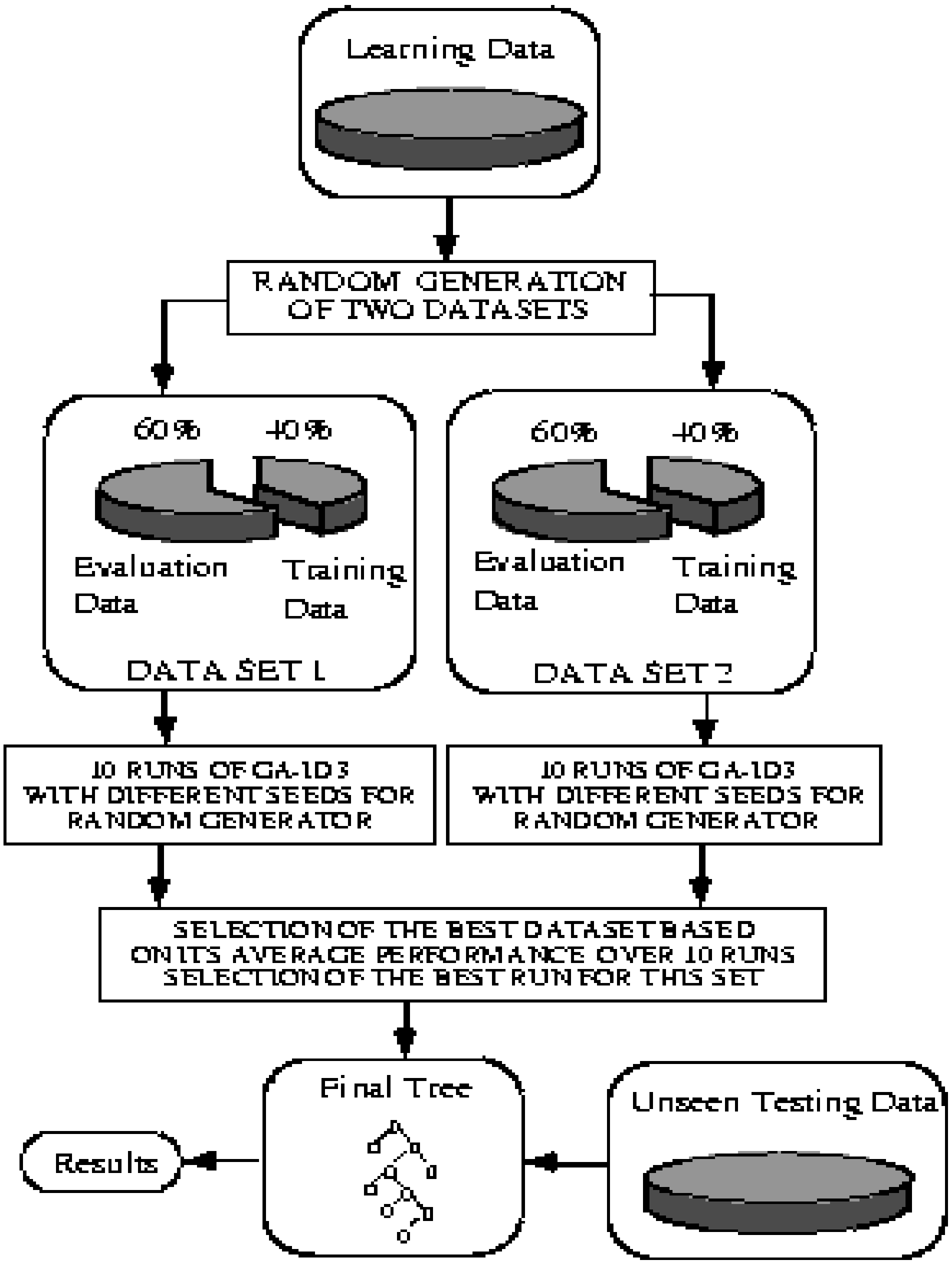
- Initial (large) feature set
- Run GA+ID3
- Recommend best feature set



GA Representation

- Fixed length binary string
- i^{th} position $== 1 \rightarrow i^{th}$ feature is included.
- Genetic Algorithm modifies a population of such strings.
- For each individual in the population
  - Run ID3 on training set containing only these features
  - Evaluate resulting DT on test data
  - Return accuracy to GA as fitness of individual

Methodology



Methodology (cont'd)

- Standard GA, popsize 50, standard parameter values
- C4.5, standard parameter values
- 2-fold Cross-validation
- 40% training 60% testing
- 10 runs of the system with different seeds
- Best tree out of ten is applied to testing data
- Compare
  1. Full feature set
  2. Same number of features but use ranking
- Satellite data (36 features total)
- Facial data (105 features total)

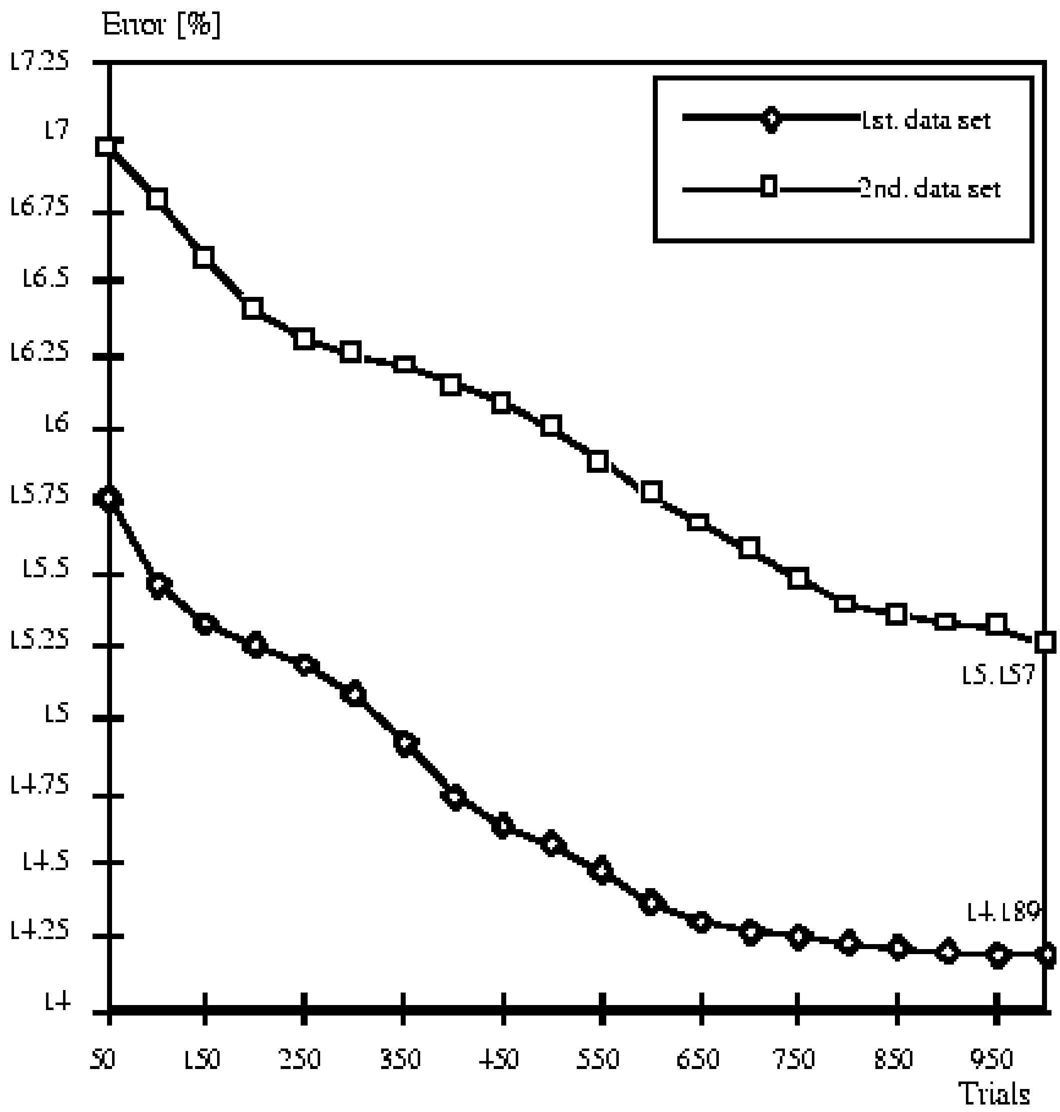
Satellite Data

- Predict central pixel classification based on 3x3 neighborhood multi-spectral values
- Nasa Landsat images
- 6 classes
- 4 spectral bands, 9 pixel values $\rightarrow$ 36 features
- Feature/pixel values are $0 - 255$
- Learning/training set $=$ 4435 examples, test data $=$ 2000 examples

Results

FULL FEAURE SET 36 Features		REDUCED FEATURE SET BY THE GA-ID3 SYSTEM 17 Features		REDUCED FEATURE SET BY FEATURE RANKING 17 Best Features Chosen	
Error Rate	Tree Complexity	Error Rate	Tree Complexity	Error Rate	Tree Complexity
18.5%	99 nodes	16.9%	72 nodes	20.6%	83 nodes

Results



Error [%]
17.25
17
16.75
16.5
16.25
16
15.75
15.5
15.25
15
14.75
14.5
14.25
14
1st. data set
2nd. data set
15.157
14.189
50
150
250
350
450
550
650
750
850
950
Trials

Facial Data

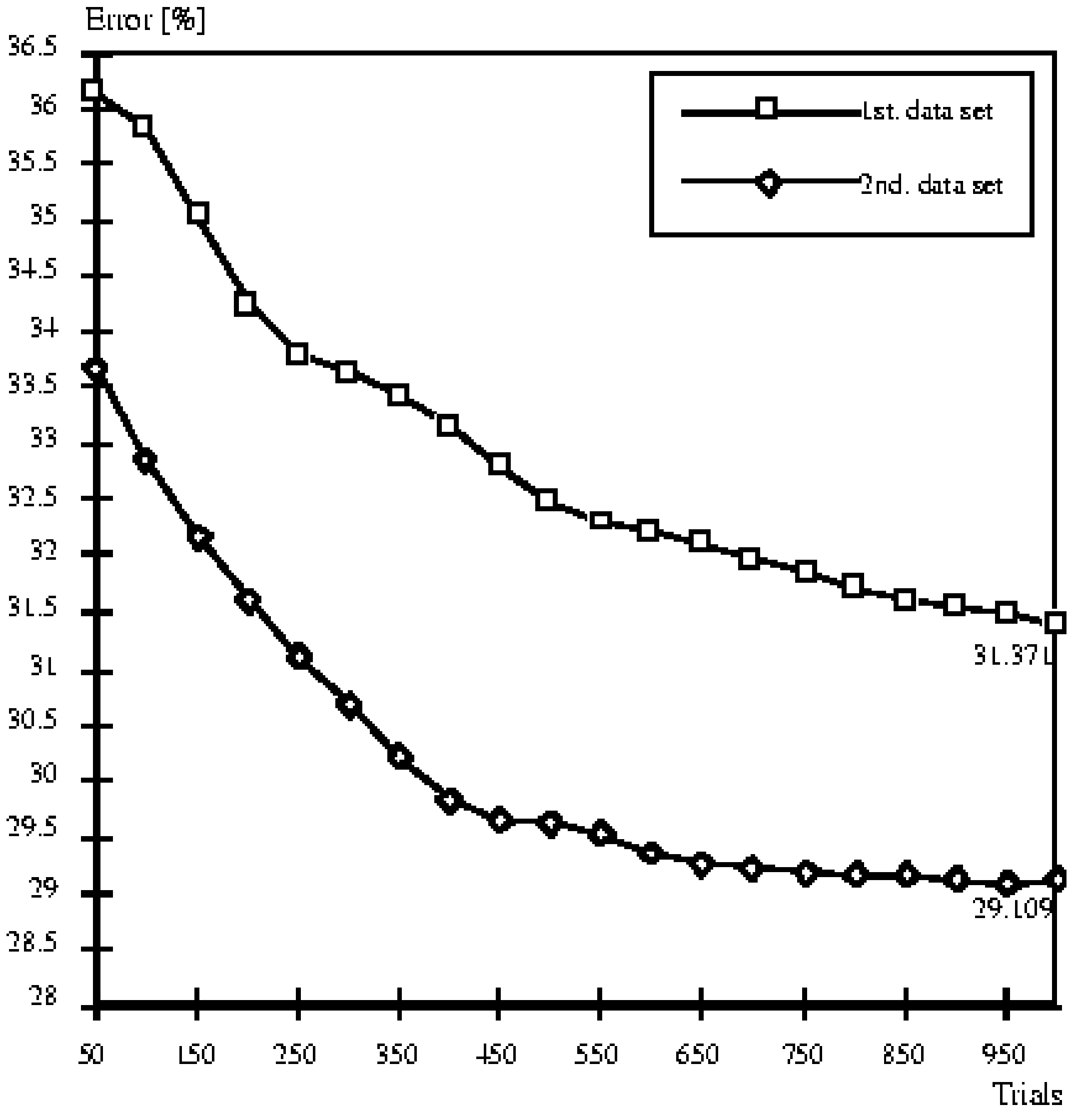
- Detecting eyes very important for face recognition
- 102 eyes, 102 nose, 102 other facial region examples for training
- 52 eyes, 52 nose, 52 other facial region for testing
- 105 features for each example
- Feature values between $0 - 255$
- Three classes

FEATURES	DESCRIPTION
From x_1 to x_{35}	Obtained by averaging a 4x4 window which has 50% (2 pixels) overlap in each shift.
From x_{36} to x_{70}	They represent the standard deviation of a 4x4 window.
From x_{71} to x_{105}	They represent the entropy for a 4x4 window.

Results

FULL FEATURE SET *105 Features*		REDUCED FEATURE SET BY THE GA-ID3 SYSTEM *41 Features*		REDUCED FEATURE SET BY FEATURE RANKING *41 Best Features Chosen*	
Error Rate	Tree Complexity	Error Rate	Tree Complexity	Error Rate	Tree Complexity
38.4%	8 nodes	27.5%	13 nodes	38.5%	11 nodes

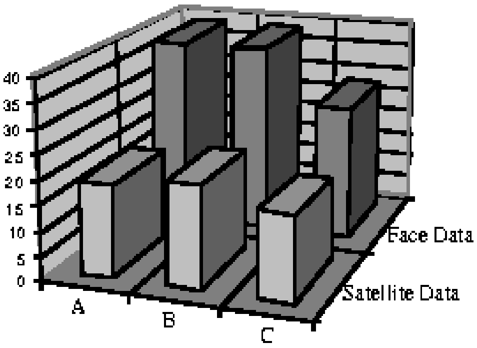
Face Results



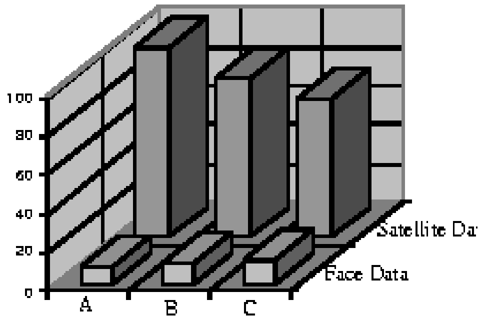
Results

- Better error rates
- Reduced tree complexity for Satellite
- 60% reduction in facial features, 52% in satellite

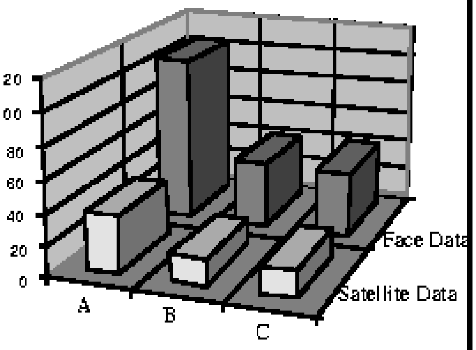
Results



Recognition Error Rates in Percentages



Description Complexities Expressed as the Number of Nodes



Number of Features in Sets

A: Full Feature Set
B: Reduced by Independent Ranking
C: Reduced by the GA-ID3 System

Conclusions and Future Work

- These preliminary results are encouraging
- Larger more complex problems in image processing
- Use information other than classification accuracy as GA fitness