AI*IA 2003
Tutorial
Fusion of Multiple Pattern Classifiers

Lecturer

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Lectures Aims and Outline

- An introductive tutorial on fusion of multiple classifiers

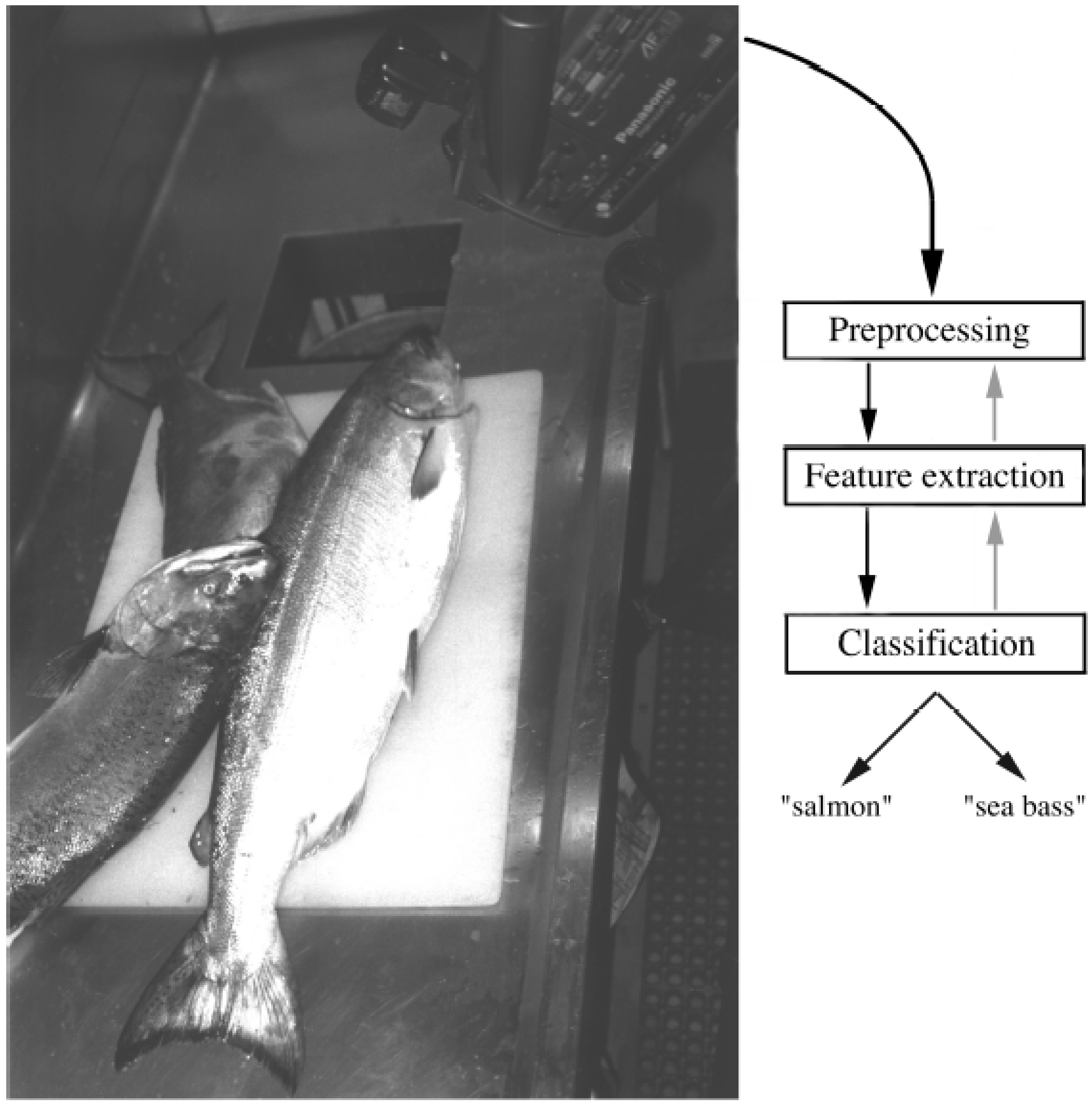
➢Part 1: Rationale, Motivations and Basic Concepts

➢Part 2: Main methods for creating multiple classifiers

➢Part 3: Main methods for fusing multiple classifiers

➢Part 4: Applications, Achievements, Open Issues and Conclusions

Pattern Classification: an example (Duda, Hart, and Stork, 2001)



The traditional approach to Pattern Classification

- Unfortunately, no dominant classifier exists for all the data distributions ("no free lunch" theorem), and the data distribution of the task at hand is usually unknown

•CLASSIFIER EVALUATION AND SELECTION: *evaluation* of a set of different classification algorithms (or different "versions" of the same algorithm) against a *representative* pattern sample, and *selection* of the best one

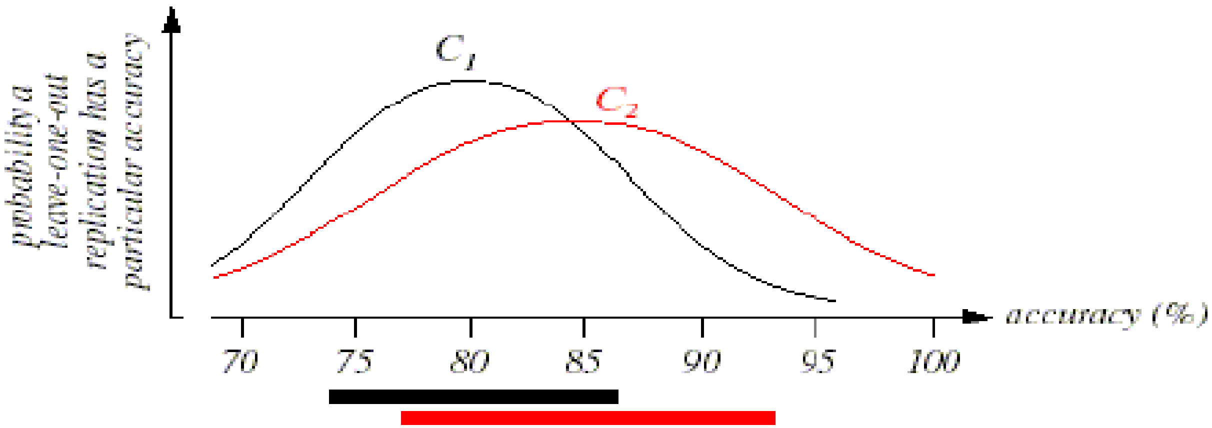
➢I design a set of N classifiers $C_1, C_2, \ldots, C_N$

➢I *evaluate* classifier errors $E_1 < E_2 < E_3 < \ldots < E_N$ (with related confidence intervals) using a validation set

➢I *select* the best classifier C_1 , and consider it the "optimal" one (in the Bayes sense, for example)

The traditional approach: Small Sample Size Issue

- The traditional approach works well when a large and representative data set is available *("large" sample size cases),* so that estimated errors allow to select the best classifier



•However, in many small sample-size real cases, validation set provides just *apparent* errors that differ from true errors E_i:

$$\hat{E}_i = E_i \pm \Delta_i$$

*This can make impossible the selection of the optimal, if any, classifier, and, in the **worst case**, I could select the **worst** classifier*

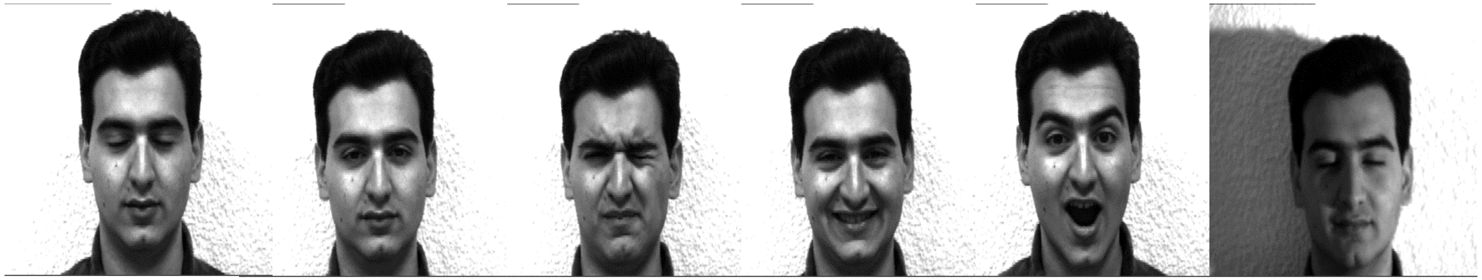
A practical example

Face recognition using PCA and LDA algorithms

Faces in the **validation set** (*Yale data base*)

High "Variance"

Faces in the **test set**



Apparent error caused from poorly representative validation set can make impossible to select the best one between PCA and LDA

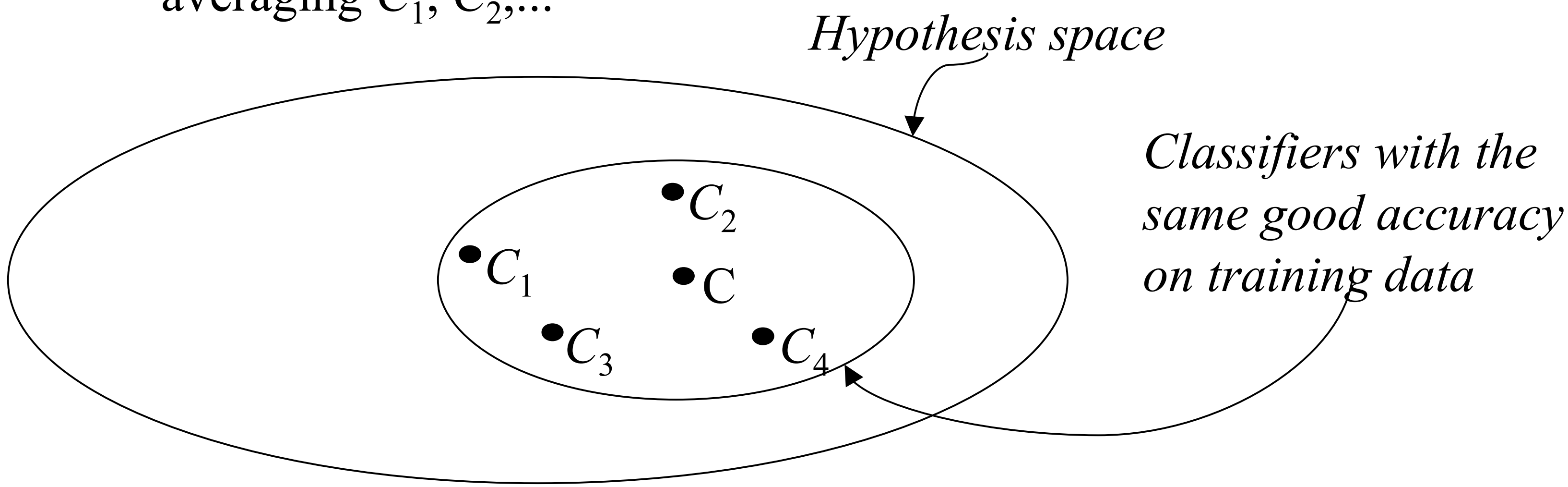
Multiple Classifier Fusion: *Worst Case* Motivation

- In the small sample size case, it is quite intuitive that I can avoid selection of the worst classifier by, for example, averaging over the individual classifiers

A paradigmatic example (Tom Dietterich, 2000)

Few training data with respect to the size of the hypothesis space

- several classifiers (C_1,C_2,...) can provide the same accuracy on validation data
- a good approximation of the optimal classifier C can be found by averaging C_1, C_2,...



A practical example

Face recognition using PCA and LDA algorithms (Yale data base)

For different choices of the training set (different "trials"), the best classifier varies. Fusion by averaging avoids to select the worst classifier for some test cases (Marcialis and Roli, 2003).

	Trial 1	**Trial 2**	**Trial 3**	**Trial 4**	**Trial 5**
PCA	76,7%	87,8%	**92,2%**	84,4%	**88,9%**
LDA	**83,3%**	**90,0%**	85,6%	84,4%	86,7%
Fusion by Average	80,0%	92,2%	88,9%	86,7%	88,9%

Multiple Classifier Fusion: *Best Case* Motivation

- Beside avoiding the selection of the worst classifier, under particular hypotheses, fusion of multiple classifiers can improve the performance of the best individual classifiers and, in some special cases, provide the optimal Bayes classifier

•This is possible if individual classifiers make “different” errors.

•*Luckily, we have many experimental evidences about that ! !*

•Theoretical support for some classes of fusers (e.g., linear combiners, majority voting)

•For linear combiners, Tumer and Ghosh (1996) showed that averaging outputs of individual classifiers with unbiased and uncorrelated errors can improve the performance of the best individual classifier and, for infinite number of classifiers, provide the optimal Bayes classifier

Experimental evidences: Multimodal Biometrics
(Roli et al., 2002)

- XM2VTS database
  - face images, video sequences, speech recordings
  - 200 training and 25 test clients, 70 test impostors

•Eight classifiers based on different techniques: two speech classifiers, six face classifiers

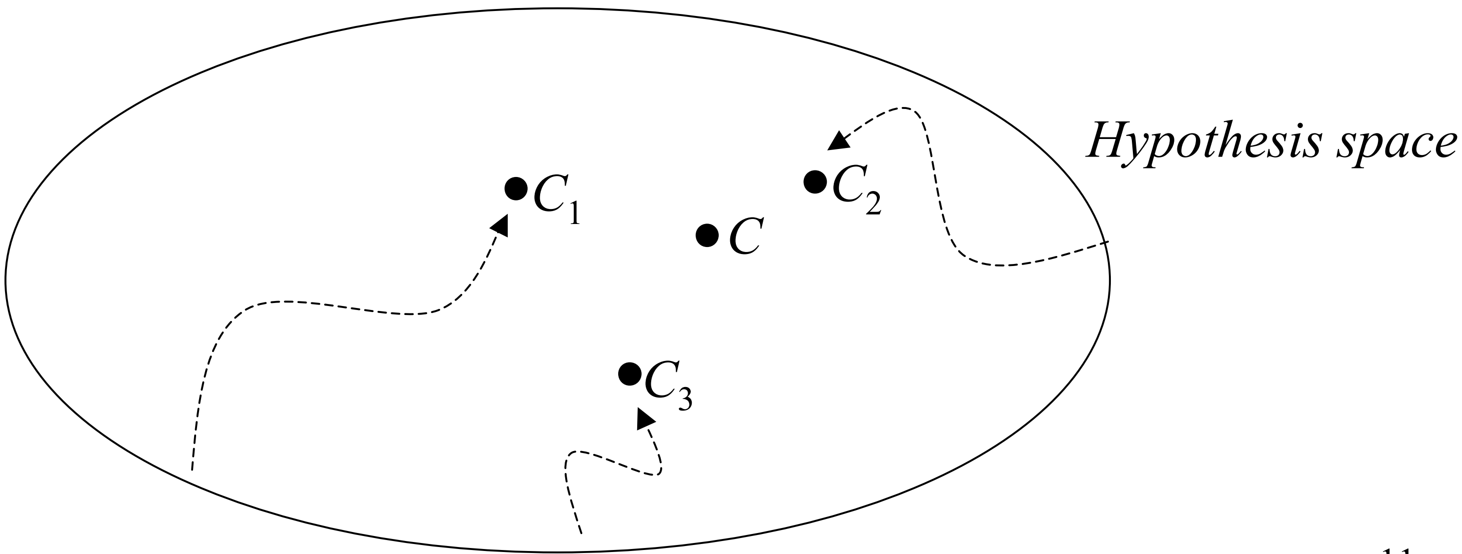
•Simple averaging allows avoiding the selection of the worst classifier for some test cases and, in some experiments, outperformed the best individual classifier

Fusion of multiple classifiers: Computational motivation (T.Dietterich, 2000)

Many learning algorithms suffer from the problem of local minima

- Neural Networks, Decision Trees (optimal training is NP-hard!)
- Finding the best classifier C can be difficult even with enough training data

➢ Fusion of multiple classifiers constructed by running the training algorithm from different starting points can better approximate C



Further Motivations for Multiple Classifiers

- In ***sensor fusion***, multiple classifiers are naturally motivated by the application requirements

•The ***"curse" of*** pattern classifier ***designer***

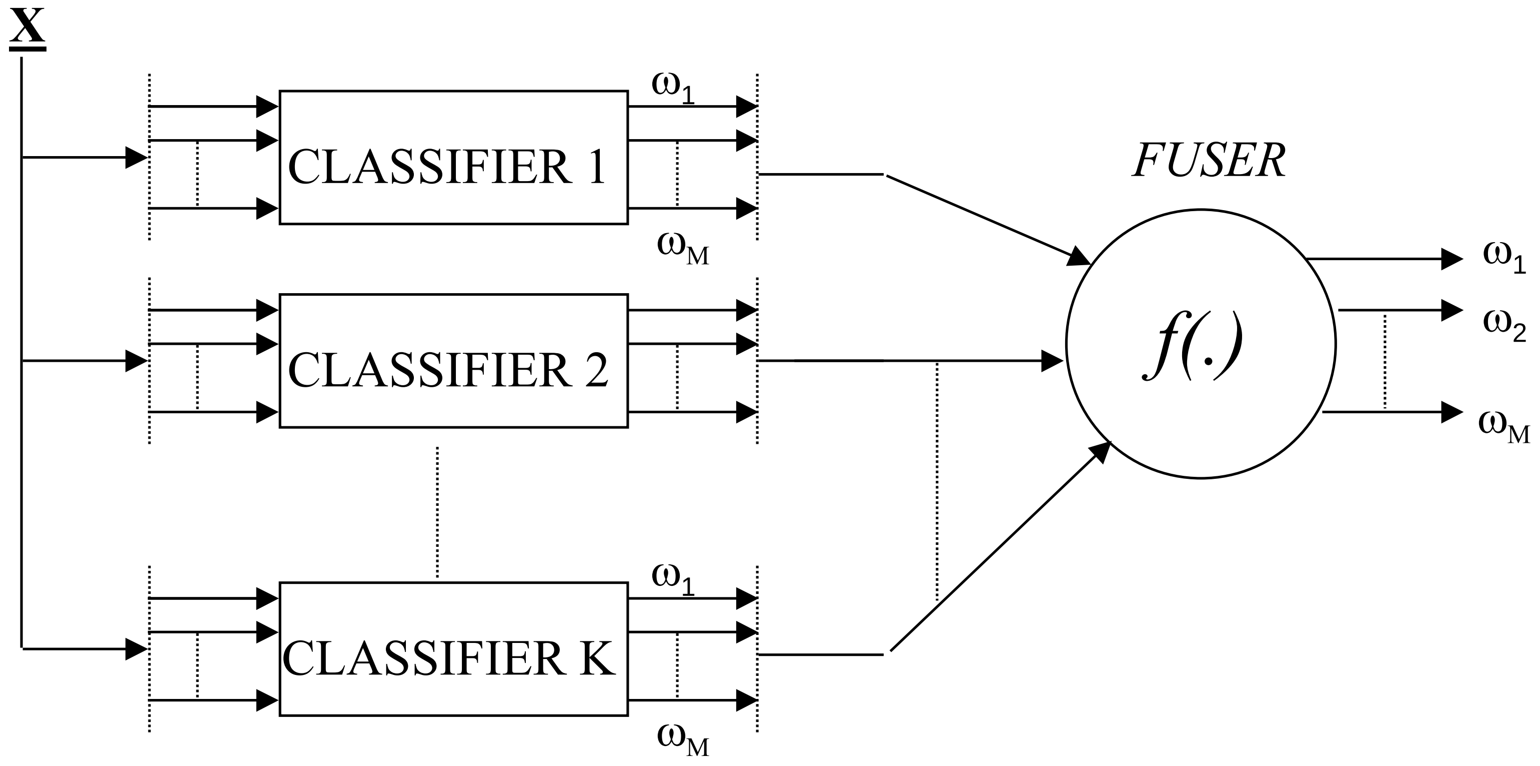
•The need of avoiding having to make a meaningful choice of some arbitrary initial condition, such as the initial weights for a neural network

•The intrinsic difficulty of choosing appropriate design parameters

•Saturation of design improvement

•**Monolithic** vs. **Modular** classifier systems: different classifiers can have different domains of competence

Basic Architecture of Multiple Classifier System



Basically, Multiple Classifier System (MCS) consists of an ensemble of different classification algorithms and a “function” f(.) to “fuse” classifiers outputs. The parallel architecture is very natural !

MCS: Basic Concepts

MCS can be characterized by:

- The **Architecture/Topology**

- The classifier **Ensemble**: type and number of combined classifiers. The ensemble can be subdivided into subsets in the case of non parallel architectures

- The **Fuser**

MCS Architectures/Topologies

•**Parallel** topology: multiple classifiers operate in parallel. A single combination function merges the outputs of the individual classifiers

•**Serial/Conditional** topology

-Classifiers are applied in succession, with each classifier producing a reduced set of possible classes

-A primary classifier can be used. When it rejects a pattern, a secondary classifier is used, and so on

•**Hybrid** topologies

Fuser ("combination" rule)

Two main categories of fuser:

Integration (fusion) functions: for each pattern, all the classifiers contribute to the final decision. Integration assumes **competitive** classifiers

Selection functions: for each pattern, just one classifier, or a subset, is responsible for the final decision. Selection assumes **complementary** classifiers

- Integration and Selection can be "merged" for designing hybrid fuser
- *Multiple* functions for non parallel architecture can be necessary

Focus on Parallel Architecture

•So far research on MCS focused on parallel architectures

•Accordingly, general methodologies and clear foundations are mostly available for parallel architectures

•MCSs based on other architectures (serial, hierarchical, hybrid, etc) were highly specific to the particular application

•In the following, we focus on parallel architectures and briefly discuss the relation between classifier ensemble and combination function. Many of the concepts we discuss also hold for different architectures

Classifiers "Diversity" vs. Fuser Complexity

•*Fusion is obviously useful only if the combined classifiers are mutually complementary*

•Ideally, classifiers with high accuracy and high diversity

➢ The required degree of error diversity depends on the fuser complexity

•Majority vote fuser: the majority should be always correct

•Ideal selector ("oracle"): only one classifier should be correct for each pattern

An example, four diversity Levels (A. Sharkey, 1999)

Level 1: no more than one classifier is wrong for each pattern

Level 2: the majority is always correct

Level 3: at least one classifier is correct for each pattern

Level 4: all classifiers are wrong for some patterns

Classifiers Diversity Measures: An Example

- Various measures (classifier outputs correlation, Partridge's diversity measures, Giacinto and Roli compound diversity, etc.) can be used to assess how similar two classifier are.

L. Kuncheva (2000) proposed the use of Q statistics:

$$Q_{i,k} = \frac{N^{11}N^{00} - N^{01}N^{10}}{N^{11}N^{00} + N^{01}N^{10}}$$

Q varies between –1 and 1. Classifiers that tend to classify the same patterns correctly will have values of Q close to 1, and those which commit errors on different patterns will render Q negative

Classifiers Diversity

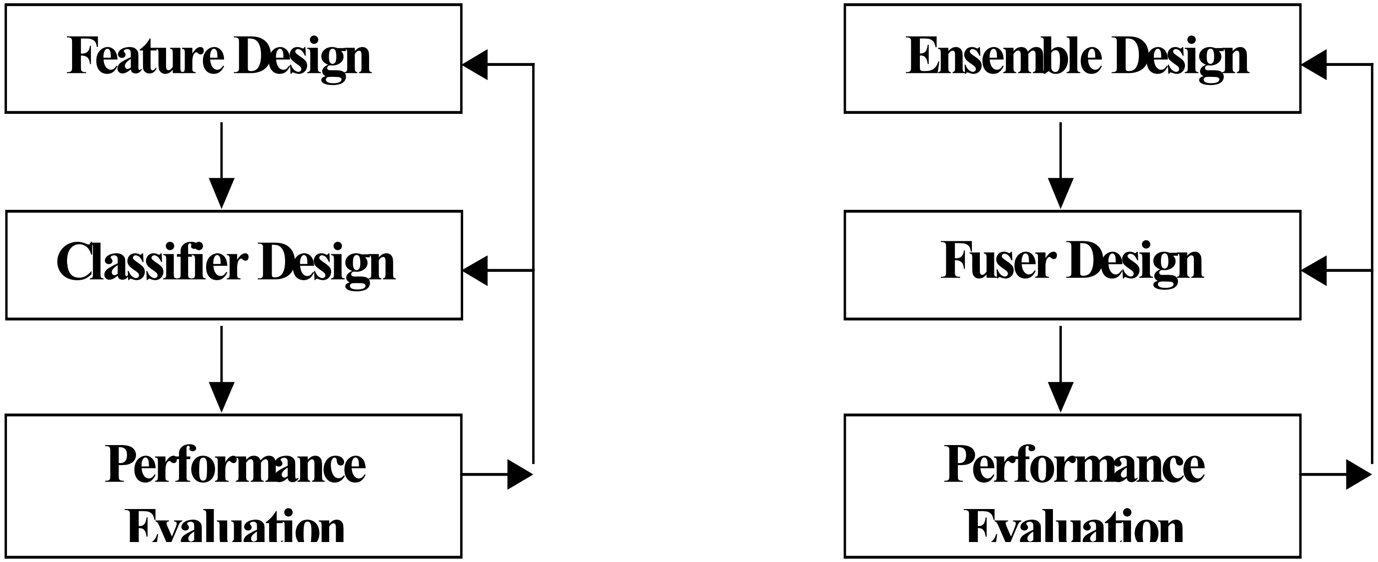
•Measures of diversity in classifier ensembles are a matter of on-going research (L.I. Kuncheva)

•Key issue: how are the diversity measures related to the accuracy of the ensemble ?

- •Simple fusers can be used for classifiers that exhibit a simple complementary pattern (e.g., majority voting)
- •Complex fusers, for example, a dynamic selector, are necessary for classifiers with a complex dependency model

•*The required "complexity" of the fuser depends on the degree of classifiers diversity*

Analogy between MCS and Single Classifier Design



Design cycles of single classifier and MCS (Roli and Giacinto, 2002)

Two main methods for MCS design (T.K. Ho, 2000):

•Coverage optimization methods

•Decision optimization methods

MCS Design

•The design of MCS involves two main phases: the design of the classifier ensemble, and the design of the fuser

•The design of the classifier ensemble is aimed to create a set of complementary/diverse classifiers

•The design of the combination function/fuser is aimed to create a fusion mechanism that can exploit the complementarity/diversity of classifiers and optimally combine them

•The two above design phases are obviously linked (Roli and Giacinto, 2002)

•In the following (Parts II and III), we illustrate the main methods for constructing and fusing multiple classifiers