LIVIA
Laboratoire d'imagerie, de vision et d'intelligence artificielle

Intelligent Feature Extraction for Ensemble of Classifiers

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Summary

- Motivation
- Problem Statement
- IFE Methodology
- EoC Optimization
- Experimental Results
- Conclusions

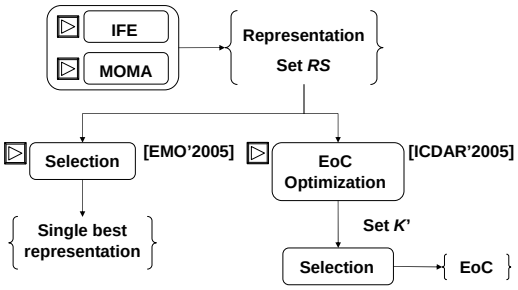
Motivation

- An Ensemble of Classifiers (EoC) can provide higher accuracy than a single classifier
- EoCs are usually created running specific learning algorithm (boosting, bagging, random subspace method, etc)

Problem Statement

- Key issue: to generate and select a set of *diverse* and *fairly accurate* base classifiers
- Two-level approach:
  - Intelligent Feature Extraction (IFE)
  - Classifier Selection (EoC)
- Multi-objective Genetic Algorithms
- Experiments on isolated handwritten digits recognition

System overview



Experimental Protocol

- Test the IFE on a known problem:
  - Isolated handwritten digits
  - 22 features extracted per zone [Oliveira al., PAMI'02]
  - IFE: Zoning & feature extraction (without FSS)
- IFE & EoCs processes implemented with MOMA

Experimental Protocol

- MOMA
  - One point crossover operator (Pc = 0.8)
  - Bitwise mutation operator (Pm = 1/L)
  - Local search:
    - NI = 3 iterations
    - Neighborhood size = 1
  - Archive size:
    - 5 solutions/slot
  - Population size:
    - IFE = 64 EoC = 186
  - Maximum search time:
    - 1 000 generations

Experimental Protocol

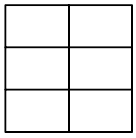
- Digits extracted from the NIST SD19 database:
  - *learn'/learn* and *validation*: used to train the PD and MLP classifiers
  - *optimization*: used to evaluate classifier accuracy during optimization
  - *selection*: post-processing of candidate solutions
  - $test_1$: hsf_4 [not showed in the icdar2005 proceedings]
  - $test_2$: hsf_7

Experimental Protocol

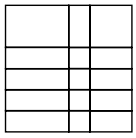
1. Optimize IFE using MOMA
   - PD classifier in a wrapper mode (learn'/validation databases)
   - Fitness evaluated with the optimization database
2. Select a single best solution SB from RS
   - Train $|RS| = p$ classifiers (learn/validation databases)
   - Select the best solution with the selection database
3. Optimize a PD EoC and MLP EoC using MOMA
   - $|K| = p$ base classifiers created from RS (learn/validation databases)
   - Fitness evaluated with the optimization database
   - Selection of the best EoC in K' with the selection database

Experimental Results

Baseline representation (human expert)



Single best representation found by the IFE & PD classifier



Note1: IFE found $|RS| = 82$ solutions

Note2: The same representation was also found with the MLP classifier

Experimental Results

- PD classifier results:

Classifier	$\|G\|$	e_{sel}	$E_{test\ hsf\_4}$	$E_{test\ hsf\_7}$	$\|EoC\|$
Baseline	132	3.01%	6.83%	2.96%	-
SB_{PD}	330	2.31%	5.47%	2.18%	-
EoC_{PD}	-	1.51%	5.06%	1.94%	19

Experimental results not showed in the ICDAR2005 proceedings

Experimental Results

- MLP classifier results:

Classifier	$\|G\|$	e_{sel}	$E_{test\ hsf\_4}$	$E_{test\ hsf\_7}$	$\|EoC\|$
Baseline	132	0.44%	2.89%	0.89%	-
SB_{MLP}	330	0.41%	2.44%	0.79%	-
EoC_{MLP}	-	0.37%	2.37%	0.74%	4

Experimental results not showed in the ICDAR2005 proceedings

Computational Burden

- Beowulf cluster, 25 machines (Athlon XP 2300+), Linux Red Hat 7.3, MPI v7.
- IFE Optimization: 36 hours (estimated)
  - Synchronous Master-Slave, without load balancing
  - 64 000 solutions (PD classifiers)
- MLP training ($|K|$=82 classifiers): 3 weeks.
  - Asynchronous Master-Slave, with load balancing
- EoC optimization (PD/MLP): 30 minutes

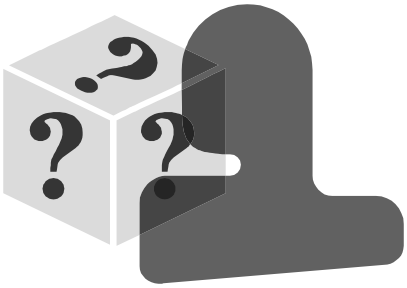
Conclusions

- The IFE methodology outperformed the traditional human expert approach on a known problem
- Expert knowledge on the PR domain can be take into account more easily in the feature extraction process
- The solution set RS (representations) produced by IFE is effective for EoC creation

Conclusions

- MOMA proved itself suitable for the IFE methodology and EoC creation
- MOMA performs better than traditional multi-objective Pareto-based optimization algorithms when applied in machine learning
- To avoid over fitting, a *selection* (validation) database to select solutions in the archive IS MANDATORY

Questions?



Databases

Database	Origin	Size	Subset definition
learn	hsf_0123	150 000	1- 150 000
learn'	hsf_0123	50 000	1- 50 000
validation	hsf_0123	15 000	150 001 – 165 000
optimization	hsf_0123	15 000	165 001 – 180 000
selection	hsf_0123	15 000	180 001 – 195 000
test$_1$	hsf_7	60 089	
test$_2$	hsf_4	58 646	

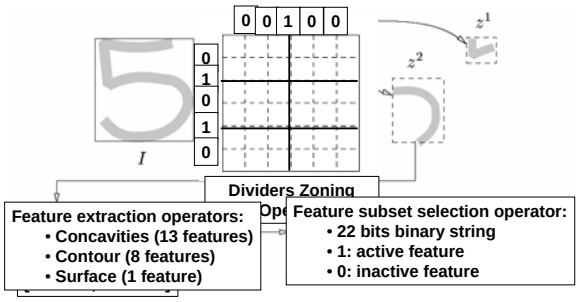
IFE Motivation

- Need to adapt pattern recognition (PR) systems to different problems related to the same domain
  - Ex: Isolated Numerals Rec. ⇨ Upper Case Letters Rec.
- Lack of methodologies to extract and adapt automatically representations to several PR problems who belong to the same domain
- *Intelligent Feature Extraction* (**IFE**) methodology

IFE Methodology

- Case Study: Handwritten symbols modeled with features extracted from *foci* of attention in images
- Three hierarchical operations: *zoning*, *feature extraction* and *feature subset selection*
- Human knowledge is related to:
  - the zoning mechanism (location & size and number of retinas)
  - the choice of feature extraction operators

IFE Methodology



IFE Methodology

- Uses a wrapper approach:
  - Projection Distance classifier (PD, Kimura et al, 1998)
- Hypothesis: representations found with PD classifier can be used to train more discriminant classifiers
- Optimization objectives:
  - Minimize classifier error rate
  - Minimize the feature set cardinality (e.g. number of zones)

MOMA

- Multi-Objective Memetic Algorithm (MOMA)
  - Memetic Algorithm: GA & Local search mechanism
- MOMA is well suited for the IFE methodology:
  - Modified genetic selection strategy
  - Archiving strategy is considered during the optimization process
  - Local search mechanism (RRT algorithm) to improve convergence
- Two-objective optimization:
  - o_1: classifier error rate
  - o_2: feature set cardinality

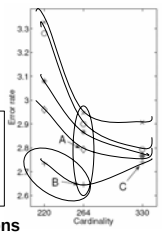
Solution Selection

- IFE:
  - Provides the N best solutions for each cardinality in the Archive
- A post-processing stage selects the best solution based on the classifier's capacity to generalize well on unseen data
- This step is performed to remove the over-fitting in the optimization stage

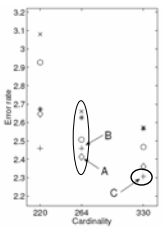
MOMA

- Genetic selection emphasizes the best solutions for each o_1 value, regardless of domination.

Optimization

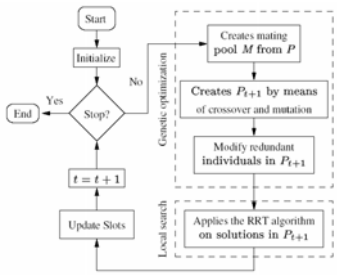


Unseen data



Non dominated solutions

MOMA



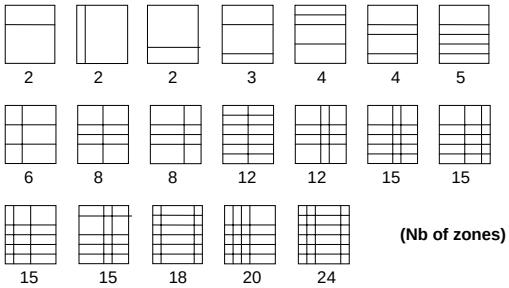
EoC optimization: MOMA

- The IFE generates the set *RS={G¹,..., Gᵖ}*
- We use RS to create the set *K={K¹,..., Kᵖ} of base classifiers*
- To encode the EoC, we use a binary string *E* of p bits
  - The ith bit in *E* indicates if classifier K^i is selected (1) or not (0)
- At the end of the optimization process, MOMA produces a set *K '* of EoCs

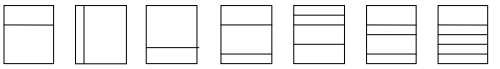
EoC optimization: MOMA

- Two objectives guide the optimization:
  - o_1 : |EoC| cardinality
  - o_2: EoC combined error rate
- Fusion function:
  - PD EoC: simple majority voting
  - MLP EoC: output averaging

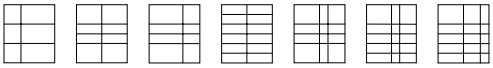
PD EoC – Selected Solutions



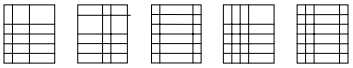
PD EoC – Selected Solutions



7.66% 13.27% 7.53% 5.02% 3.53% 3.80% 3.27%



2.88% 2.62% 3.06% 2.59% 2.72% 2.57% 2.43%



2.46% 2.18% 2.36% 2.37% 2.35%

(error rates on hsf_7)

30

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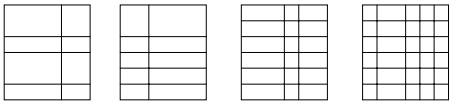
MLP EoC – Selected Solutions

Representations selected for each base classifier
(Nb of zones)



8 10 18 30

31

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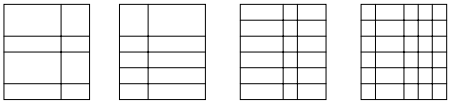
MLP EoC – Selected Solutions

Individual performance of base classifiers
(error rates on hsf_7)



0.9% 0.83% 0.86% 0.87%

32

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