New Developments on the Hybridizations of Fuzzy Systems and Evolutionary Algorithms

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Outline

1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms
2. Fuzzy Classifier Ensembles Designed with Multiobjective Evolutionary Algorithms
4. Forensic Identification by Craniofacial Superimposition using Evolutionary Algorithms and Fuzzy Sets
5. Conclusions
The fuzzy sets and systems-evolutionary algorithms (EAs) combination has become one of the main Soft Computing branches since the early nineties:

1. Genetic fuzzy systems (GFSs): Genetic algorithms (GAs) (and in general EAs) are used to design fuzzy systems
   - In genetic fuzzy rule-based systems, some components of a fuzzy rule-based system (FRBS) are adapted or learnt using a GA
   - Other approaches: genetic fuzzy neural networks and genetic fuzzy clustering

2. Fuzzy genetic algorithms: GA components are fuzzified to improve performance
   - Examples: crossover and mutation operators, representation schemes, stop criteria, and fitness functions (taking advantage of a tolerance for imprecision)
   - Fuzzy controllers for dynamically adapting the GA parameters are also used
1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms

**Genetic Fuzzy Systems**

**Fuzzy Processing**
1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms

GFS bibliography

GENETIC FUZZY SYSTEMS
Evolutionary Tuning and Learning of Fuzzy Knowledge Bases

O. Cordón, F. Herrera, F. Hoffmann, L. Magdalena
World Scientific, July 2001

1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms

2. Fuzzy Rule-based Multiclassification Systems Designed with Multiobjective Evolutionary Algorithms


4. Forensic Identification by Craniofacial Superimposition using Evolutionary Algorithms and Fuzzy Sets

5. Conclusions
1. Introduction

Problem description and objectives

- Interest on classifier ensembles/multiclassifier systems in the classical machine learning field: High accuracy
- Fuzzy rule-based classification systems (FRBCSs) are catchy: Interpretability and soft boundaries
- Problems with high dimensional data: Curse of dimensionality
- Existing mechanisms to look for the best accuracy-complexity tradeoff: overproduce-and-choose (OCS)
- Evolutionary multiobjective optimization (EMO) ability to deal with conflicting optimization criteria
- **Our proposal:** Fuzzy rule-based multiclassification systems (FRBMCSs) with EMO OCS for high dimensional problems
1. Introduction
Multiclassifier systems

One person

QUESTION

CORRECT ANSWER?

Several people

QUESTION

CORRECT ANSWER?

Diversity helps to improve accuracy

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**OVERVIEW**

1. **Introduction**
   - Multiclassifier system design issues

2. Proposed Framework

3. Bagging FURIA-based fuzzy multiclassification systems

4. Evolutionary Multiobjective Selection of the component classifiers

5. Experiments

6. Conclusions

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**Diversity** – An individual classifier must provide different patterns of generalization in order to obtain a diverse set of classifiers composing a highly accurate ensemble.

Different methods to induce diversity to the base classifiers:

- Different classifiers:
- Different “inputs”: [Images of faces with arrows indicating diversity]
Our approach combines several techniques to quickly generate accurate and diverse base fuzzy classifiers:

- A parallel approach: bootstrap aggregating (bagging)
- A quick and accurate fuzzy rule generation method (FURIA) including a dimensionality reduction method (feature selection)
- A mechanism to deal with the accuracy-complexity tradeoff (classifier selection by OCS) in an EMO fashion: error, diversity, and #classifiers
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2. Proposed Framework

Graphical representation

- Training Dataset
- Test Dataset
- Dataset (normalized)
- Instance selection (resampling)
- Bagging

50% 50%

BAG 1  BAG 2  BAG n
FURIA 1  FURIA 2  FURIA n

Final Set of Classifiers

Classical validation:
- GA Training Error
- GA Test Error
- Complexity

Biobjective Fitness:
- Training Error
- Complexity
- Variance (Div)
- Double Fault (Div)

Validation:
- Ensemble Training Error
- Ensemble Test Error
- Complexity

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3. Bagging FURIA-based fuzzy multiclassification systems

Bagging Predictors (Breiman, 1996):

- Bootstrap AGGregatING: create multiple bootstrap samples, train a classifier on each, and combine the classifier outputs by voting.
- The individual classifiers (weak learners) are independently learnt from resampled training sets (“bags”), which are randomly selected with replacement from the original training data set.

Good for unstable (large bias) classifiers (e.g. decision trees)
3. Bagging FURIA-based fuzzy multiclassification systems

FURIA (Fuzzy Unordered Rule Induction Algorithm) (Hüllermeier et al., 2009):

- A rule learning algorithm extending RIPPER
- Generates simple and compact fuzzy classification rules
- Deals with high dimensional datasets
- Very quick generation method
- Performs well comparing to C4.5 and RIPPER

AIM: Improve accuracy by embedding FURIA into the fuzzy MCS framework

OVERVIEW

1. Introduction
2. Proposed Framework
3. Bagging FURIA-based fuzzy multiclassification systems
4. Evolutionary Multiobjective Selection of the component classifiers
5. Experiments
6. Conclusions
OVERVIEW

1. Introduction
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   Evolutionary multiobjective optimization-based overproduce & choose
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OCS strategy (Partridge and Yates, 1996):

- Generate many classifiers and select the best cooperating subset
- Decrease complexity/eliminate useless classifiers to improve accuracy

EMO-based OCS:

- Up to three different kinds of criteria jointly optimized by an EMO algorithm: accuracy, diversity, and complexity (#classifiers)
NSGA-II (Deb et al., 2002): 
- Produces a set of efficient solutions (Pareto-optimal set)
- Based on Pareto dominance depth approach, when population is divided into several fronts
- Solutions in the same front have the same fitness rank
- Crowding distance to promote Pareto front spreading
NSGA-II-based MO OCS method components:

- **Binary coding** – a binary value is assigned to each classifier (if equal to 1, current classifier is selected; if equal to 0, that classifier is discarded)

- Generational approach and **elitist** replacement strategy

- **Binary tournament**

- Classical **two-point crossover** and **bit-flip mutation**
4. Evolutionary Multiobjective Selection of the component classifiers

NSGA-II-based multiobjective classifier selection method (II)

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**MO fitness functions:** 5 different biobjective fitness functions designed from 4 evaluation criteria of 3 different kinds:

- **accuracy** (training error (TE)),
- **complexity** (#classifiers), and
- **diversity:** variance ($\theta$) and double-fault ($\delta$)

<table>
<thead>
<tr>
<th>abbreviation</th>
<th>1st obj.</th>
<th>2nd obj.</th>
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<td>2a</td>
<td>TE</td>
<td>Complx</td>
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<td>TE</td>
<td>$\theta$</td>
</tr>
<tr>
<td>2c</td>
<td>TE</td>
<td>$\delta$</td>
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<td>2d</td>
<td>$\theta$</td>
<td>Complx</td>
</tr>
<tr>
<td>2e</td>
<td>$\delta$</td>
<td>Complx</td>
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5. Experiments

Experimental setup (I)

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<th>#classes</th>
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<tr>
<td>yeast</td>
<td>1484</td>
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UCI considered datasets:

- Every attribute is continuous
- From small to large number of features (64), classes (28), instances (19020); 20 datasets
- Pentium 2.4 GHz, 2 GB, 2-4 cores (Granada cluster)

Validation: Dietterich’s 5x2-fold cross validation
5. Experiments

Bagging fuzzy multiclassification system results (I)

FURIA-based fuzzy MCSs are competitive with classical MCSs:
13 wins (Random Forests = 8 wins; Bagging Decision Trees = 1 tie)

<table>
<thead>
<tr>
<th>FURIA-based MCSs</th>
<th>tra. err.</th>
<th>test err.</th>
<th>feat sel.</th>
<th>feat. sub. size</th>
<th>nr of cl.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>aba</td>
<td>bre</td>
<td>gla</td>
<td>hea</td>
<td>ion</td>
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<td>R</td>
<td>-</td>
<td>-</td>
<td>RG</td>
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<td>feat. sub. size</td>
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<td>L</td>
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<td>7</td>
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<table>
<thead>
<tr>
<th>C4.5 ensembles with bagging</th>
<th>tra. err.</th>
<th>test err.</th>
<th>nr of cl.</th>
</tr>
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<tr>
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<td>bre</td>
<td>gla</td>
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<tr>
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</table>

<table>
<thead>
<tr>
<th>Random forests</th>
<th>tra. err.</th>
<th>test err.</th>
<th>nr of cl.</th>
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<td></td>
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<td>gla</td>
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</table>
5. Experiments

Bagging fuzzy multiclassification system results (II)

**FURIA-based fuzzy MCSs are competitive with classical MCSs:**

13 wins (Random Forests = 8 wins; Bagging Decision Trees = 1 tie)

<table>
<thead>
<tr>
<th>FURIA-based MCSs</th>
<th>pho</th>
<th>pim</th>
<th>sat</th>
<th>seg</th>
<th>son</th>
<th>spa</th>
<th>tex</th>
<th>veh</th>
<th>wav</th>
<th>win</th>
<th>yea</th>
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<tr>
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<td>0.005</td>
<td>0.028</td>
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<tr>
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<td>L</td>
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<table>
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<tr>
<th>C4.5 ensembles with bagging</th>
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<tbody>
<tr>
<td>pho</td>
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<td>-----</td>
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<tr>
<td>tra. err.</td>
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<td>nr of cl.</td>
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</table>

<table>
<thead>
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<tbody>
<tr>
<td>pho</td>
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<tr>
<td>tra. err.</td>
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<td>test err.</td>
</tr>
<tr>
<td>nr of cl.</td>
</tr>
<tr>
<td>feat. sel.</td>
</tr>
</tbody>
</table>
Parameter values:

- **50 classifiers** generated
- Pre-compute classification matrix to speed up the runs
- NSGA-II parameters: 50 individuals, 1000 generations, crossover prob. 0.6, mutation prob. 0.1
- Test accuracy and #classifiers of each Pareto-optimal solution are measured to allow for a global comparison
- To compare the obtained Pareto front approximations the HVR and C-measure indicators are considered
5. Experiments
EMO-based OCS results (I)

PFs obtained for **abalone** using ffs. 2a (O1:TE, O2:Complx) on top-left, 2b (O1:TE, O2:Var) on top-right, 2c (O1:TE, O2:DF) on bottom-left, and 2d (O1:Var, O2:Complx) on bottom-right.
5. Experiments
EMO-based OCS results (II)

Comparison of PFs using the HVR measure

The reference PFs are considered (O1: Test Error, O2: #classifiers)

Otherwise, the comparison is not feasible!!!

Fitness function 2b (O1: TE, O2: Var) clearly reports the best performance

<table>
<thead>
<tr>
<th></th>
<th>2a</th>
<th>2b</th>
<th>2c</th>
<th>2d</th>
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<td>0.8314</td>
<td>0.8376</td>
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<td>hea</td>
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<td><strong>0.9858</strong></td>
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<td>ion</td>
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5. Experiments
EMO-based OCS results (III)

REFERENCE Pareto Fronts (O1: Test Error, O2: Complexity)
obtained for waveform with the 5 fitness functions

![Graph showing Pareto Fronts for waveform with 5 fitness functions.](image-url)
### 5. Experiments

#### EMO-based OCS results (IV)

Comparison of averaged performance of four single solutions selected from the obtained Pareto sets

<table>
<thead>
<tr>
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<th>Best of 2nd obj.</th>
<th>Best tradeoff</th>
<th>Best test</th>
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<td>Tra</td>
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<td>2a</td>
<td>avg.</td>
<td>0.064</td>
<td>0.199</td>
<td>8.770</td>
</tr>
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<td></td>
<td>dev.</td>
<td>0.140</td>
<td>0.207</td>
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<tr>
<td>2b</td>
<td>avg.</td>
<td>0.054</td>
<td>0.201</td>
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<tr>
<td>2c</td>
<td>avg.</td>
<td>0.053</td>
<td>0.193</td>
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<td>2d</td>
<td>avg.</td>
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<td>0.223</td>
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### 5. Experiments

**EMO-based OCS results (V)**

#### Comparison of NSGA-II FURIA-based fuzzy MCSs versus static FURIA-based MCS and classical MCSs

<table>
<thead>
<tr>
<th>NSGA-II combined with FURIA-based MCSs.</th>
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<tr>
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<td>abu</td>
<td>brc</td>
</tr>
<tr>
<td>fitness func.</td>
<td>0.734</td>
<td>0.017</td>
</tr>
<tr>
<td>nrof cl.</td>
<td>56</td>
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<table>
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<tr>
<th>FURIA-based MCSs algorithms. Small ensemble sizes.</th>
<th>~</th>
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<td>brc</td>
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<tr>
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<tr>
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<td>0.041</td>
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<td>fitness func.</td>
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<td>nrof cl.</td>
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<table>
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<th>Random forests. Small ensemble sizes.</th>
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<tbody>
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<td>test err.</td>
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<td>brc</td>
</tr>
<tr>
<td>fitness func.</td>
<td>0.777</td>
<td>0.041</td>
</tr>
<tr>
<td>nrof cl.</td>
<td>7</td>
<td>7</td>
</tr>
</tbody>
</table>
6. Conclusions

- A framework to design FRBMCSs has been presented based on the used of FURIA, Bagging, and an EMO-OCS method for classifier selection.

- 5 different biobjective fitness functions were tested, considering 3 sets of optimization criteria (accuracy, complexity, and diversity).

- Combining training error with diversity measures got a promising performance (as opposite to the diversity-complexity couple).

Future works:

- Use of 3 objectives in the EMO-based OCS method
- Design of an interpretable GFSs for both classifier selection & fusion
- Dynamic Classifier Selection and static-dynamic hybridization
6. Conclusions

Publications and research team

OVERVIEW

1. Introduction

2. Proposed Framework

3. Bagging FURIA-based fuzzy multiclassification systems

4. Evolutionary Multiobjective Selection of the component classifiers

5. Experiments

6. Conclusions

Dr. Oscar Cordón
UGR Professor
ECSC Scientific Consultant

Dr. Arnaud Quirin
ECSC
Postdoctoral Researcher

Mr. Krzysztof Trawinski
ECSC
Research Assistant


Outline

1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms
2. Fuzzy Classifier Ensembles Designed with Multiobjective Evolutionary Algorithms
4. Forensic Identification by Craniofacial Superimposition using Evolutionary Algorithms and Fuzzy Sets
5. Conclusions
Body posture recognition:

- Personal applications:
  - Detection of user behaviors
  - Context awareness

- Security:
  - Proactive care for elderly people
  - Safety applications based on fall detection

Objectives:

- To design an accurate and interpretable model
- To incorporate the available expert knowledge
1. Introduction
Problem description and objectives

OVERVIEW

1. Introduction
2. Fuzzy Finite State Machine for Body Posture Recognition
3. Genetic Fuzzy Finite State Machine
4. Experiments
5. Conclusions

Our proposal:

- **Sensor-based approach**: wireless three-axial accelerometer attached to a belt, centered in the subject’s back

- **Modeling tool**: genetic fuzzy finite state machine (GFFSM)

- **Advantages**:
  - Flexibility to represent the variations in both signal amplitude and states time span
  - Use of a descriptive knowledge representation scheme based on linguistic variables and fuzzy if-then rules
  - Hybrid human expert-automatic data-driven design
Fuzzy finite state machines (FFSMs) are tools for modeling time-evolving dynamical processes, extending classical FSMs.

Their main advantage is that they are able to handle imprecise and uncertain data in the form of fuzzy states and transitions.

A FFSM is a tuple:

- $Q$ is the set of fuzzy states: $\{q_1, \ldots, q_n\}$, with $S[t] = (s_1, \ldots, s_n)$, $s_i \in [0,1]$, being the state activation vector.
- $U[t]=(u_1[t], \ldots, u_{nu}[t])$ is the input vector, where $u_i[t] = \{A_{u_i}^1, \ldots, A_{u_i}^{nu}\}$
- $f$ is the transition function: $S[t+1] = f(S[t], U[t])$.
- $Y$ is the output vector: $(y_1, \ldots, y_{ny})$.
- $g$ is the output function: $Y[t] = g(S[t], U[t])$. 
2. A Fuzzy Finite State Machine for Body Posture Recognition

FFSM graphical representation
The transition function is implemented by means of a fuzzy KB. There are fuzzy rules $R_{ii}$ to remain in a state $q_i$, and rules $R_{ij}$ to change from state $q_i$ to state $q_j$:

$$R_{ij}: \text{IF } (S[t] \text{ is } q_i) \text{ AND } C_{ij} \text{ THEN } S[t+1] \text{ is } q_j$$

$C_{ij}$ describes the constraints imposed on the input variables that are required to change the state as a DNF fuzzy premise:

$$C_{ij} = (u_1[t] \text{ is } A_{u_1}^3) \text{ AND } (u_2[t] \text{ is } A_{u_2}^4 \text{ OR } A_{u_2}^5)$$

The fuzzy reasoning mechanism considers a weighted average.

It also mimics that of FRBCSs using fuzzy rules with a certainty degree for each class in the consequent but the sum must add up to 1.
OVERVIEW

1. Introduction

2. Fuzzy Finite State Machine for Body Posture Recognition

3. Genetic Fuzzy Finite State Machine

4. Experiments

5. Conclusions

1. Identify the **set of fuzzy states** that represent the different body postures: \( q_1 \rightarrow \text{Seated}; q_2 \rightarrow \text{Upright}; q_3 \rightarrow \text{Walking} \)

2. Define the **input linguistic variables** based on the three accelerations \((a_x, a_y, a_z)\) provided by the accelerometer:
   - \( a_x \rightarrow \text{dorso-ventral acceleration} \)
   - \( mov \rightarrow \text{amount of movement calculated using the variations of } a_x, a_y \text{ and } a_z \text{ in 1 second} \)
   - \( tilt \rightarrow \text{tilt of the body defined as } |a_y| + |a_z| \)

3. Define the **transition function** by specifying the allowed transitions in the form of fuzzy linguistic rules

4. Identify the output variables and output function: \( Y[t] = S[t] \)
Specified as fuzzy DNF premises being constrains on the input linguistic variables.

\[
\begin{align*}
R_{11} : & \text{IF } (S[t] \text{ is } q_1) \text{ AND } C_{11} \text{ THEN } S[t+1] \text{ is } q_1 \\
R_{22} : & \text{IF } (S[t] \text{ is } q_2) \text{ AND } C_{22} \text{ THEN } S[t+1] \text{ is } q_2 \\
R_{33} : & \text{IF } (S[t] \text{ is } q_3) \text{ AND } C_{33} \text{ THEN } S[t+1] \text{ is } q_3 \\
R_{12} : & \text{IF } (S[t] \text{ is } q_1) \text{ AND } C_{12} \text{ THEN } S[t+1] \text{ is } q_2 \\
R_{21} : & \text{IF } (S[t] \text{ is } q_2) \text{ AND } C_{21} \text{ THEN } S[t+1] \text{ is } q_1 \\
R_{23} : & \text{IF } (S[t] \text{ is } q_2) \text{ AND } C_{23} \text{ THEN } S[t+1] \text{ is } q_3 \\
R_{32} : & \text{IF } (S[t] \text{ is } q_3) \text{ AND } C_{31} \text{ THEN } S[t+1] \text{ is } q_1 \\
R_{31} : & \text{IF } (S[t] \text{ is } q_3) \text{ AND } C_{32} \text{ THEN } S[t+1] \text{ is } q_2
\end{align*}
\]
Determining the FFSM transitions is a complex task for a human designer.

They can be automatically derived using an EA by means of a classical GFS learning the whole KB (RB + DB).

In our approach, fuzzy states and transitions will be defined by the expert while fuzzy rules and membership functions (MFs) regulating the state changes will be automatically derived by the GFS.

The use of this expert knowledge and the prefixed FFSM structure allows us to only learn the MFs and part of the rules to build the KB, dealing with a reduced search space.
3. Genetic Fuzzy Finite State Machine

Coding scheme

OVERVIEW

1. Introduction
2. Fuzzy Finite State Machine for Body Posture Recognition
3. Genetic Fuzzy Finite State Machine
4. Experiments
5. Conclusions

Classical binary coding for DNF rules in GFSs

Trapezoidal-shaped strong fuzzy partition real-coding

Two chromosome information levels
The MAE computes the difference between the actual state activation vector \((S^*[t])\) and the inferred one \((S[t])\) in the whole time series data set:

\[
\text{MAE} = \frac{1}{3} \cdot \frac{1}{T} \cdot \sum_{i=1}^{3} \sum_{j=0}^{T} |S_i[j] - S_i^*[j]|
\]

However, the expert needs to define \(S^*[t]\) for each input time series pattern by labeling the time series to create a training vector:

\[(a_x(t), a_y(t), a_z(t), s_1^*(t), s_2^*(t), s_3^*(t))\]
4. Experiments

Dataset: Ten repetitions of different consecutive activities

<table>
<thead>
<tr>
<th>Duration (s)</th>
<th>Description</th>
<th>Posture</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>Seated and typing</td>
<td>Seated ($q_1$)</td>
</tr>
<tr>
<td>30</td>
<td>Standing up</td>
<td>Upright ($q_2$)</td>
</tr>
<tr>
<td></td>
<td>Walking towards the coffee area</td>
<td>Walking ($q_3$)</td>
</tr>
<tr>
<td>75</td>
<td>Staying up in front of the coffee machine</td>
<td>Upright ($q_2$)</td>
</tr>
<tr>
<td></td>
<td>Sitting and having the coffee</td>
<td>Seated ($q_1$)</td>
</tr>
<tr>
<td>25</td>
<td>Standing up</td>
<td>Upright ($q_2$)</td>
</tr>
<tr>
<td></td>
<td>Walking until the office of a colleague</td>
<td>Walking ($q_3$)</td>
</tr>
<tr>
<td>50</td>
<td>Staying up and waiting for the colleague</td>
<td>Upright ($q_2$)</td>
</tr>
<tr>
<td>30</td>
<td>Walking towards the meeting room</td>
<td>Walking ($q_3$)</td>
</tr>
<tr>
<td>100</td>
<td>Seated in the meeting room</td>
<td>Seated ($q_1$)</td>
</tr>
<tr>
<td>40</td>
<td>Standing up</td>
<td>Upright ($q_2$)</td>
</tr>
<tr>
<td></td>
<td>Walking back to the work-desk</td>
<td>Walking ($q_3$)</td>
</tr>
<tr>
<td>100</td>
<td>Seated and typing</td>
<td>Seated ($q_1$)</td>
</tr>
</tbody>
</table>
### 4. Experiments

**Results and comparisons**

<table>
<thead>
<tr>
<th>FOLD</th>
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<th>GFFSM TEST</th>
<th>ARX* TRAIN</th>
<th>ARX* TEST</th>
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</thead>
<tbody>
<tr>
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<td>0.010</td>
<td>0.016</td>
<td>0.071</td>
<td>0.083</td>
</tr>
<tr>
<td>2</td>
<td>0.009</td>
<td>0.007</td>
<td>0.072</td>
<td>0.093</td>
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<td>3</td>
<td>0.010</td>
<td>0.009</td>
<td>0.076</td>
<td>0.064</td>
</tr>
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<td>4</td>
<td>0.009</td>
<td>0.010</td>
<td>0.078</td>
<td>0.059</td>
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<tr>
<td>5</td>
<td>0.010</td>
<td>0.013</td>
<td>0.076</td>
<td>0.072</td>
</tr>
<tr>
<td>6</td>
<td>0.009</td>
<td>0.012</td>
<td>0.075</td>
<td>0.073</td>
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<tr>
<td>7</td>
<td>0.010</td>
<td>0.010</td>
<td>0.075</td>
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<td>0.009</td>
<td>0.009</td>
<td>0.076</td>
<td>0.072</td>
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**Leave-One-Out Cross Validation**

<table>
<thead>
<tr>
<th>DATASET</th>
<th>FFSM</th>
<th>GFFSM</th>
<th>ARX*</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>0.023</td>
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<td>0.083</td>
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<tr>
<td>2</td>
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<tr>
<td>10</td>
<td>0.018</td>
<td>0.009</td>
<td>0.072</td>
</tr>
</tbody>
</table>

**Mean and STD**

- **GFFSM**: Mean 0.009, STD 0.001
- **ARX***: Mean 0.011, STD 0.002

* Autoregressive linear models with a delay of 20 samples
† FFSM manually defined by the expert
4. Experiments

Example of one of the derived KBs

\[ R_{11} : \text{IF} (S[t] \text{ is } q_1) \text{ AND } (a_x \text{ is } M_{ax}) \text{ AND } (mov \text{ is } -M_{mov}) \text{ AND } (tilt \text{ is } B_{tilt}) \text{ THEN } S[t+1] \text{ is } q_1 \]

\[ R_{22} : \text{IF} (S[t] \text{ is } q_2) \text{ AND } (a_x \text{ is } B_{ax}) \text{ THEN } S[t+1] \text{ is } q_2 \]

\[ R_{33} : \text{IF} (S[t] \text{ is } q_3) \text{ AND } (mov \text{ is } M_{mov}) \text{ THEN } S[t+1] \text{ is } q_3 \]

\[ R_{12} : \text{IF} (S[t] \text{ is } q_1) \text{ AND } (a_x \text{ is } -S_{ax}) \text{ AND } (mov \text{ is } -S_{mov}) \text{ AND } (tilt \text{ is } -B_{tilt}) \text{ THEN } S[t+1] \text{ is } q_2 \]

\[ R_{21} : \text{IF} (S[t] \text{ is } q_2) \text{ AND } (a_x \text{ is } S_{ax}) \text{ AND } (mov \text{ is } -M_{mov}) \text{ AND } (tilt \text{ is } B_{tilt}) \text{ THEN } S[t+1] \text{ is } q_1 \]

\[ R_{23} : \text{IF} (S[t] \text{ is } q_2) \text{ AND } (a_x \text{ is } B_{ax}) \text{ AND } (mov \text{ is } -S_{mov}) \text{ AND } (tilt \text{ is } S_{tilt}) \text{ THEN } S[t+1] \text{ is } q_3 \]

\[ R_{32} : \text{IF} (S[t] \text{ is } q_3) \text{ AND } (mov \text{ is } S_{mov}) \text{ AND } (tilt \text{ is } -B_{tilt}) \text{ THEN } S[t+1] \text{ is } q_2 \]

\[ R_{31} : \text{IF} (S[t] \text{ is } q_3) \text{ AND } (a_x \text{ is } S_{ax}) \text{ AND } (mov \text{ is } S_{mov}) \text{ AND } (tilt \text{ is } M_{tilt}) \text{ THEN } S[t+1] \text{ is } q_1 \]
We have presented how to build a FFSM to recognize the body posture in a dynamical environment.

FFSMs allow the designer to introduce constrains in the model based on her/his expert knowledge.

The GFS can automatically obtain the rules and membership functions associated with each FFSM.

We have managed to increase the accuracy of the FFSM keeping its interpretability level.

Other real-world problems have also be tackled as human gait modeling.
5. Conclusions
Publications and research team

OVERVIEW

1. Introduction
2. Fuzzy Finite State Machine for Body Posture Recognition
3. Genetic Fuzzy Finite State Machine
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5. Conclusions

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ECSC Scientific Consultant

Dr. Gracián Triviño
ECSC Principal Researcher

Mr. Alberto Álvarez
ECSC Research Assistant


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1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms
2. Fuzzy Classifier Ensembles Designed with Multiobjective Evolutionary Algorithms
4. Forensic Identification by Craniofacial Superimposition using Evolutionary Algorithms and Fuzzy Sets
5. Conclusions
1. Forensic identification by craniofacial superimposition
Forensic Anthropology: Identification from skeletal remains

New Developments on the Hybridizations of Fuzzy Systems and Evolutionary Algorithms
ESTYLFF 2012. February, 3, Valladolid (Spain)
1. Forensic identification by craniofacial superimposition

Basis

**OVERVIEW**

1. Forensic identification by craniofacial superimposition (CS)

2. CS, Uncertainty and Image Registration = Soft Computing

3. First stage: 3D skull model reconstruction

4. Second stage: Skull-face overlay

5. Real cases

6. Conclusions

- Craniofacial superimposition is a forensic process where photographs or video shots of a missing person are compared with “a model” of a skull that is found.

- Projecting one above the other (skull-face overlay) the anthropologist can try to determine whether that is the same person.
1. Forensic identification by craniofacial superimposition

Cranial and facial landmarks

OVERVIEW

1. Forensic identification by craniofacial superimposition (CS)

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6. Conclusions
1. Forensic identification by craniofacial superimposition

Landmarks matching

OVERVIEW

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1. Forensic identification by craniofacial superimposition

Methodology

OVERVIEW

1. Forensic identification by craniofacial superimposition (CS)

2. CS, Uncertainty and Image Registration = Soft Computing

3. First stage: 3D skull model reconstruction

4. Second stage: Skull-face overlay

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6. Conclusions

1. Photo and skull model development

2. Manual skull-face overlay

3. Decision making

Identification {Positive/negative/likely positive/likely negative/indeterminate}
No systematic CS method exists

Manual craniofacial superimposition is very time consuming. There is a need of automatic techniques able to deal properly with incomplete information

Uncertainty is inherent to landmark location

Clear situation of partial matching: landmarks are located in a different location in the skull and the face, some of them do not have a correspondence, etc.

Degrees of confidence in the identification decision

OPPORTUNITY FOR SOFT COMPUTING!
2. CS, uncertainty and image registration = soft computing

Image registration (I)

OVERVIEW

1. Forensic identification by craniofacial superimposition (CS)

2. CS, Uncertainty and Image Registration = Soft Computing

3. First stage: 3D skull model reconstruction

4. Second stage: Skull-face overlay

5. Real cases

6. Conclusions

- Image Registration (IR) aims to superimpose an image on a similar one considering the same coordinate system

- IR Components:
  - Scene \((I_s \subset R^2/R^3)\) and model \((I_m \subset R^2/R^3)\) images
  - Transformation \((f: R^2/R^3 \rightarrow R^2/R^3)\)
  - Similarity metric \((F)\)
  - Optimizer \((\text{search for the optimal } f)\)

New Developments on the Hybridizations of Fuzzy Systems and Evolutionary Algorithms
ESTYLFF 2012. February, 3, Valladolid (Spain)
2. CS, uncertainty and image registration = soft computing

Image registration (II)

OVERVIEW

1. Forensic identification by craniofacial superimposition (CS)

2. CS, Uncertainty and Image Registration = Soft Computing

3. First stage: 3D skull model reconstruction

4. Second stage: Skull-face overlay

5. Real cases

6. Conclusions

- Scene image
- Model image
- $f(\text{Scene})$
- Transformed (Scene)
- Optimizer
- Similarity Metric
- Is Transformed(\text{Scene}) optimal?
- Best $f$ found
- New $f$

New Developments on the Hybridizations of Fuzzy Systems and Evolutionary Algorithms

ESTYLF 2012. February, 3, Valladolid (Spain)

Oscar Cordón
2. CS, uncertainty and image registration = soft computing
Image registration and craniofacial superimposition

OVERVIEW

1. Forensic identification by craniofacial superimposition (CS)

2. CS, Uncertainty and Image Registration = Soft Computing

3. First stage: 3D skull model reconstruction

4. Second stage: Skull-face overlay

5. Real cases

6. Conclusions

1. Photo and skull model development

3D skull reconstruction

Image processing and landmark location

2. Automatic skull face overlay

3D-2D IR: translation, rotation, scaling, and 2D projection

3. Decision making

Identification {Positive/negative/likely positive/likely negative/indeterminate}
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- Development of an automatic computer-based procedure to assist the forensic anthropologist in the identification task by craniofacial superimposition:
  - Design of automatic RIR methods to achieve accurate 3D skull models (using EAs)
  - Design of automatic 3D-2D IR methods to perform the skull-face overlay (using EAs and fuzzy sets)

- Initial work supported by two granted projects (national and regional research calls). International patent granted in February 2011
3. 3D skull model reconstruction using evolutionary algorithms

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- Reconstruction error: less than 1 mm
- 3D reconstruction time: 2 minutes
- Method robustness: low standard deviation in 30 different runs with extreme conditions
4. Skull-face overlay using EAs and fuzzy sets
Problem issues, requirements and tools

The skull-face overlay is a very complex problem:

- The available photographs are provided by the family:
  - Not always good quality, neither good pose
  - Landmarks may be occluded
  - Camera data are unknown

- Uncertainty is inherent both to the landmark location and matching (the latter due to the flesh lack in the skull)

- It is a very time consuming trial and error manual procedure

- Need of automatic techniques for skull-face overlay (3D-2D IR) being robust, fast, and able to deal with incomplete information

- We exploit the suitability of EAs and fuzzy sets to tackle the IR problem and to deal with the sources of uncertainty, respectively
4. Skull-face overlay using EAs and fuzzy sets

**Considered methodology**

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**Search for the best superimposition (Evolutionary algorithm)**

Rotation = \{60°, (0,1,0)\}
Translation = \{2, 0, 1\}...

Distance measuring between every pair of landmarks

Registration error

f' ≅ f*

f' evaluation
4. Skull-face overlay using EAs and fuzzy sets

Our proposal

- Evolutionary 3D skull-2D face IR problem with a complex registration transformation: translation, rotation, scaling, and projection. Twelve parameters

- Real-coding scheme, better suited for IR

- Advanced EAs: elitist GA, binary tournament, BLX-α/SBX crossovers, random mutation. CMA-ES, SS, multimodal GAs, co-evolutionary approaches, …

- Realistic conditions: Variable number of landmarks according to the photograph and the skull conditions. Robustness under multiple runs to allow a single run

- Fitness function: mean of the distances between the facial and the projected cranial landmarks (mean error, ME)
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🌟 Projective transformations are hard to be estimated. Cameras use them to provide a realistic picture of the scene from the observer’s viewpoint.

🌟 In computer graphics, the pinhole camera is modeled using a frustum given by the near clipping plane (NCP) and the far clipping plane (FCP):

The frustum determines the visible region.
Thus, our coding scheme is a vector of 12 real values:

\[
\begin{bmatrix}
    r_x & r_y & r_z & d_x & d_y & d_z & \theta & s & t_x & t_y & t_z & \phi
\end{bmatrix}
\]

ranging in the following intervals:

- \( r_i \in [\text{Centroid} - \text{radius}, \text{Centroid} + \text{radius}] \), \( i \in \{x, y, z\} \)
- \( d_i \in [-1, 1], \  i \in \{x, y, z\} \)
- \( \theta \in [0^\circ, 360^\circ] \)
- \( s \in [0.25, 2] \)
- \( \phi \in [10^\circ, 150^\circ] \)
- \( t_x \in [-\text{length}_{FB} - (C_x + \text{radius}), \text{length}_{FB} - (C_x - \text{radius})] \)
- \( t_y \in [-\text{length}_{FB} - (C_y + \text{radius}), \text{length}_{FB} - (C_y - \text{radius})] \)
- \( t_z \in [\text{NCP} - (C_z + \text{radius}), \text{FCP} - (C_z - \text{radius})] \)

where:

\[
\text{radius} = \max(||\text{Centroid} - C_i||)
\]

FB is the frustum Base

\[
\text{length}_{FB} = \frac{(\min_{FD} + \text{FCP}) \times \sin\left(\frac{\theta_{max}}{2}\right)}{\sin(90^\circ - (\frac{\theta_{max}}{2}))}
\]

with FD being the Focal Distance and

\[
\min_{FD} = \frac{1}{\tan\left(\frac{\theta_{max}}{2}\right)}
\]
Two different sources of uncertainty:

1. **Inherent uncertainty associated with the two different objects under study (a skull and a face):**
   - **Landmark location:** Every forensic expert is prone to locate the landmarks in a slightly different place
   - **Landmark matching:** Partial matching of the two landmark sets (cephalometric and craniometric)

4. **Second stage: Skull-face overlay**

5. Real cases

6. Conclusions
4. Skull-face overlay using EAs and fuzzy sets
Kinds of uncertainty in skull-face overlay (II)

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2. Uncertainty associated with the 3D skull-2D photo overlay process:

- **Landmark location**: Difficulty to select a good (cephalometric) landmark set due to the photo conditions:
  - face pose, partial occlusions, and poor image quality
  - forensic anthropologists are prone to locate only those landmarks which can be unquestionably identified!

- **Landmark matching**: The selected reduced landmark set is usually coplanar or near-coplanar:
  - the equation system becomes undetermined and the 3D-2D IR process gets inaccurate results
  - the preferred photos by the forensic anthropologists are usually those with a frontal pose!
4. Skull-face overlay using EAs and fuzzy sets

Fuzzy landmarks to jointly tackle location and coplanarity problems (I)

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Each cephalometric landmark is a fuzzy point defined by a bi-dimensional fuzzy set. The higher the uncertainty related to a landmark → the broader the fuzzy region

Solution for the two landmark location problems:
- The inherent difficulty to locate the landmark in the right place
- The complexity of locating a significant and unquestionable number of landmarks in a photo

Thanks to the flexibility given to the forensic expert, (s)he is able to mark a larger number of landmarks located in different planes, thus also solving the coplanarity problem
4. Skull-face overlay using EAs and fuzzy sets
Fuzzy landmarks to jointly tackle location and coplanarity problems (II)

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- There is a mask with the membership degree of each pixel to the fuzzy point associated to every landmark

- Need of a new fuzzy fitness function considering a distance between crisp and fuzzy points
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- **α-cuts** to calculate the distance from a crisp point (projected craniometric landmark) to a fuzzy point (cephalometric landmark)

- Crisp-fuzzy distance and new fitness function:

\[
d^* (x, \tilde{F}) = \sum_{i=1}^{m} d_i \cdot \alpha_i
\]

\[
fuzzy \ ME = \frac{\sum_{i=1}^{N} d^*(f(cl^i), \tilde{F}^i)}{N}
\]
5. FI by CS using EAs and fuzzy sets: Real cases

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5. Real cases

6. Conclusions

Manual

Area deviation error: 34.70%

several hours

Fuzzy AE

Area deviation error: 13.23%

2-4 minutes
5. FI by CS using EAs and fuzzy sets: Real cases

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5. Real cases

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Manual

Area deviation error: 32.64%
several hours

Fuzzy AE

Area deviation error: 15.84%
2-4 minutes
5. FI by CS using EAs and fuzzy sets: **Real cases**

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6. Conclusions

**Manual**

Area deviation error: 38.22%

Several hours

**Fuzzy AE**

Area deviation error: 18.95%

2-4 minutes
5. FI by CS using EAs and fuzzy sets: **Real cases**

**OVERVIEW**

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5. **Real cases**

6. Conclusions

**Manual**

Area deviation error: 31.73%

several hours

**Fuzzy AE**

Area deviation error: 11.92%

2-4 minutes
5. FI by CS using EAs and fuzzy sets: Real cases
5. FL by CS using EAs and fuzzy sets: **Real cases**

### OVERVIEW

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**Manual**

Area deviation error: 37.54%

several hours

**Fuzzy AE**

Area deviation error: 21.04%

2-4 minutes
OVERVIEW

1. Forensic identification (FI) by craniofacial superimposition

2. Image Registration (IR)

3. IR, Uncertainty and FI = Soft Computing

4. First stage: 3D skull model reconstruction

5. Second stage: Skull-face overlay

6. Conclusions

- We have successfully tackled the automation of the forensic identification by craniofacial superimposition in order to assist the forensic anthropologist

- Soft Computing (in particular, AEs and fuzzy sets) is suitable for this task given the intrinsic characteristics of this identification technique

- Our method has been used in the identification of a real-world case for the Spanish Scientific Police (Guardia Civil)

- A web site has been developed for the project: www.softcomputing.es/socovifi
6. Conclusions

Obtained results (I)

OVERVIEW
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Research Projects:

- Two Spanish R&D Plan projects: SOCOVIFI (2007-09, 79.860€) and SIMMRA (2010-12, 147.400€)
- Two Andalusian Government Research projects (2007-10, 122.787€) and (2012-15, 168.000€)

Technology Transfer:

- An international PCT patent (WO/2011/01274) was approved by the European Agency in February, 2011
- It will be commercialized in Mexico along 2012
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PhD Dissertations:


❖ Dr. Oscar Ibáñez. University of Santiago. Spain. Sept. 2010

International Awards:

❖ IFSA Award for Outstanding Applications of Fuzzy Technology. 2011

❖ EUSFLAT Best Ph.D. Thesis Award. 2011. Author: Dr. Oscar Ibáñez. Advisors: Drs. Cordón and Damas
6. Conclusions
Obtained results (IV)

Publications in SCI-JCR journals: Methodology:


Publications in SCI-JCR journals: First stage:


6. Conclusions

Obtained results (V)

Publications in SCI-JCR journals: Second stage:


6. Conclusions

Future works

Improve the automatic soft computing-based SFO method developed to make it more reliable and customizable to different forensic scenarios:

- A web-based poll is being developed with forensic experts to estimate the landmark location variability
- New fuzzy distances will be considered
- The uncertainty in landmark matching will be shortly tackled
- Objective and semi-automatic SFO validation techniques will be developed (based on anthropometric aspects & computer vision).
- We aim to properly model old-fashioned cameras to tackle identification cases related to the Spain’s civil war
- Mexico: 3D reconstruction of fragmented skulls and multiple comparisons
- A fuzzy classification system for pubic bone-based age assessment will be designed from the forensic anthropologists’ expert knowledge
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New Developments on the Hybridizations of Fuzzy Systems and Evolutionary Algorithms
ESTYLF 2012. February, 3, Valladolid (Spain)

Oscar Cordón
Outline

1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms
2. Fuzzy Classifier Ensembles Designed with Multiobjective Evolutionary Algorithms
4. Forensic Identification by Craniofacial Superimposition using Evolutionary Algorithms and Fuzzy Sets
5. Conclusions
5. Conclusions

- Hybridizations of fuzzy sets/systems and EAs are a good **general purpose** problem solving approach allowing us to get **accurate**, **simple**, **cheap**, and **robust** solutions.

- They constitute an **extensive research area nowadays**, with a large number of researchers and practitioners, thousands of scientific publications, special sessions in international conferences, specific workshops, etc.

- These hybrid systems have been applied to **many problem domains** and have resulted in a significant **knowledge transfer to real business**.
Thank you for your attention

Questions?