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European Centre for Soft Computing

New Developments on the Hybridizations of Fuzzy Systems and Evolutionary Algorithms

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Outline

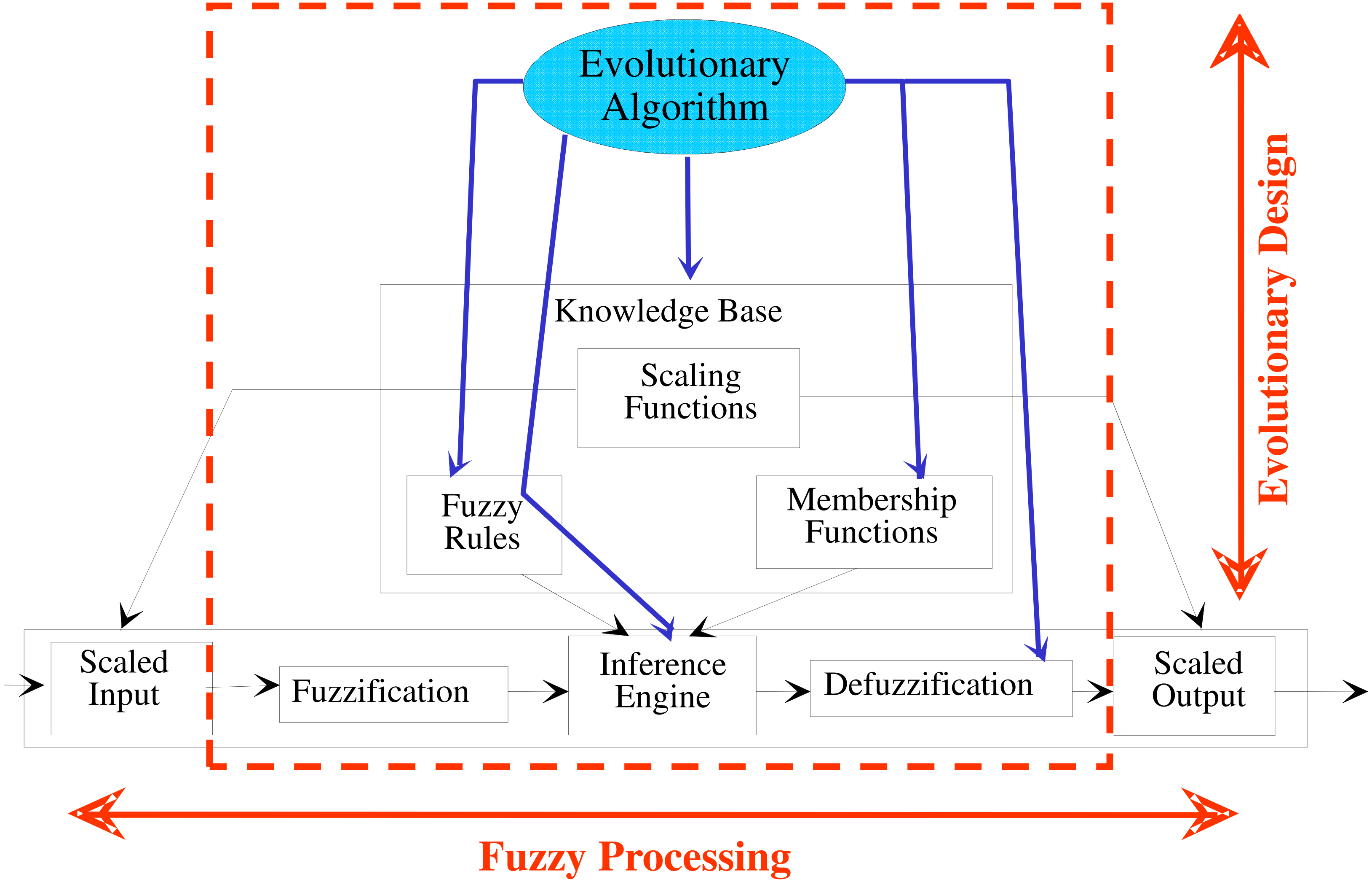
1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms
2. Fuzzy Classifier Ensembles Designed with Multiobjective Evolutionary Algorithms
3. Body Posture Recognition by means of a Genetic Fuzzy Finite State Machine
4. Forensic Identification by Craniofacial Superimposition using Evolutionary 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

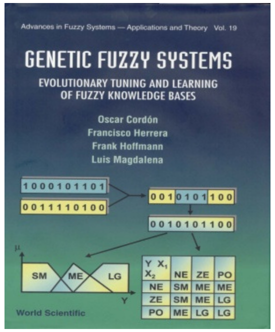
Genetic Fuzzy Systems



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



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Outline

1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms
2. Fuzzy Rule-based Multiclassification Systems Designed with Multiobjective Evolutionary Algorithms
3. Body Posture Recognition by means of a Genetic Fuzzy Finite State Machine
4. Forensic Identification by Craniofacial Superimposition using Evolutionary Algorithms and Fuzzy Sets
5. Conclusions

OVERVIEW

- 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

One person

QUESTION

CORRECT ANSWER?

Several people

QUESTION

CORRECT ANSWER?

Diversity helps to improve accuracy

1. Introduction
Multiclassifier system design issues

OVERVIEW

1. Introduction

2. Proposed Framework

3. Bagging FURIA-based fuzzy multiclassification systems

4. Evolutionary Multiobjective Selection of the component classifiers

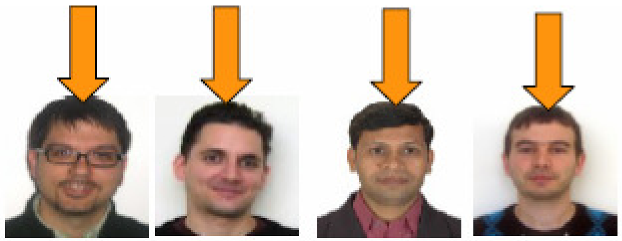
5. Experiments

6. Conclusions

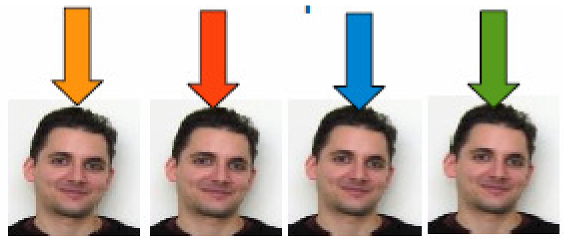
Diversity – An individual classifier must provide different patterns of generalization in order to obtain a diverse set of classifiers composing a highly accurate ensemble

Different methods to induce diversity to the base classifiers:

Different classifiers:



Different “inputs”:



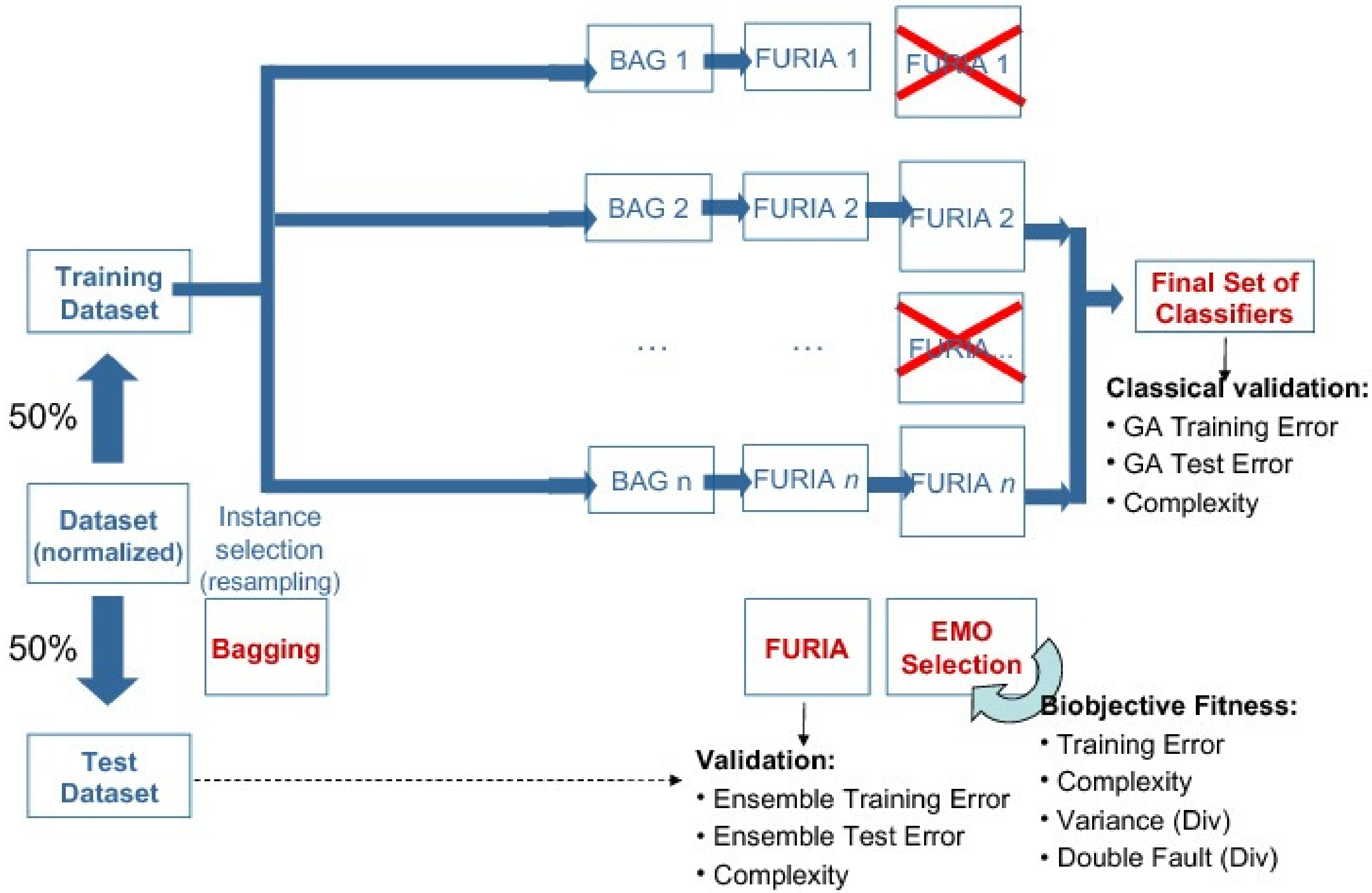
Description

OVERVIEW

Our approach combines several techniques to quickly generate accurate and diverse base fuzzy classifiers:

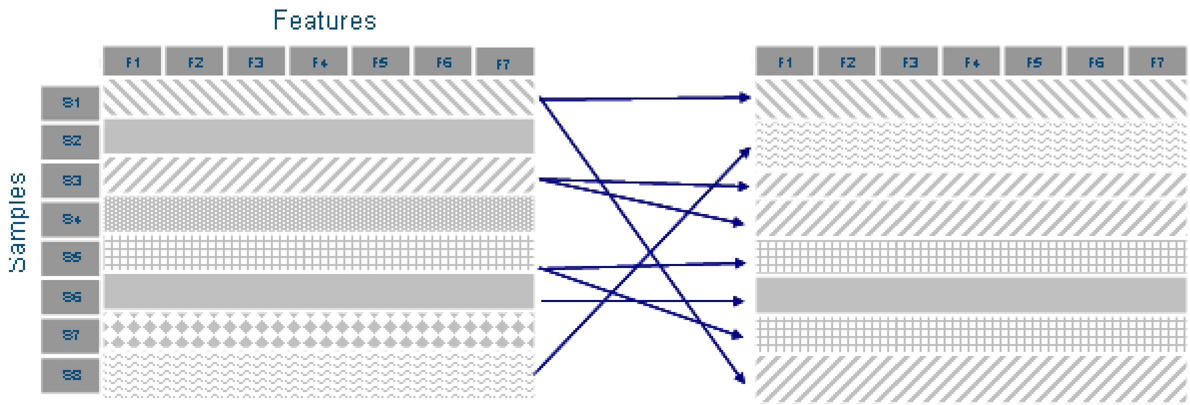
- A parallel approach: bootstrap aggregating (bagging)
- A quick and accurate fuzzy rule generation method (FURIA) including a dimensionality reduction method (feature selection)
- A mechanism to deal with the accuracy-complexity tradeoff (classifier selection by OCS) in an EMO fashion: error, diversity,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

OVERVIEW


BAG 1
FURIA 1
FURIA 1
BAG 2
FURIA 2
FURIA 2
Training Dataset
Final Set of Classifiers
...
...
FURIA...
Classical validation:
• GA Training Error
• GA Test Error
• Complexity
50%
BAG n
FURIA n
FURIA n
Dataset (normalized)
Instance selection (resampling)
50%
Bagging
FURIA
EMO Selection
Biobjective Fitness:
• Training Error
• Complexity
• Variance (Div)
• Double Fault (Div)
Test Dataset
Validation:
• Ensemble Training Error
• Ensemble Test Error
• Complexity

Bagging Predictors (Breiman, 1996):

- Boostrap AGGregatING: create multiple boostrap 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)

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

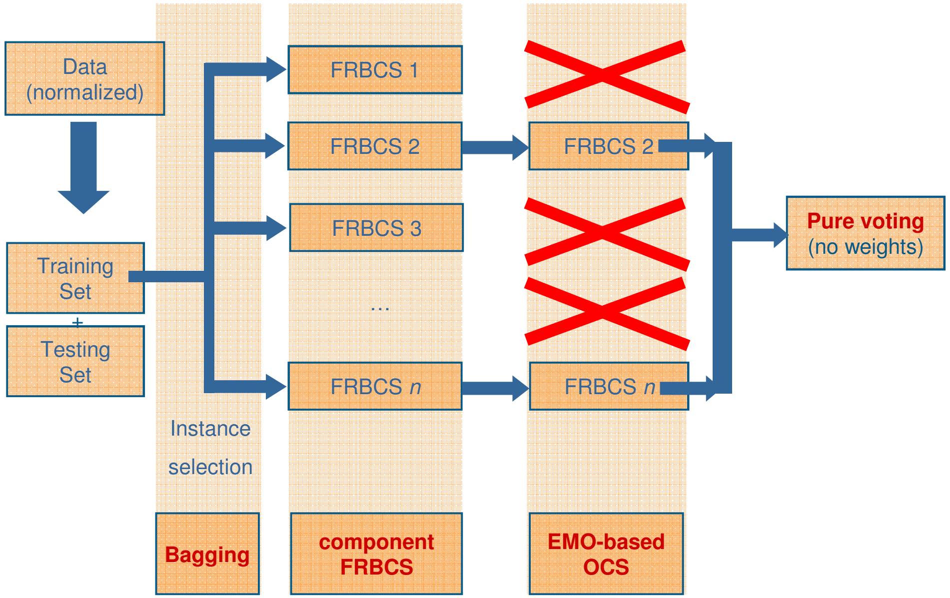
Evolutionary multiobjective optimization-based overproduce & choose

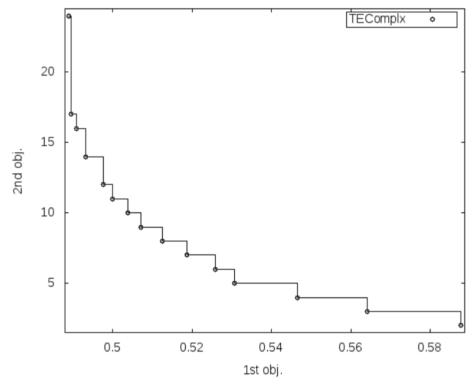
OVERVIEW

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

OCS strategy (Partridge and Yates, 1996) :

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





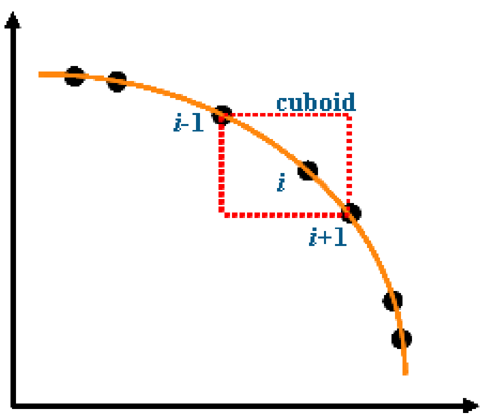
EMO-based OCS:

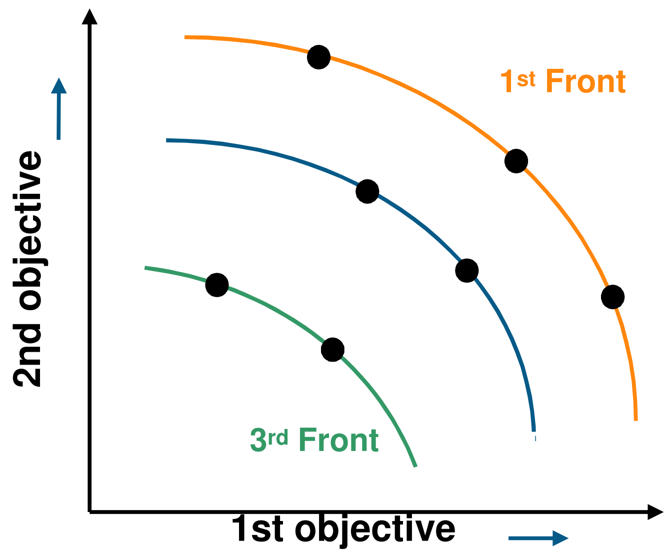
- Up to three different kinds of criteria jointly optimized by an EMO algorithm: accuracy, diversity, and complexity (#classifiers)

OVERVIEW

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 multiobjective classifier selection method (I)

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**

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

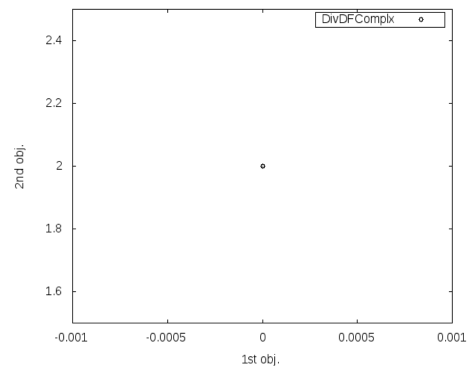
OVERVIEW

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 (θ) and double-fault (δ)

abbreviation	1st obj.	2nd obj.
2a	TE	Complx
2b	TE	θ
2c	TE	δ
2d	θ	Complx
2e	δ	Complx

Deceptive combination



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)

Data set	#examples	#attr.	#classes
abalone	4178	7	28
breast	700	9	2
glass	214	9	7
heart	270	13	2
ionosphere	352	34	2
magic	19020	10	2
optdigits	5620	64	10
pblocks	5474	10	5
pendigits	10992	16	10
phoneme	5404	5	2
pima	768	8	2
sat	6436	36	6
segment	2310	19	7
sonar	208	60	2
spambase	4602	57	2
texture	5500	40	11
waveform	5000	40	3
wine	178	13	3
vehicle	846	18	4
yeast	1484	8	10

Validation: Dietterich's 5x2-fold cross validation

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)

FURIA-based MCSs										
	aba	bre	gla	hea	ion	let	mag	opt	pbl	pen
tra. err.	0.622	0.018	0.096	0.052	0.050	0.016	0.110	0.627	0.014	0.002
test err.	0.753	0.037	0.313	0.178	0.134	0.091	0.136	0.628	0.028	0.015
feat sel.	G	R	-	-	RG	-	-	RG	R	R
feat. sub. size	L	L	-	-	S	-	-	L	L	L
nr of cl.	10	10	7	7	7	10	7	10	10	10

C4.5 ensembles with bagging										
	aba	bre	gla	hea	ion	let	mag	opt	pbl	pen
tra. err.	0.118	0.017	0.075	0.053	0.021	0.018	0.052	0.105	0.012	0.005
test err.	0.772	0.043	0.306	0.194	0.149	0.103	0.134	0.697	0.030	0.028
nr of cl.	10	7	10	10	10	10	10	10	10	10

random forests										
tra. err.	0.002	0.001	0.001	0.001	0.001	0.000	0.003	0.003	0.002	0.000
test err.	0.777	0.041	0.282	0.211	0.140	0.080	0.134	0.695	0.031	0.016
nr of cl.	7	7	10	10	10	10	10	10	10	10

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)

FURIA-based MCSs											
	pho	pim	sat	seg	son	spa	tex	veh	wav	win	yea
tra. err.	0.085	0.109	0.025	0.006	0.005	0.028	0.004	0.051	0.017	0.002	0.223
test err.	0.136	0.235	0.105	0.035	0.198	0.061	0.036	0.276	0.156	0.036	0.408
feat sel.	R	RG	-	-	R	-	-	-	-	RG	-
feat. sub. size	L	L	-	-	L	-	-	-	-	M	-
nr of cl.	10	10	10	10	10	10	10	10	10	10	10

C4.5 ensembles with bagging											
	pho	pim	sat	seg	son	spa	tex	veh	wav	win	yea
tra. err.	0.044	0.056	0.021	0.009	0.024	0.025	0.007	0.047	0.015	0.020	0.119
test err.	0.131	0.253	0.112	0.042	0.247	0.067	0.051	0.289	0.193	0.097	0.415
nr of cl.	10	10	10	10	10	10	10	10	10	10	10

random forests											
tra. err.	0.001	0.003	0.002	0.001	0.002	0.001	0.000	0.002	0.001	0.000	0.005
test err.	0.119	0.264	0.104	0.034	0.239	0.060	0.040	0.269	0.185	0.048	0.438
nr of cl.	10	10	10	10	10	10	10	10	10	10	10
feat. sel.	R	R	G	R	RG	RG	R	R	RG	R	

Experimental setup (II)

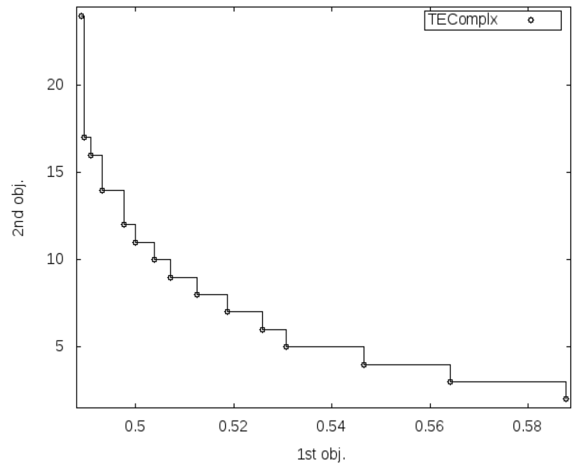
OVERVIEW

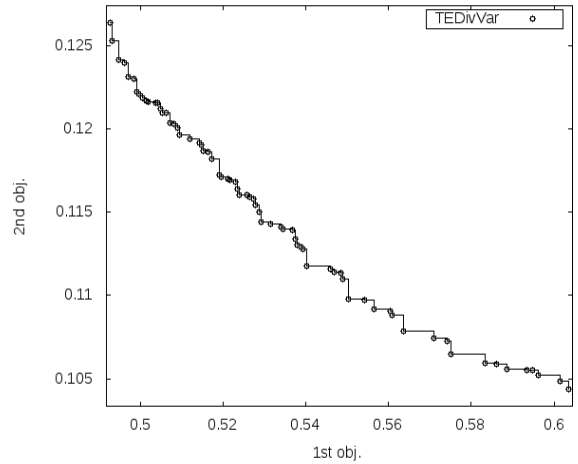
Parameter values:

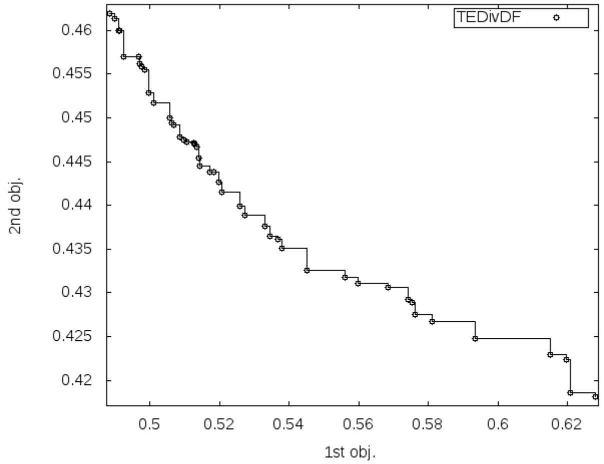
- **50 classifiers** generated
- Pre-compute classification matrix to speed up the runs
- NSGA-II parameters: 50 individuals, 1000 generations, crossover prob. 0.6, mutation prob. 0.1
- Test accuracy and #classifiers of each Pareto-optimal solution are measured to allow for a global comparison
- To compare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

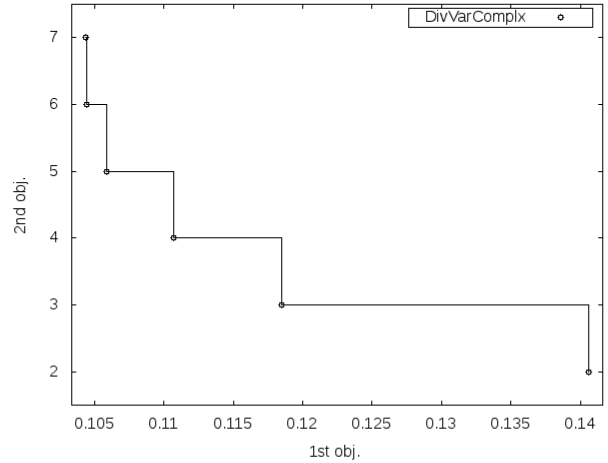
5. Experiments
EMO-based OCS results (I)

*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*









EMO-based OCS results (II)

Comparison of PFs using the HVR measure

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

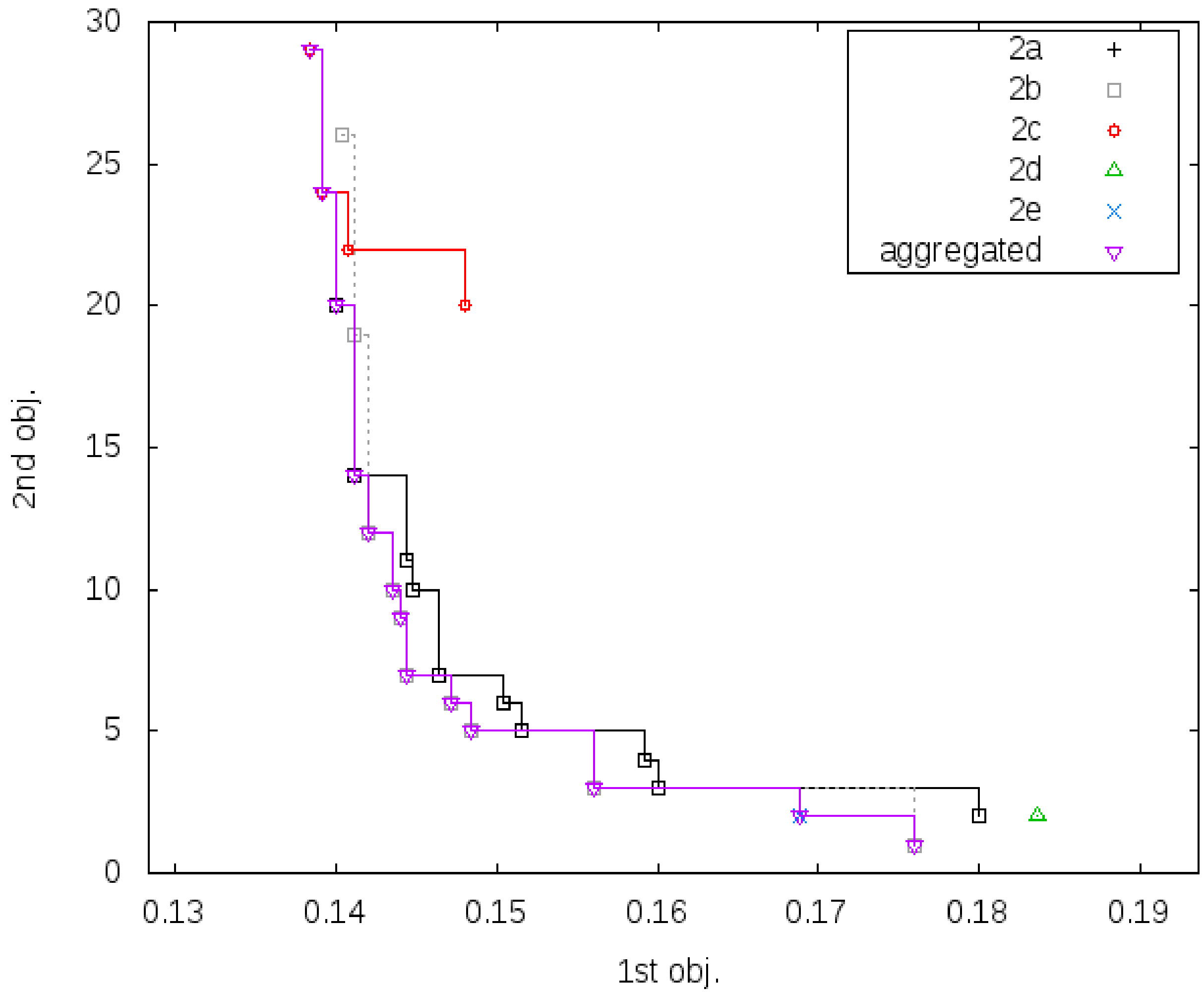
Otherwise, the comparison is not feasible!!!

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

	2a	2b	2c	2d	2e
aba	**0.9973**	0.5126	**0.9973**	0.9961	0.9962
bre	0.6632	**0.9955**	0.3321	0.6627	0.6644
gla	0.8455	**0.9867**	0.8314	0.8376	0.8469
hea	0.6582	**0.9858**	0.5915	0.6564	0.6625
ion	0.9437	**0.9796**	0.5294	0.9416	0.9464
mag	0.9323	**0.9988**	0.9324	0.9300	0.9307
opt	**0.9952**	0.3335	0.3335	**0.9952**	**0.9952**
pbl	0.8555	**0.9983**	0.8555	0.8547	0.8553
pen	0.9609	**0.9992**	0.4307	0.9580	0.9587
pho	0.9267	**0.9978**	0.9266	0.9224	0.9241
pim	0.8700	**0.9944**	0.8700	0.8650	0.8730
sat	0.9554	**0.9988**	0.1738	0.9510	0.9528
seg	0.9483	**0.9982**	0.3295	0.9452	0.9472
son	0.6544	**0.9797**	0.3927	0.6492	0.6597
spa	0.9071	**0.9978**	0.1542	0.9047	0.9060
tex	0.9587	**0.9983**	0.3518	0.9525	0.9542
veh	0.8523	**0.9940**	0.8520	0.8459	0.8521
wav	0.9638	**0.9984**	0.2068	0.9554	0.9585
win	0.9240	**0.9893**	0.1066	0.9213	0.9265
yea	0.9315	**0.9947**	0.9311	0.9256	0.9301
avg.	0.8450	**0.8920**	0.5299	0.8415	0.8870
dev.	0.2202	0.2682	0.3263	0.2194	0.1058

EMO-based OCS results (III)

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



EMO-based OCS results (IV)

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

		Best of 1st obj.			Best of 2nd obj.			Best tradeoff			Best test		
		Tra	Tst	Cmpl	Tra	Tst	Cmpl	Tra	Tst	Cmpl	Tra	Tst	Cmpl
2a	avg.	0.064	0.199	8.770	0.103	0.221	2.000	0.103	0.221	2.000	0.047	0.193	7.085
	dev.	0.140	0.207	5.373	0.152	0.210	0.000	0.152	0.210	0.000	0.116	0.202	4.135
2b	avg.	0.054	0.201	10.875	0.095	0.220	2.880	0.063	0.205	8.800	0.056	0.191	8.235
	dev.	0.120	0.200	7.337	0.134	0.202	6.698	0.118	0.201	8.752	0.122	0.197	6.411
2c	avg.	0.053	0.193	14.470	0.090	0.210	10.660	0.062	0.198	13.800	0.047	0.189	13.235
	dev.	0.119	0.203	7.681	0.148	0.214	10.212	0.118	0.204	9.518	0.116	0.200	7.878
2d	avg.	0.112	0.223	2.370	0.117	0.225	2.000	0.117	0.225	2.000	0.083	0.221	2.300
	dev.	0.150	0.206	1.655	0.166	0.211	0.000	0.166	0.211	0.000	0.064	0.202	1.342
2e	avg.	0.107	0.223	2.000	0.107	0.223	2.000	0.107	0.223	2.000	0.000	0.200	2.000
	dev.	0.153	0.210	0.000	0.153	0.210	0.000	0.153	0.210	0.000	0.000	0.203	0.000

EMO-based OCS results (V)

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

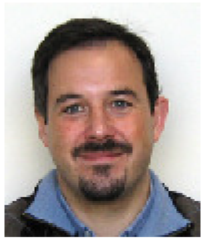
	aba	bre	gla	hea	ion	mag	opt	pbl	pen	pho	pim	sat	seg	son	spa	tex	veh	wav	win	yea
NSGA-II combined with FURIA-based MCSs.																				
test err.	0.741	0.037	0.283	0.170	0.126	0.132	0.625	0.027	0.014	0.125	0.231	0.101	0.027	0.188	0.056	0.028	0.255	0.146	0.018	0.396
fitness func.	2b	2b	2c	2b	2c	2a	2b	2c	2c	2c	2e	2b	2c	2e	2b	2c	2b	2c	2c	2b
nr of cl.	18.6	2.7	5.5	2	18.7	5.6	26	4.8	21.8	9	2	14.6	17.6	2	6.8	23.2	7.5	18.7	18.7	7.1
FURIA-based MCSs algorithms Small ensemble sizes.																				
test err.	0.753	0.037	0.313	0.178	0.134	0.136	0.628	0.028	0.015	0.136	0.235	0.105	0.035	0.198	0.061	0.036	0.276	0.156	0.036	0.408
nr of cl.	10	10	7	7	7	7	10	10	10	10	10	10	10	10	10	10	10	10	10	10
FURIA-based MCSs algorithms. Ensemble size 50.																				
test err.	0.748	0.041	0.287	0.182	0.145	0.135	0.630	0.028	0.016	0.135	0.241	0.102	0.034	0.226	0.059	0.031	0.275	0.149	0.035	0.400
C4.5 ensembles with bagging. Small ensemble sizes.																				
test err.	0.772	0.043	0.306	0.194	0.149	0.134	0.697	0.03	0.028	0.131	0.253	0.112	0.042	0.247	0.067	0.051	0.289	0.193	0.097	0.415
nr of cl.	10	7	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10
Random forests. Small ensemble sizes.																				
test err.	0.777	0.041	0.282	0.211	0.14	0.134	0.695	0.031	0.016	0.119	0.264	0.104	0.034	0.239	0.06	0.04	0.269	0.185	0.048	0.438
nr of cl.	7	7	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10

6. Conclusions

OVERVIEW

- 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

OVERVIEW



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Outline

1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms
2. Fuzzy Classifier Ensembles Designed with Multiobjective Evolutionary Algorithms
3. Body Posture Recognition by means of a Genetic Fuzzy Finite State Machine
4. Forensic Identification by Craniofacial Superimposition using Evolutionary Algorithms and Fuzzy Sets
5. Conclusions

Problem description and objectives

OVERVIEW

Body posture recognition:

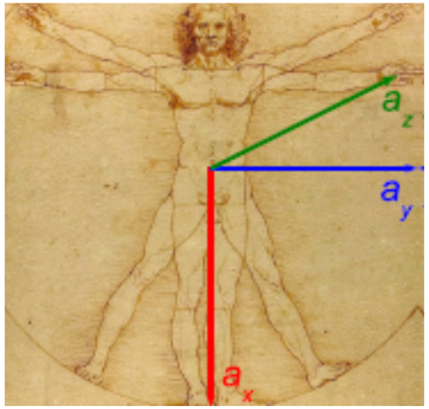
- Personal applications:
  - Detection of user behaviors
  - Context awareness
- Security:
  - Proactive care for elderly people
  - Safety applications based on fall detection

Objectives:

- To design an accurate and interpretable model
- To incorporate the available expert knowledge

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

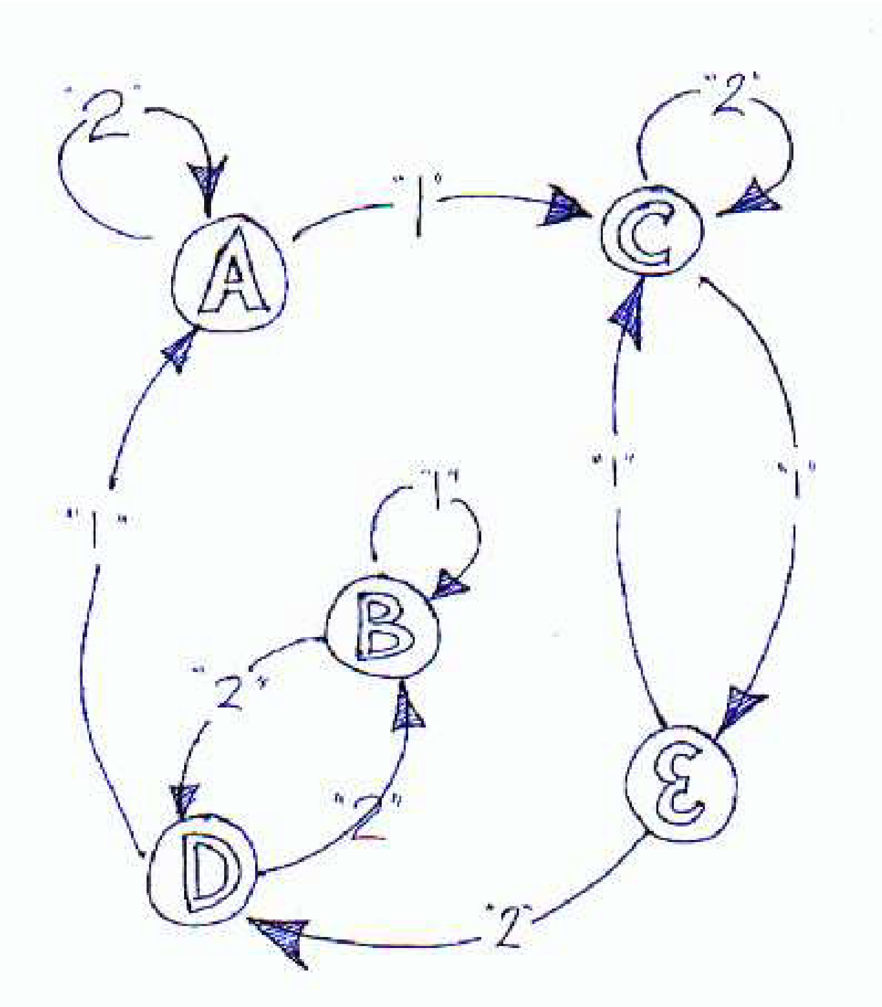
- Fuzzy finite state machines (FFSMs) are tools for modeling time-evolving dynamical processes, extending classical FSMs

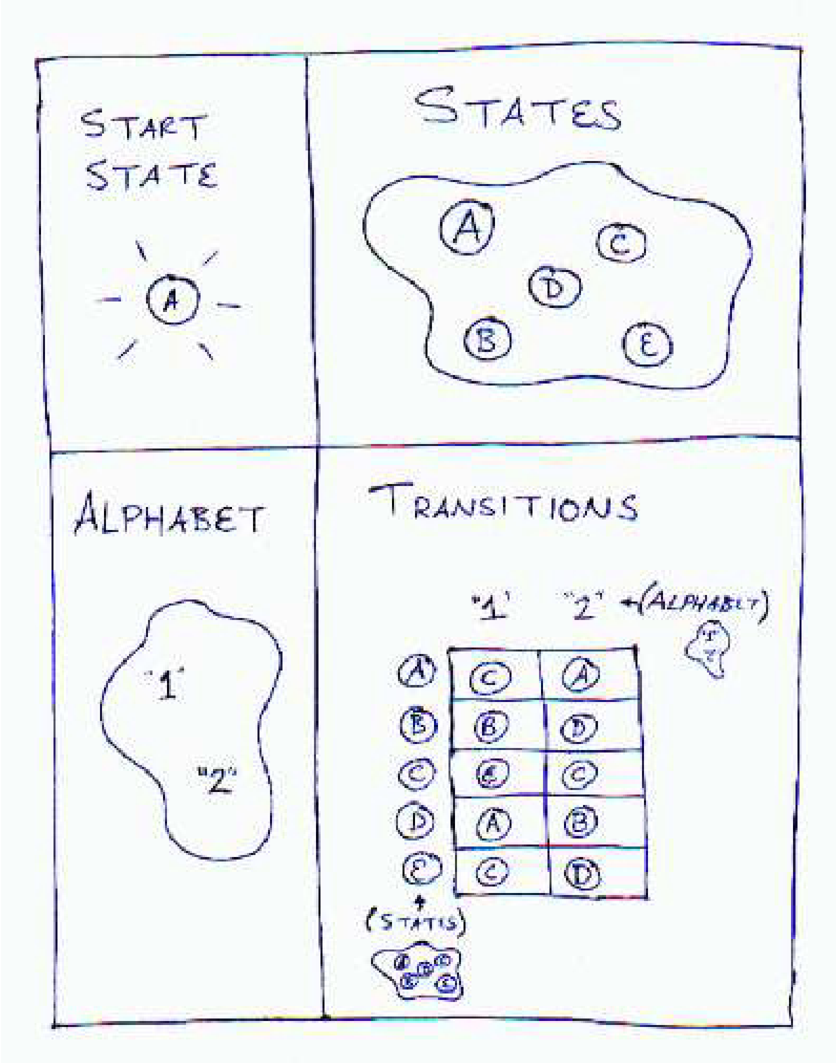
- Their main advantage is that they are able to handle imprecise and uncertain data in the form of fuzzy states and transitions

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 $u_i[t] = \{A^1_{u_i}, \ldots, A^{n_i}_{u_i}\}$
- 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: $Y[t] = g(S[t],U[t])$.

FFSM graphical representation





	"1"	"2"
A	C	A
B	B	D
C	E	C
D	A	B
E	C	D

FFSM fuzzy transition rules and reasoning mechanism

OVERVIEW

- 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:

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

- *Cij* describes the constraints imposed on the input variables that are required to change the state as a DNF fuzzy premise:

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

- 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

1. Identify the set of fuzzy states that represent the different body postures: $q_1 \rightarrow$ Seated; $q_2 \rightarrow$ Upright; $q_3 \rightarrow$ Walking

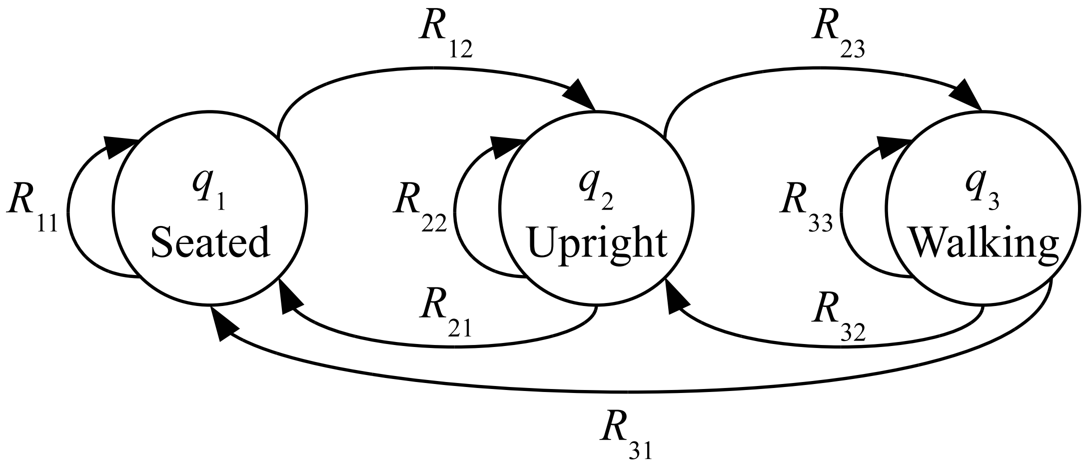
2. Define the input linguistic variables based on the three accelerations (a_x,a_y,a_z) provided by the accelerometer:
   - $a_x \rightarrow$ dorso-ventral acceleration
   - *mov* $\rightarrow$ amount of movement calculated using the variations of a_x,a_y and a_z in 1 second
   - *tilt* $\rightarrow$ 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: $Y[t] = S[t]$

2. A Fuzzy Finite State Machine for Body Posture Recognition
Transition function

OVERVIEW



R_{11} : **IF** ($S[t]$ is q_1) **AND** C_{11} **THEN** $S[t+1]$ is q_1

R_{22} : **IF** ($S[t]$ is q_2) **AND** C_{22} **THEN** $S[t+1]$ is q_2

R_{33} : **IF** ($S[t]$ is q_3) **AND** C_{33} **THEN** $S[t+1]$ is q_3

R_{12} : **IF** ($S[t]$ is q_1) **AND** C_{12} **THEN** $S[t+1]$ is q_2

R_{21} : **IF** ($S[t]$ is q_2) **AND** C_{21} **THEN** $S[t+1]$ is q_1

R_{23} : **IF** ($S[t]$ is q_2) **AND** C_{23} **THEN** $S[t+1]$ is q_3

R_{32} : **IF** ($S[t]$ is q_3) **AND** C_{31} **THEN** $S[t+1]$ is q_1

R_{31} : **IF** ($S[t]$ is q_3) **AND** C_{32} **THEN** $S[t+1]$ is q_2

Specified as fuzzy DNF premises being constrains on the input linguistic variables

GFS structure and particularities

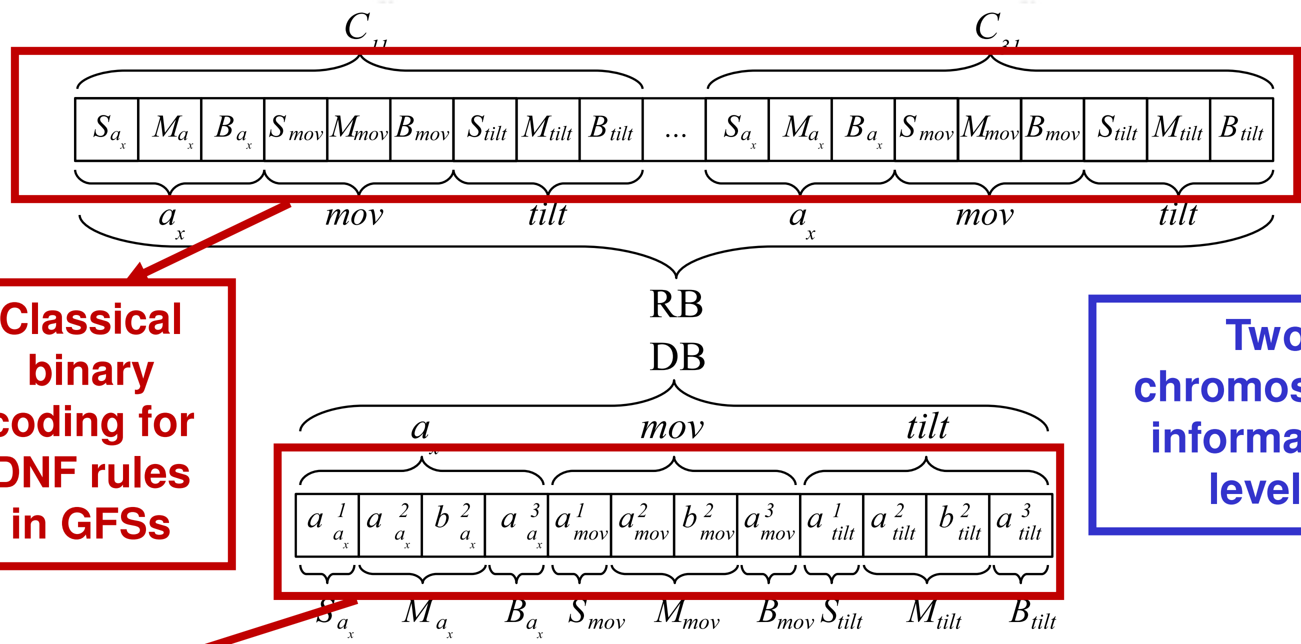
OVERVIEW

- 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

Coding scheme

OVERVIEW

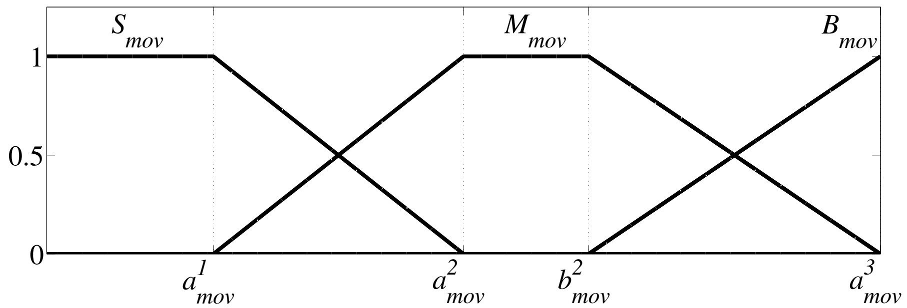
$$C_{ij} \rightarrow (a_x \text{ is } S_{a_x}) \text{ AND } (mov \text{ is } M_{mov}) \text{ AND } (tilt \text{ is } M_{tilt} \text{ OR } B_{tilt})$$



Classical binary coding for DNF rules in GFSs

Two chromosome information levels

Trapezoidal-shaped strong fuzzy partition real-coding



3. Genetic Fuzzy Finite State Machine
Fitness function

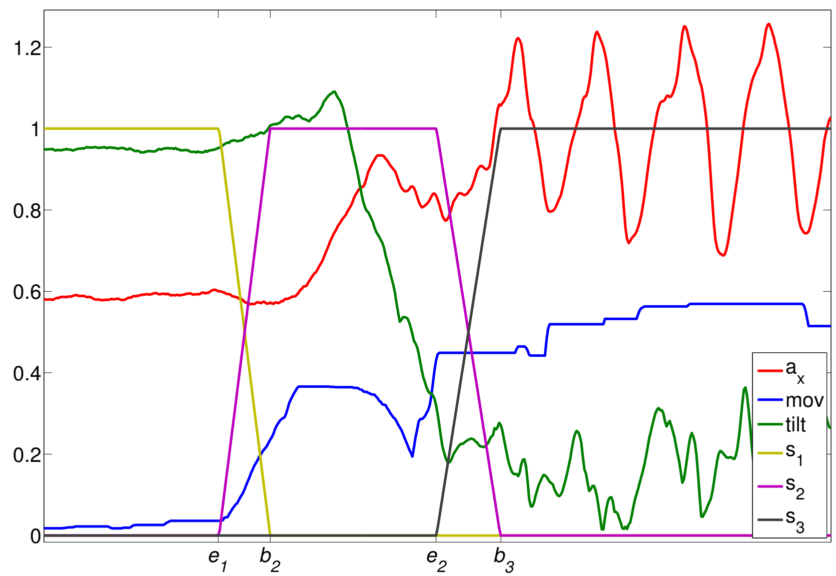
OVERVIEW

- 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:

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

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

$$(a_x(t), a_y(t), a_z(t), s_1^*(t), s_2^*(t), s_3^*(t))$$



Dataset: Ten repetitions of different consecutive activities

OVERVIEW

Duration (s)	Description	Posture
60	Seated and typing	Seated (q_1)
30	Standing up	Upright (q_2)
	Walking towards the coffee area	Walking (q_3)
75	Staying up in front of the coffee machine	Upright (q_2)
	Sitting and having the coffee	Seated (q_1)
25	Standing up	Upright (q_2)
	Walking until the office of a colleague	Walking (q_3)
50	Staying up and waiting for the colleague	Upright (q_2)
30	Walking towards the meeting room	Walking (q_3)
100	Seated in the meeting room	Seated (q_1)
40	Standing up	Upright (q_2)
	Walking back to the work-desk	Walking (q_3)
100	Seated and typing	Seated (q_1)

LEAVE-ONE-OUT CROSS VALIDATION

FOLD	GFFSM		ARX*	
	TRAIN	TEST	TRAIN	TEST
1	0.010	0.016	0.071	0.083
2	0.009	0.007	0.072	0.093
3	0.010	0.009	0.076	0.064
4	0.009	0.010	0.078	0.059
5	0.010	0.013	0.076	0.072
6	0.009	0.012	0.075	0.073
7	0.010	0.010	0.075	0.081
8	0.011	0.009	0.070	0.104
9	0.008	0.010	0.077	0.065
10	0.009	0.009	0.076	0.072
MEAN	0.009	0.011	0.074	0.077
STD	0.001	0.002	0.003	0.014

MAE FOR EACH DATASET IN TEST

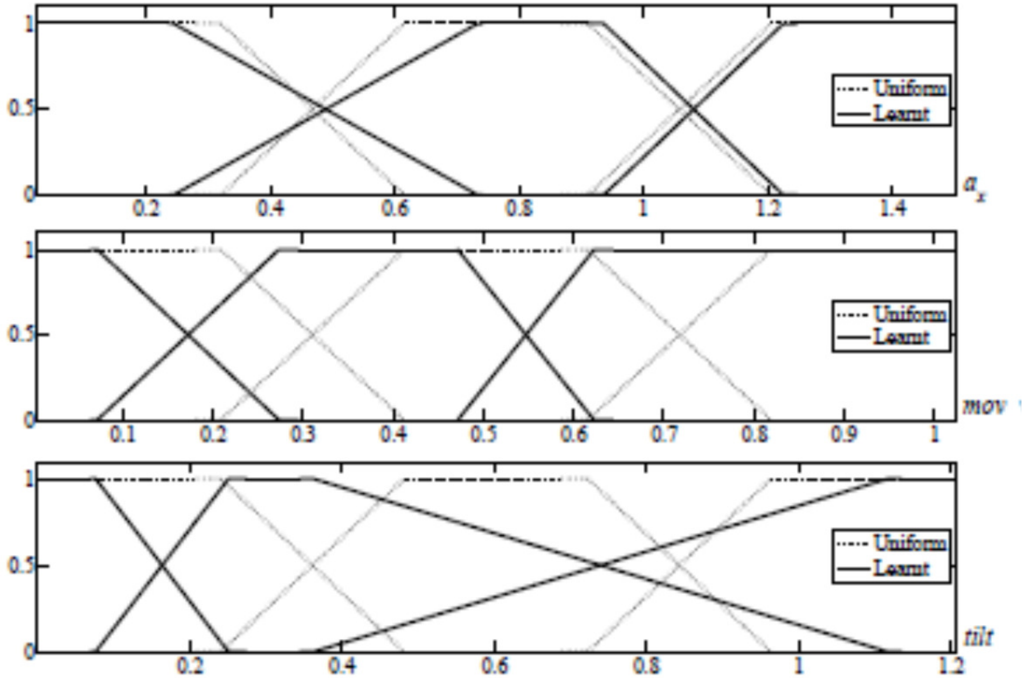
DATASET	FFSM†	GFFSM	ARX*
1	0.023	0.016	0.083
2	0.027	0.007	0.093
3	0.016	0.009	0.064
4	0.020	0.010	0.059
5	0.022	0.013	0.072
6	0.028	0.012	0.073
7	0.022	0.010	0.081
8	0.030	0.009	0.104
9	0.017	0.010	0.065
10	0.018	0.009	0.072
MEAN	0.022	0.011	0.077
STD	0.005	0.002	0.014

* 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} : IF ($S[t]$ is q_1) AND (a_x is M_{a_x}) AND (mov is $\neg M_{mov}$) AND ($tilt$ is B_{tilt}) THEN $S[t+1]$ is q_1
R_{22} : IF ($S[t]$ is q_2) AND (a_x is B_{a_x}) THEN $S[t+1]$ is q_2
R_{33} : IF ($S[t]$ is q_3) AND (mov is M_{mov}) THEN $S[t+1]$ is q_3
R_{12} : IF ($S[t]$ is q_1) AND (a_x is $\neg S_{a_x}$) AND (mov is $\neg S_{mov}$) AND ($tilt$ is $\neg B_{tilt}$) THEN $S[t+1]$ is q_2
R_{21} : IF ($S[t]$ is q_2) AND (a_x is S_{a_x}) AND (mov is $\neg M_{mov}$) AND ($tilt$ is B_{tilt}) THEN $S[t+1]$ is q_1
R_{23} : IF ($S[t]$ is q_2) AND (a_x is B_{a_x}) AND (mov is $\neg S_{mov}$) AND ($tilt$ is S_{tilt}) THEN $S[t+1]$ is q_3
R_{32} : IF ($S[t]$ is q_3) AND (mov is S_{mov}) AND ($tilt$ is $\neg B_{tilt}$) THEN $S[t+1]$ is q_2
R_{31} : IF ($S[t]$ is q_3) AND (a_x is S_{a_x}) AND (mov is S_{mov}) AND ($tilt$ is M_{tilt}) THEN $S[t+1]$ 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

Publications and research team

OVERVIEW

Dr. Oscar Cordón
UGR Professor
ECSC Scientific Consultant

Dr. Gracián Triviño
ECSC Principal Researcher

Mr. Alberto Álvarez
ECSC
Research Assistant

- A. Álvarez-Álvarez, G. Triviño, O. Cordón. Body Posture Recognition by means of a Genetic Fuzzy Finite State Machine. Proc. Fifth IEEE International Workshop GEFS 2011, IEEE SSCI 2011, Paris (France), 11-15 April, 2011, 60-65.

- A. Álvarez-Álvarez, G. Trivino, O. Cordón. Human Gait Modeling Using a Genetic Fuzzy Finite State Machine. IEEE Transactions on Fuzzy Systems 20:1 (2012). FI 2010: 2.683. Cat: E, E&E. O: 15/247. **Q1**

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Forensic Anthropology: Identification from skeletal remains

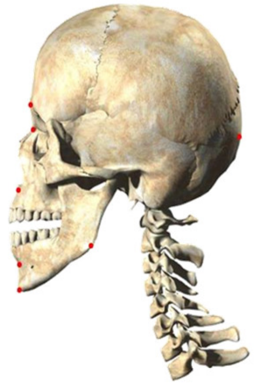
CSI: crime scene investigation

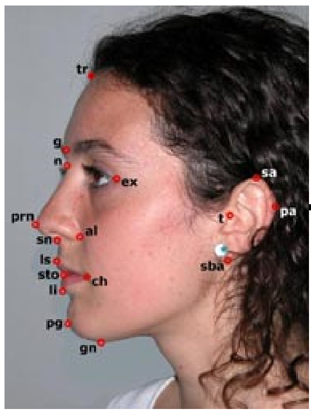
BONES

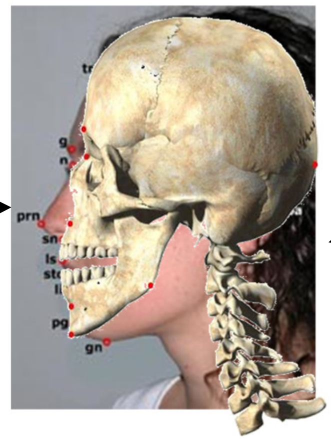
OVERVIEW

- 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

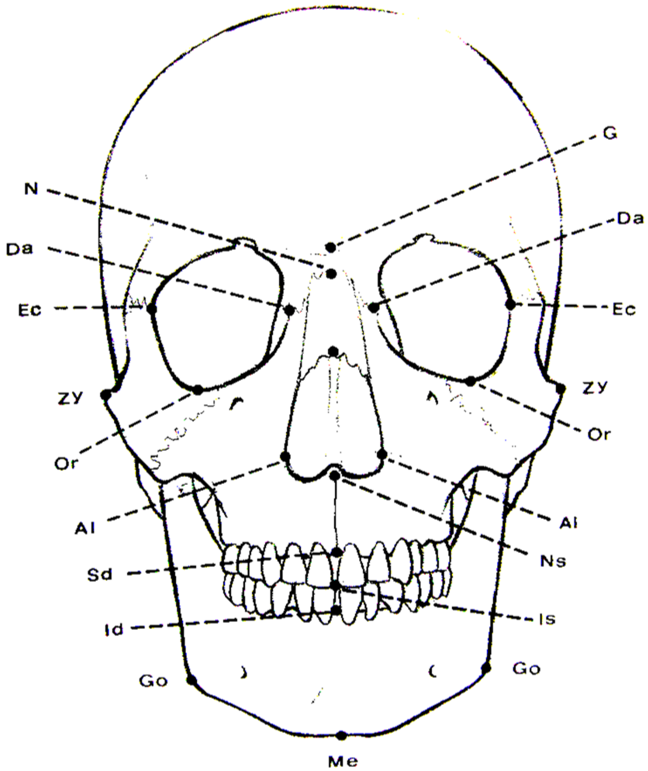




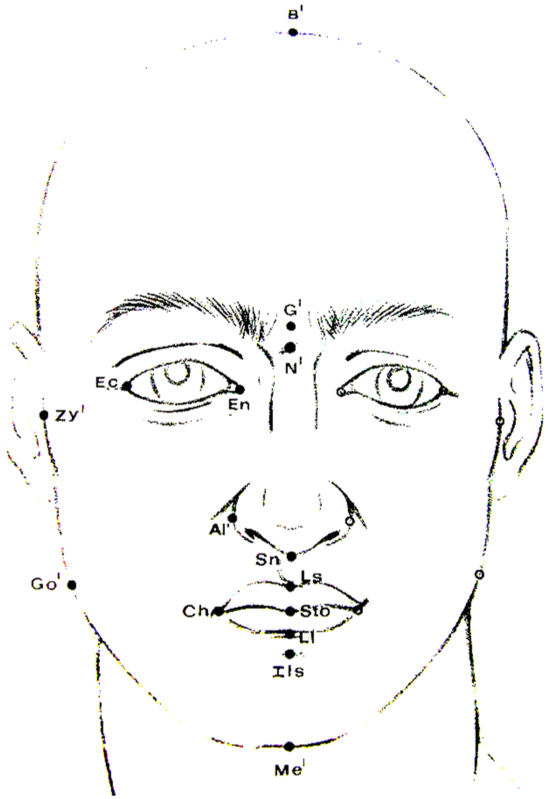


Cranial and facial landmarks

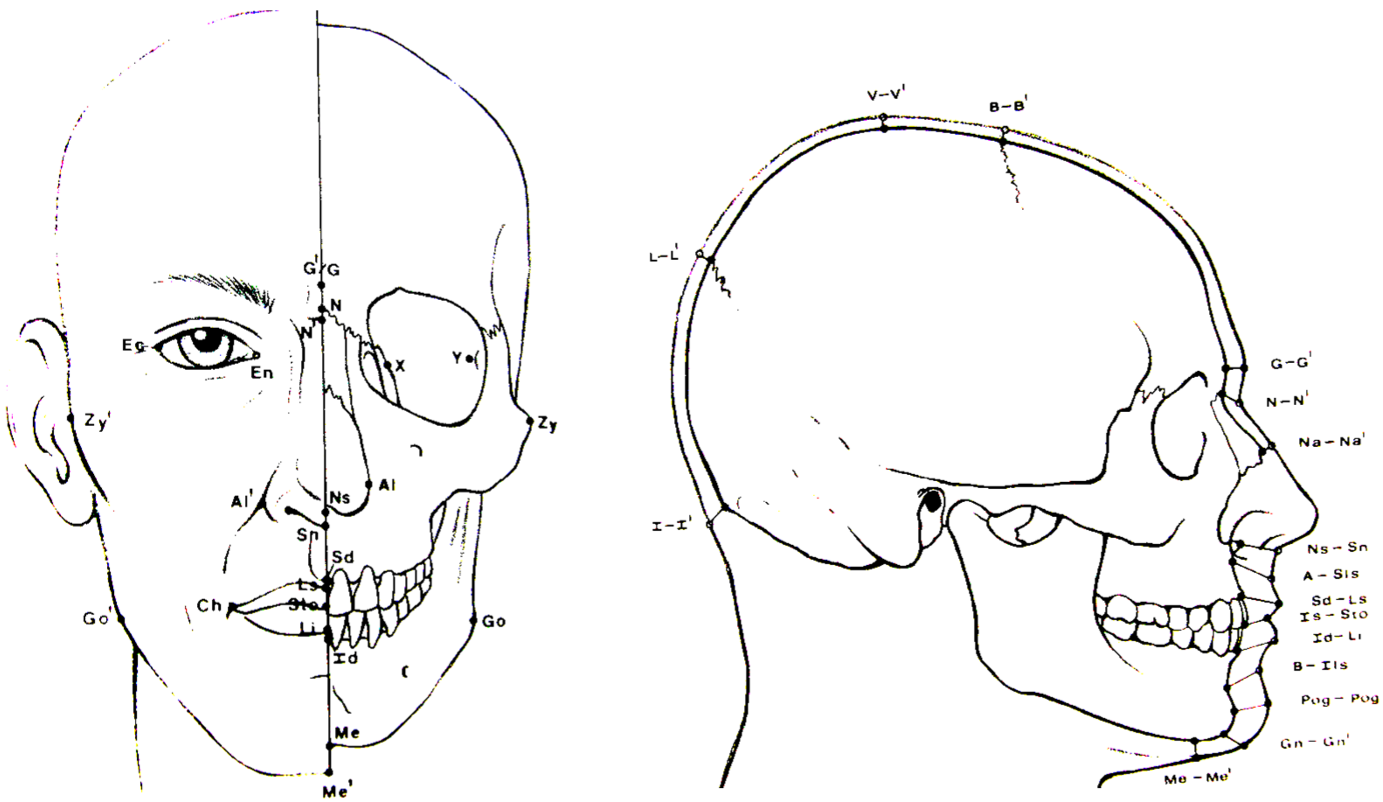
OVERVIEW



Craniometric landmarks



Cephalometric landmarks



Landmarks correlation

Real case example

OVERVIEW

1. Forensic identification by craniofacial superimposition
Methodology

OVERVIEW

1. Forensic identification by craniofacial superimposition (CS)

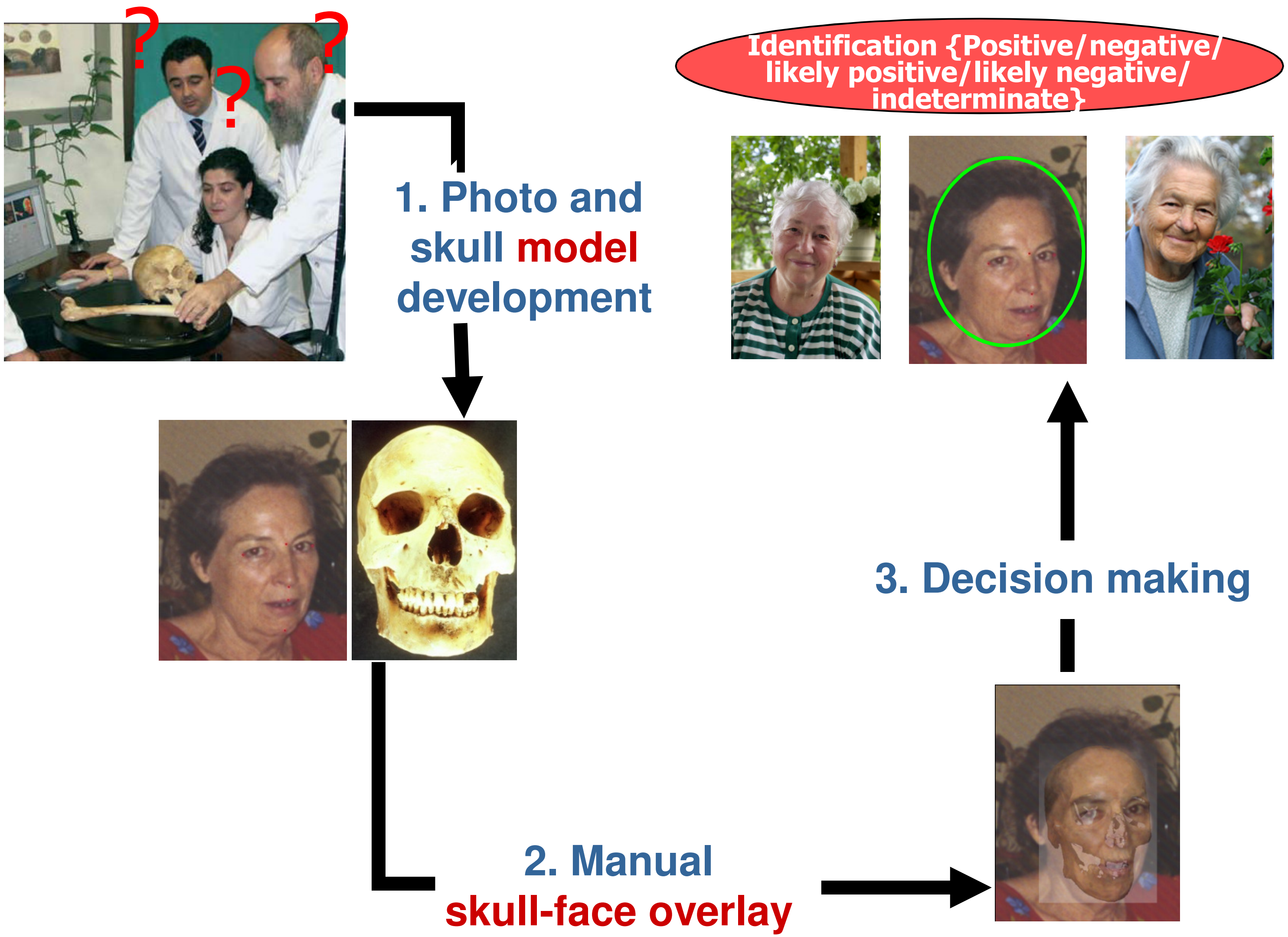
2. CS, Uncertainty and Image Registration = Soft Computing

3. First stage: 3D skull model reconstruction

4. Second stage: Skull-face overlay

5. Real cases

6. Conclusions



Framework

OVERVIEW

- 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 !

Image registration (I)

OVERVIEW

- 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 (search for the optimal f)

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

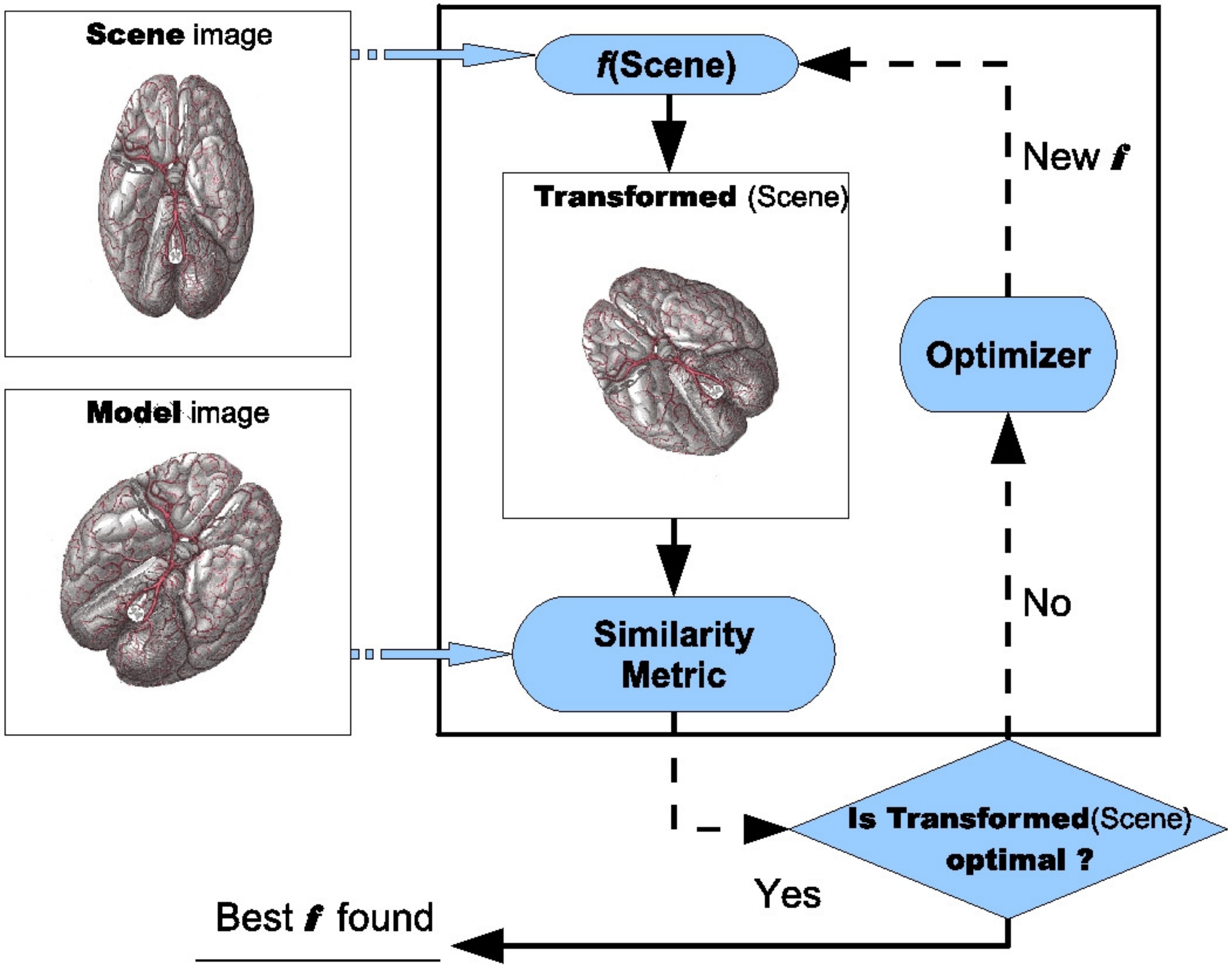
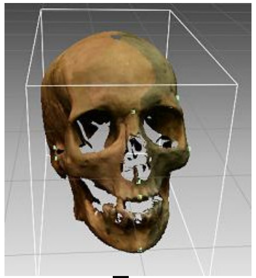


Image registration and craniofacial superimposition

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



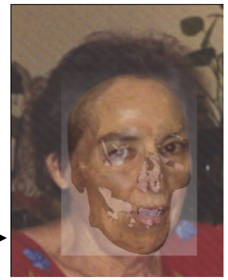
3D model reconstruction

Image processing and landmark location

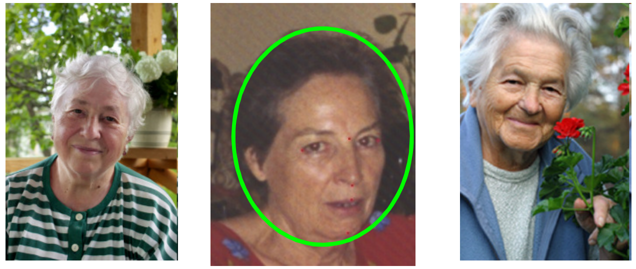
3D-2D IR: traslation, rotation, scaling, and 2D projection

2. Automatic skull-face overlay

2. Manual skull-face overlay



3. Decision making



Identification {Positive/negative/ likely positive/likely negative/ indeterminate}

Research project to automate forensic identification by CS

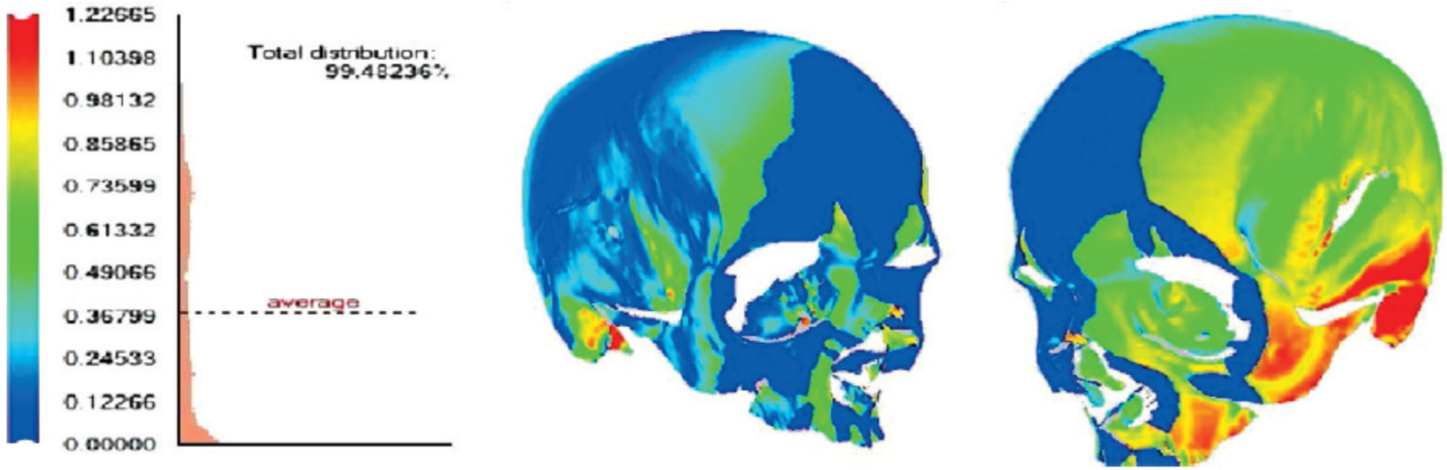
OVERVIEW

- 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

OVERVIEW

- Reconstruction error: less than 1 mm
- 3D reconstruction time: 2 minutes
- Method robustness: low standard deviation in 30 different runs with extreme conditions



Problem issues, requirements and tools

OVERVIEW

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

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

Search for the best superimposition (Evolutionary algorithm)

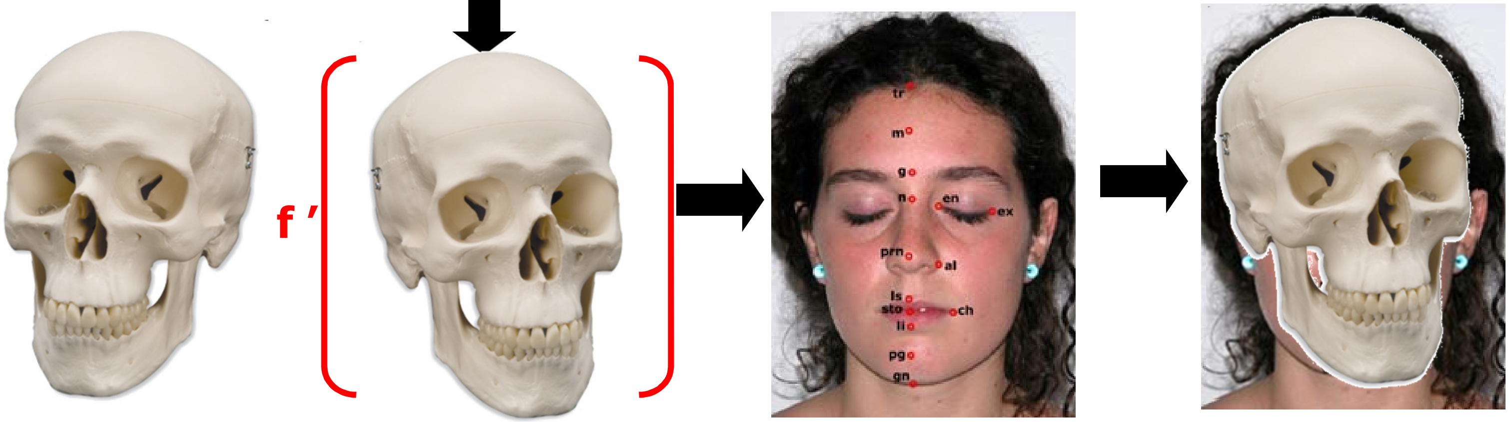
Registration error

f ´ ≅ f *

f ′ evaluation

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

Distance measuring between every pair of landmarks



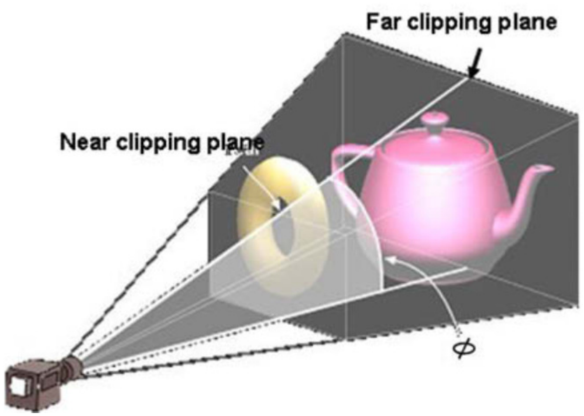
Our proposal

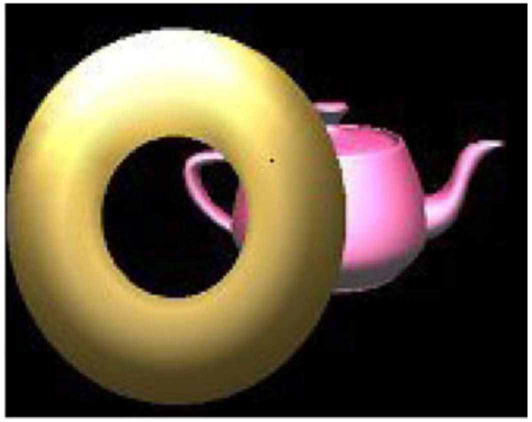
OVERVIEW

- 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)

- 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

New proposal: registration transformation (IV)

- Thus, our coding scheme is a vector of 12 real values:

$$\underbrace{r_x \; r_y \; r_z \; d_x \; d_y \; d_z \; \theta}_{\text{Rotation}} \; \underset{\text{Scaling}}{s} \; \underbrace{t_x \; t_y \; t_z}_{\text{Translation}} \; \underset{\text{Projection}}{\phi}$$

ranging in the following intervals:

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

where:

$radius = \max(\|Centroid - C_j\|)$

FB is the frustum Base

$$length_{FB} = \frac{(\min_{FD} + FCP) * \sin\left(\frac{\phi_{max}}{2}\right)}{\sin\left(90^\circ - \left(\frac{\phi_{max}}{2}\right)\right)}$$

with FD being the Focal Distance and

$$\min_{FD} = \frac{1}{\tan\left(\frac{\phi_{max}}{2}\right)}$$

Kinds of uncertainty in skull-face overlay (I)

OVERVIEW

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

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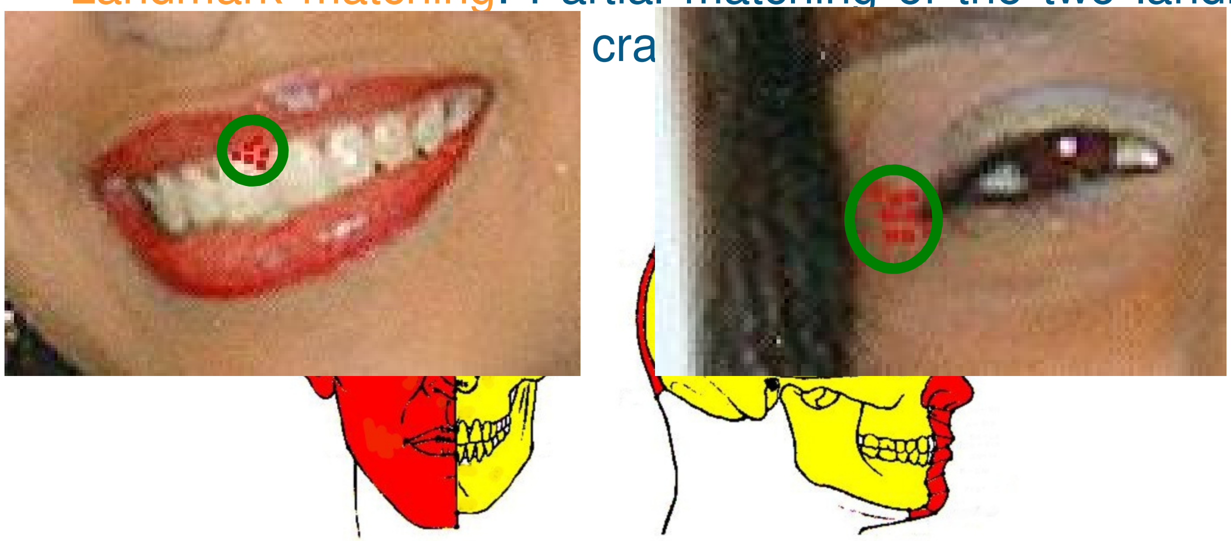


OVERVIEW

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

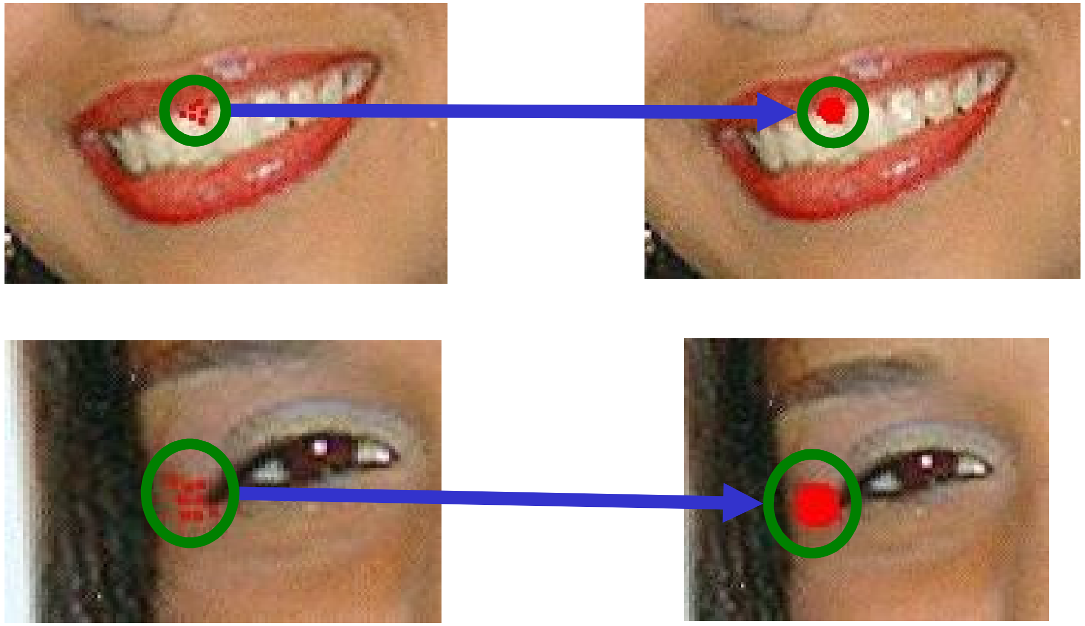
- Landmark location: Difficulty to select a good (cephalometric) landmark set due to the photo conditions:
  - face pose, partial occlusions, and poor image quality
  - forensic anthropologists are prone to locate only those landmarks which can be unquestionably identified!
- Landmark matching: The selected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

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

- 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

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

OVERVIEW



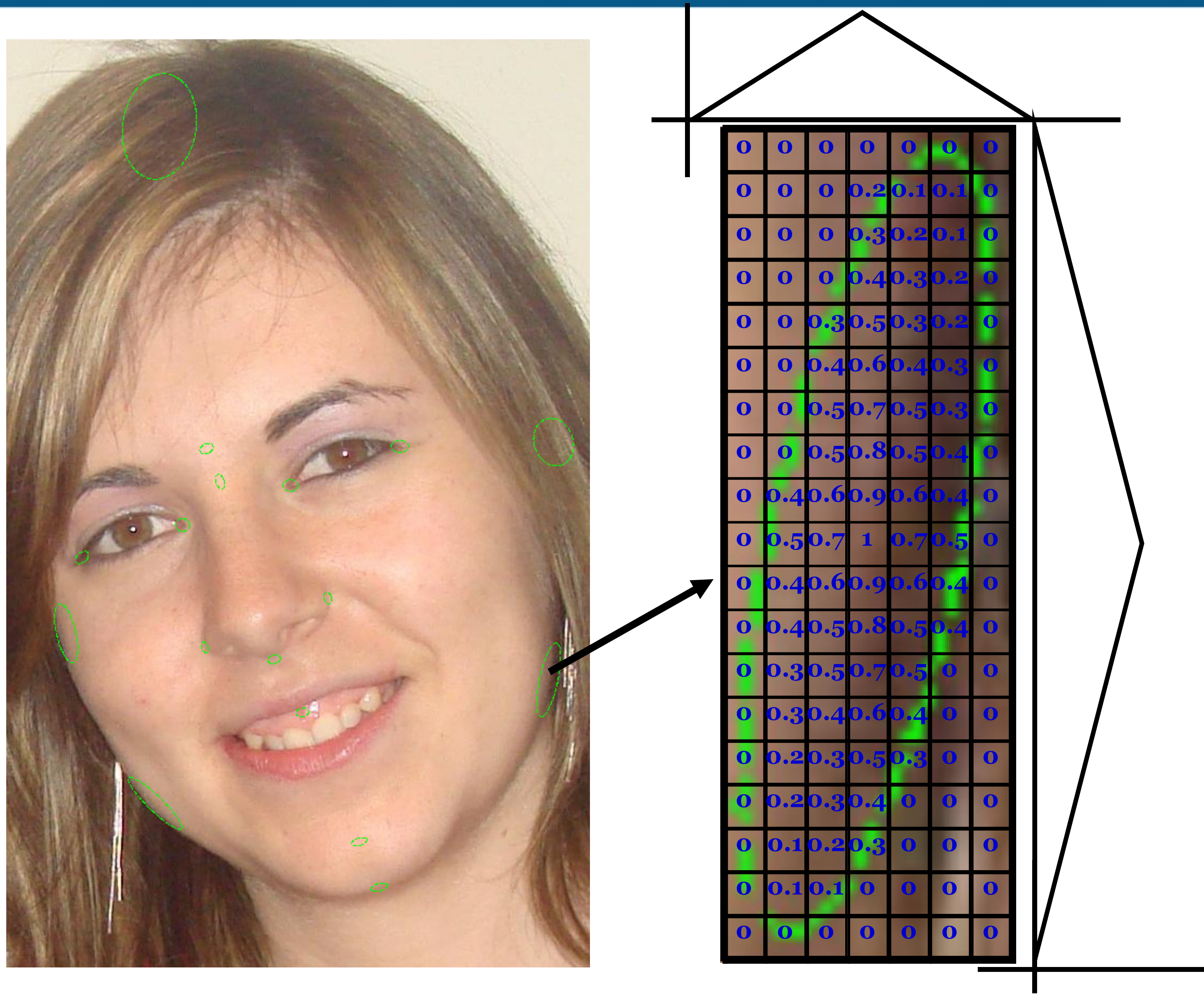
- There is a mask with the membership degree of each pixel to the fuzzy point associated to every landmark

- Need of a new fuzzy fitness function considering a distance between crisp and fuzzy points

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

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

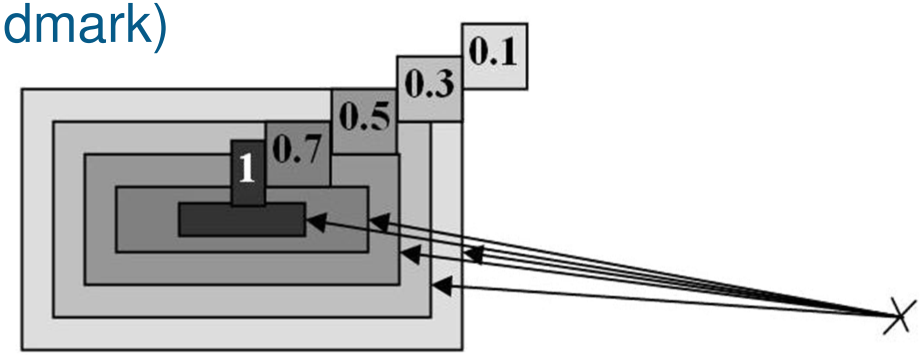


0	0	0	0	0	0	0
0	0	0	0.2	0.1	0.1	0
0	0	0	0.3	0.2	0.1	0
0	0	0	0.4	0.3	0.2	0
0	0	0.3	0.5	0.3	0.2	0
0	0	0.4	0.6	0.4	0.3	0
0	0	0.5	0.7	0.5	0.3	0
0	0	0.5	0.8	0.5	0.4	0
0	0.4	0.6	0.9	0.6	0.4	0
0	0.5	0.7	1	0.7	0.5	0
0	0.4	0.6	0.9	0.6	0.4	0
0	0.4	0.5	0.8	0.5	0.4	0
0	0.3	0.5	0.7	0.5	0	0
0	0.3	0.4	0.6	0.4	0	0
0	0.2	0.3	0.5	0.3	0	0
0	0.2	0.3	0.4	0	0	0
0	0.1	0.2	0.3	0	0	0
0	0.1	0.1	0	0	0	0
0	0	0	0	0	0	0

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

OVERVIEW

- α-cuts to calculate the distance from a crisp point (projected craniometric landmark) to a fuzzy point (cephalometric landmark)



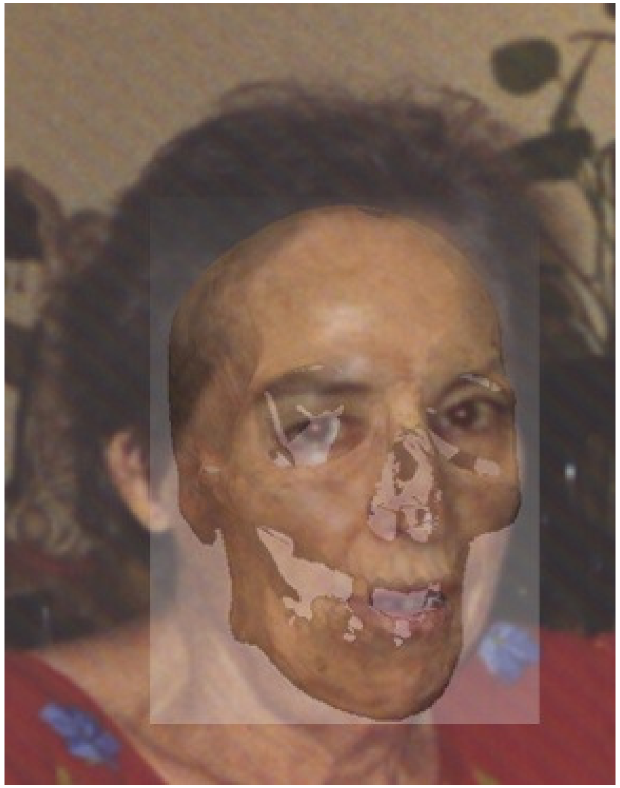
- Crisp-fuzzy distance and new fitness function:

$$d^*(x, \widetilde{F}) = \frac{\sum_{i=1}^{m} d_i \cdot \alpha_i}{\sum_{i=1}^{m} \alpha_i}$$

$$\mathit{fuzzy\ ME} = \frac{\sum_{i=1}^{N} d^*(f(cl^i), \widetilde{F}^i)}{N}$$

OVERVIEW

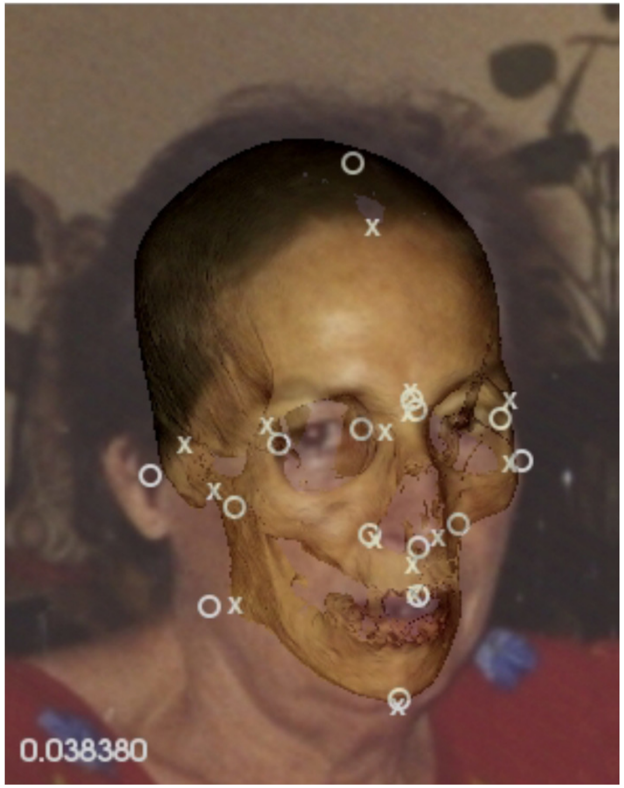
Manual



Area deviation error: 34.70%

several hours

Fuzzy AE



Area deviation error: 13.23%

2-4 minutes

OVERVIEW

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**

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

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**

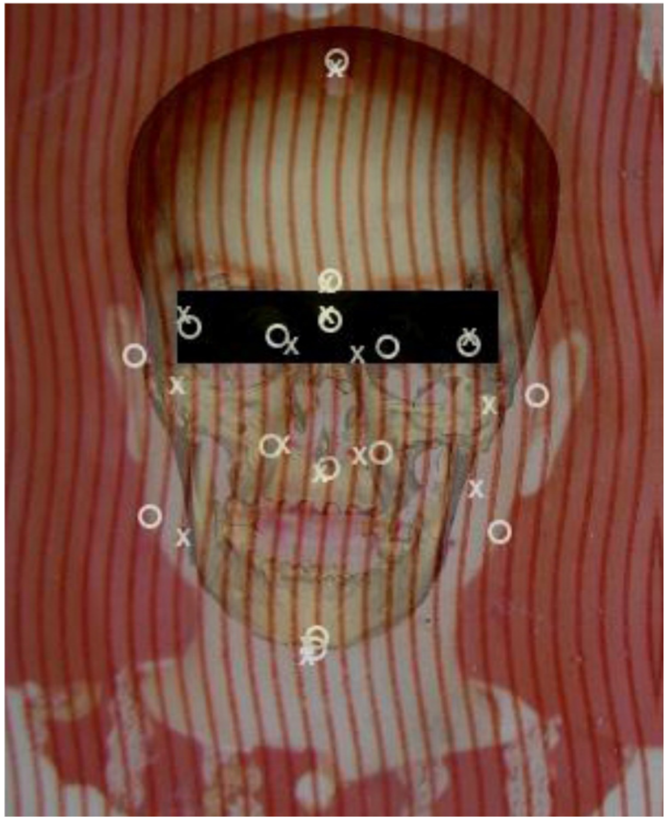
OVERVIEW

Manual

Area deviation error: 31.73%

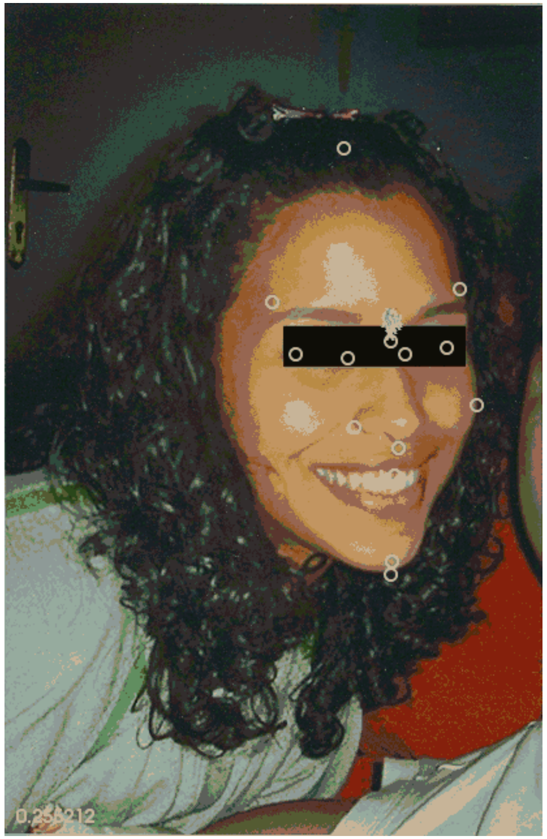
several hours

Fuzzy AE

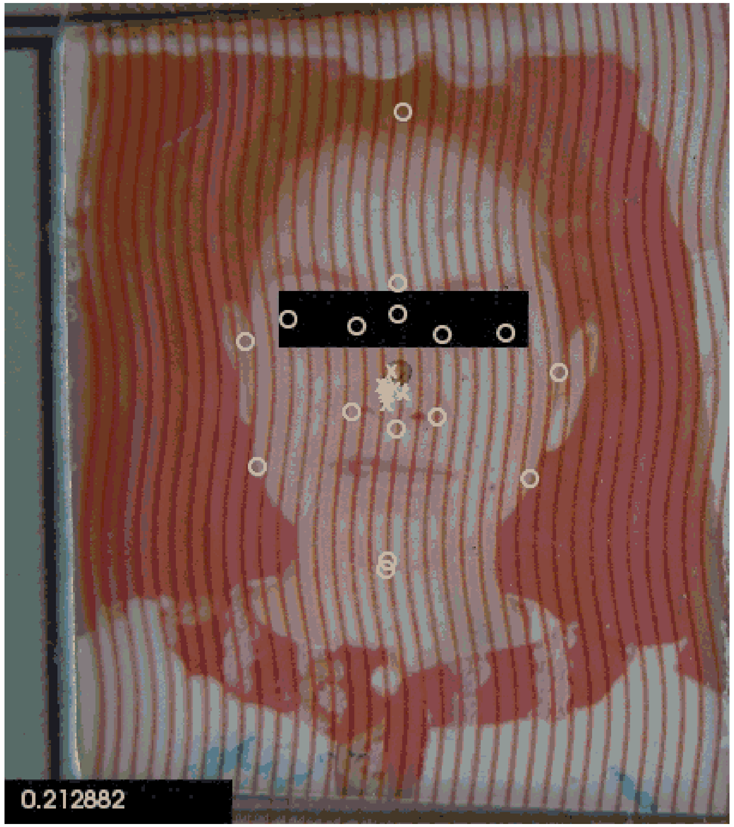


Area deviation error: 11.92%

2-4 minutes




0.306441


0.212882

OVERVIEW

Manual

Area deviation error: 37.54%

several hours

Fuzzy AE

Area deviation error: 21.04%

2-4 minutes

6. Conclusions

OVERVIEW

- 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

Obtained results (I)

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€)
- An European project: MEPROCS (2012-13). FP7-SEC-2011-285624 (Topic SEC-2011.1.4-3 - Advanced forensic framework - CSA). 1.005.000€ (218.280€ for ECSC)

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

Obtained results (III)

OVERVIEW

PhD Dissertations:

- Dr. José Santamaría. University of Granada. Spain. Dec. 2006
- 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

Publications in SCI-JCR journals: Methodology:

- S. Damas, O. Cordón, O. Ibáñez, J. Santamaría, I. Alemán, M. Botella, F. Navarro. Forensic identification by computer-aided craniofacial superimposition: A survey. ACM Computing Surveys 43:4 (2011). FI 2010: 7.806. Cat: CS, Th&M. O: 1/84. **Q1**

Publications in SCI-JCR journals: First stage:

- J. Santamaría, O. Cordón, S. Damas, I. Alemán, M. Botella. A Scatter Search-based Technique for Pair-Wise 3D Image Registration in Forensic Anthropology. Soft Computing 11:9 (2007) 819-828. FI: 0.607. Cat: CS, AI. O: 66/93. Q3
- J. Santamaría, O. Cordón, S. Damas, J.M. García-Torres, A. Quirin. Performance Evaluation of Memetic Approaches in 3D Reconstruction of Forensic Objects. Soft Computing 13:8-9 (2009) 883-904. FI: 1.328. Cat: CS, IS. O: 41/95. Q2
- J. Santamaría, O. Cordón, S. Damas. A comparative study of state-of-the-art evolutionary image registration methods for 3D modeling. Computer Vision and Image Understanding 115:9 (2011) 1340-1354. FI 2010: 2.404. Cat: E, E&E. O: 26/247. **Q1**

Publications in SCI-JCR journals: Second stage:

- O. Ibáñez, L. Ballerini, O. Cordón, S. Damas, J. Santamaría. An experimental study on the applicability of evolutionary algorithms to craniofacial superimposition in forensic identification. Information Sciences 179:23 (2009) 3998-4028. FI: 3.291. Cat: CS, IS. O: 6/116. **Q1**

- O. Ibáñez, O. Cordón, S. Damas, J. Santamaría. Modeling the skull-face overlay uncertainty using fuzzy sets. IEEE Transactions on Fuzzy Systems 19:5 (2011) 946–959. FI 2010: 2.683. Cat: E, E&E. O: 15/247. **Q1**

- O. Ibáñez, O. Cordón, S. Damas, J. Santamaría. An advanced scatter search design for skull-face overlay in craniofacial superimposition. Expert Systems with Applications 39:1 (2012) 1459–1473. FI 2010: 1.924. Cat: OR&MS. O: 15/74. **Q1**

- O. Ibáñez, O. Cordón, S. Damas, J. Santamaría. A cooperative coevolutionary approach dealing with the skull–face overlay uncertainty in forensic identification by craniofacial superimposition. Soft Computing (2012), in press. FI 2010: 1.512. Cat: CS, AI. O: 47/108. Q2

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

Research team

OVERVIEW

Dr. Oscar Cordón
UGR Professor
ECSC Scientific Consultant

Dr. Sergio Damas
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ECSC Postdoctoral Researcher

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Dr. Inmaculada Alemán
Physical Anthropology Lab
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Dr. Fernando Navarro
Physical Anthropology Lab
University of Granada

Outline

1. Hybridizations of Fuzzy Sets/Systems and Evolutionary Algorithms
2. Fuzzy Classifier Ensembles Designed with Multiobjective Evolutionary Algorithms
3. Body Posture Recognition by means of a Genetic Fuzzy Finite State Machine
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

ESTYLF Valladolid 2012

XVI CONGRESO ESPAÑOL SOBRE TECNOLOGÍAS Y LÓGICA FUZZY

ugr Universidad de Granada

European Centre for Soft Computing

Thank you for your attention

Questions?