Preliminar experiments on automatic gender recognition based on online capital letters

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Outline

- Introduction
- Human classification accuracy
- Proposed system

Gender classification

- Introduction
- State-of-the-art
- Human classification accuracy vs. Proposed system
- Future applications

Author(s) and reference	Year	Trait	Approaches	# of users	BestreportedAccuracies
Rojas et al. [1]	2011	face	SVMs, Neural Networks, ADABOOST, PCA+LDA, SIFT (BOW, EvidenceRandomTrees, NBNN and VotedNearest-Neighbor)	411 frontal imagesfrom gray FERET (304 for training + 107 fortesting)	EER= 9.7% ± 2.7%
Ramesha et al. [2]	2009	face	Posteriori classprobabilityclassifier	40 male + 18 female (¿? For training + ¿¿ fortesting)	95%
Mäkinen et al. [3]	2008	face	Multilayer neural network, SVM, adaboost	450 males + 450 femalesfrom FERET (80% for training + 20% fortesting)	90%
Hyun-Chulet al. [4]	2006	face	Gaussianprocessclassifiers (variant of Bayesiankernelclassifiers)	53 males + 50 women, 17 images per person (PF01 database) and 70 males + 56 females (4000 imagesfrom AR database)	Error > 5%
Alexandre [5]	2010	face	Shape, texture and plainintensityfeatures gathered at differentscales	Same as [3] and 487imagesfrom UND database (130 images of eachgenderfor training + 56 female and 171 maleimagesfortesting	90%
Tolba [6]	2001	face	LVQ, RBF	171 imagesfrom 13 females and 36 males (training: 69 faceimages (27 imagesfrom 9females and 42 imagesfrom 13 males) + testing: 102 images (28 imagesfrom 13 females + 74 imagesfrom 36 males)	100%
Guo [7]	2009	face	Local binarypattern (LBP)and histograms of orientedgradients (HOG)	YGA database (4000 males + 4000 females)	92.25%
Shan[8]	2012	face	Local BinaryPatterns + Adaboost, SVM	Labeled Faces in the Wilddatabase, 7,443 faceimages (2,943 females and4,500 males)5-fold cross-validation	94.81%
Castrillón et al. [9]	2010	face	PCA, LBP + SVM	5847 heterogeneousfaceimages(3380 correspondingtomale and 2467 tofemale) takenfromInternet and personal archives	87.5%
Bekios et al. [10]	2011	face	SVM, boosting	Severaldatabases, includingsameconditions as [3]	93.57%
Duan at al. [11]	2010	face	block-based color andedgefeatures + Adaboost	469 testing faces (210 male + 259 female)	87.63%
Fellous [12]	1997	face	Fiducialpoints + discriminantfunctions	109 imagestraining: 26 males + 26 females. Testing: 26 females + 31 males.	90%
Lapedriza et al. [13]	2006	face	Adaboost, Jointboosting	FRGC database3440 controlledimagesand1886clutteredimages.10-fold crossvalidation test	96.77% controlled 91.72% uncontrolled
Li [14]	2010	Face + fingerprint	DiscriminativeLatentDirichletAllocation	197 females and 201 males. Testing: 50 males + 50 females	80% fingerprint 92% face 95% combined
Li [15]	2012	Clothing +Hair +Face	Local binatrypatterns + SVM	FERET: 227 training + 114 testing BCMI: 821 training + 274 testing	73% Clothing 80.6% Hair 88.6% Face 95.8%combined
Zhang et al. [16]	2008	Face + gait	PCA + SVM	32 male+ 28 female. Leave-one-out. Onepersonchosen as probe data in turn and alltheotheras gallery data	90% face 90% gait 90% combined
Kos et al. [17]	2011	Speech	Average MFCC+GMM	36 hours of speech of labeledspeech	91.76%
Nguyen et al. [18]	2011	Speech	MFCC+F0+ZCR+E+HNR+SVM-RBF	54 male 54 female 10-fold crossvalidation	100%
Yingle et al. [19]		Speech	3D features +Backpropagation neural network	20 male 20 female	85.2% forisolatedwords 90.9%forcontinousspeech
Ting et al. [20]		Speech	MFCC+pitch+GMM	20 male 20 female	96.7%

Ichino et al. [21]		Speech	MFCC+pitch+Adaboost	40 speakers	98.6%
[22]		Speech	A combination of acoustic parameters, including MFCC, pitch, formants, harmonic structure	472 speakers, 32527 utterancesfor training 300 speakers, 20549 utterancesforvalidation 17332 utterancesfortesting	TBA
[23]		Speech	A combination of acousticparameters, including HFCC, ACW SVM wasused as a classifier	TBA	TBA
Davis et al. [24]	2004	Gait	Threemode PCA	40 people (20 male + 20 female). Leaveone-outcross-validation	90%
Livne et al. [25]	2012	Gait	Modifiedversion of anAnnealedParticleFilter (APF)	46 mocapsequences(2 walks/subject), and 86 pose trajectoriesfrom video tracking (2 tracking trials per sequence), 24 test subjects	93%
Amayeh et al. [26]	2008	Hand	region and boundaryfeaturesbasedonZernikemoments and Fourier descriptors + LDA	20 males + 20 females. Leave-one-outcross-validation.	98%
Wang et al. [x]	2010	Hand	33 features (25 fingerwidthsamples, 2 palmmeasurements, 3 fingerlength ratios), normalizedsize of images, SVM-RBF	85 males + 90 females. (125 training + 50 validation) 10 round cross-validation	72%
Font et al. [x2]	2012	Hand	39 anthropometricfeatures of hand, BiometricDispersionMethod	104 people (68% male, 32% female), 1040 images (10 forperson), training – 36 male(284 images) +19 female (132 images)	97.8%
Liwicki et al. [27]	2012	Online text	Gaussian mixture models	Training: 40 male + 40 female; validation: 10 male + 10 female; testing: 25 male+ 25 female	67.57%
Yuan et al. [28]	2010	footwear	Histogram of orientedgradient (HOG), PCA + SVM	100 male + 100 female (50% training + 50% testing)	85.49%
Collins et al. [29]	2009	Full body	HOG, Spatialpyramid bag of words + SVM	600 male + 288 female, 5 cross-folddivisions	80.62%
Zura et al. [30]	2010	Bodyradiation	Chakrapointsmeasurements	26 (14 male + 12 female)	statisticallysignificantdifferencebetweenmales and femalesoncombinedchakrasradiation

State-of-the-art

Authors	Accuracy	Online/off-line	Classification and experimental conditions	Population
[6]	73.2%	Off-line	Single neural network; CEDAR database, cursive letters	training set =800, testing set=400
[7]	67.06%	On-line	GMM, IAM-OnDB database, cursive letters	Training set =100 Testing set=50
[8]	64.25%	On-line	GMM, IAM-OnDB database, cursive letters	Training set =100 Testing set=50
Our approach	76%	On-line	SOM, BIOSECURID database	Training set = Testing set=

Gender classification: human performance

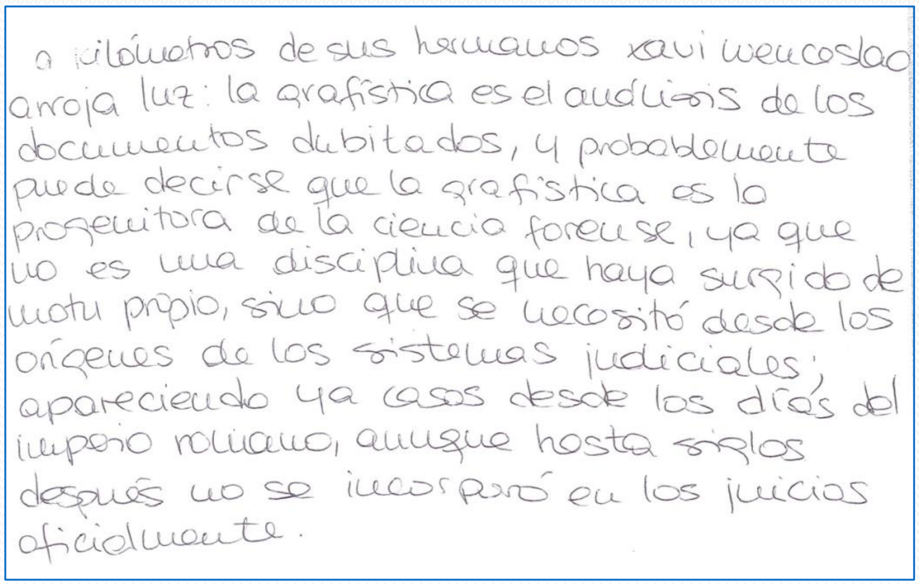
	Success rate males	Success rate females	Success rate average	Figure of merit
Range	[0,100%]	[0,100%]	[0,100%]	[-25, 25]
Expert 1	71,62%	61,02%	66.92%	3.72
Expert 2	71,62%	61,02%	66.92%	3.87
Amateur 1	52.70%	84.75%	66.92%	3.50
Amateur 2	67.58%	61.02%	64.66%	4.44
Amateur 3	85.14%	54.24%	71.43%	4.85

Ground truth: score for males =5, for females = -5
Manual score: [-5, 5]
Figure of merit: Ground truth x manual score

Handwriting: gender recognition

- Male or female?

1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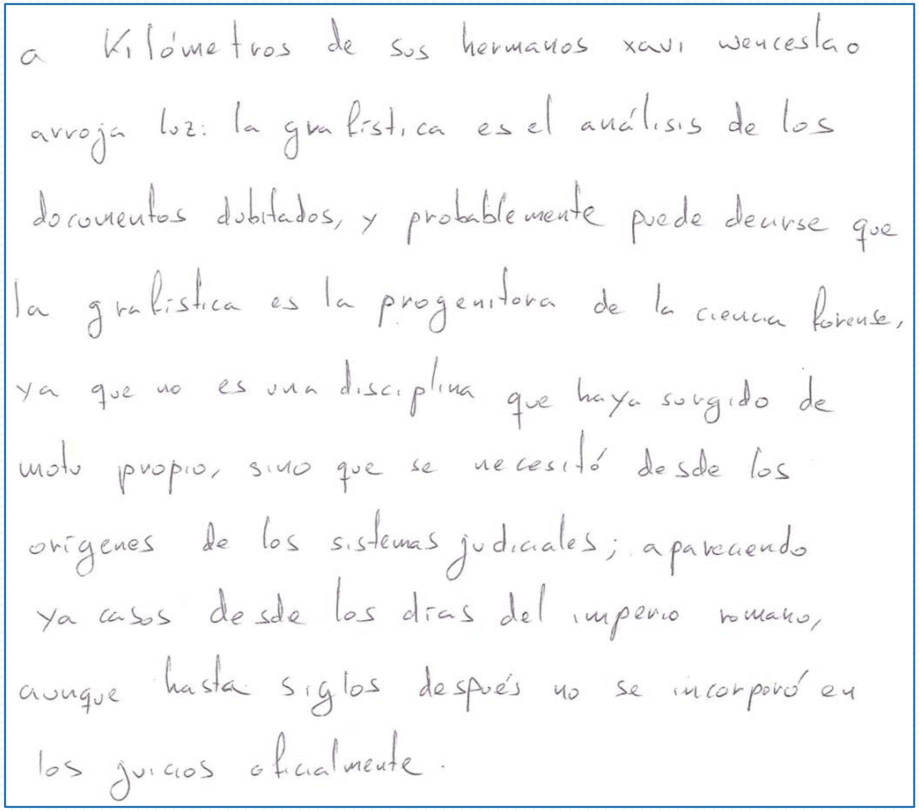
arroja luz: la grafística es el análisis de los
documentos dubitados, y probablemente
puede decirse que la grafística es la
progenitora de la ciencia forense, ya que
no es una disciplina que haya surgido de
motu propio, sino que se necesitó desde los
orígenes de los sistemas judiciales;
apareciendo ya casos desde los días del
imperio romano, aunque hasta siglos
después no se incorporó en los juicios
oficialmente.

2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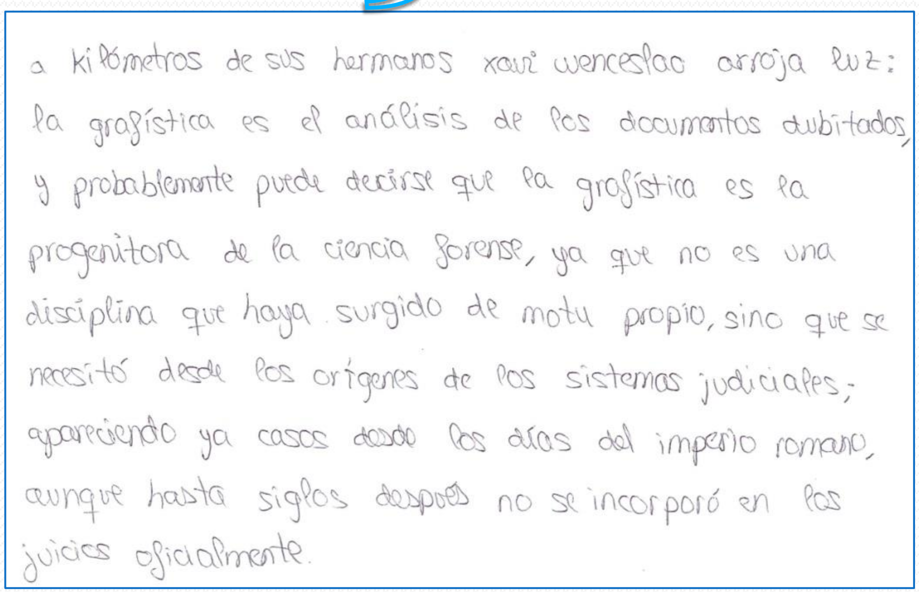
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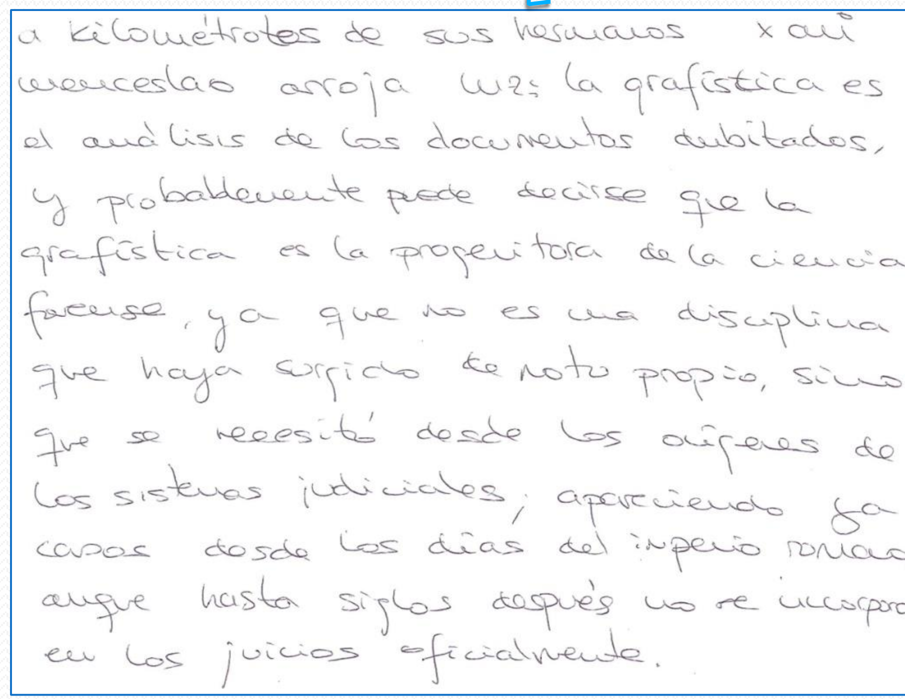
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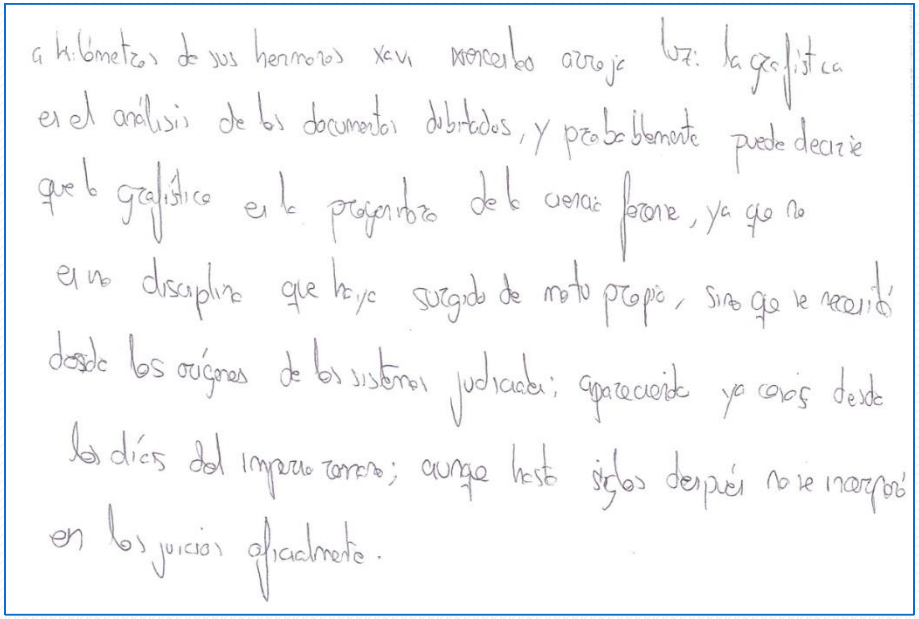

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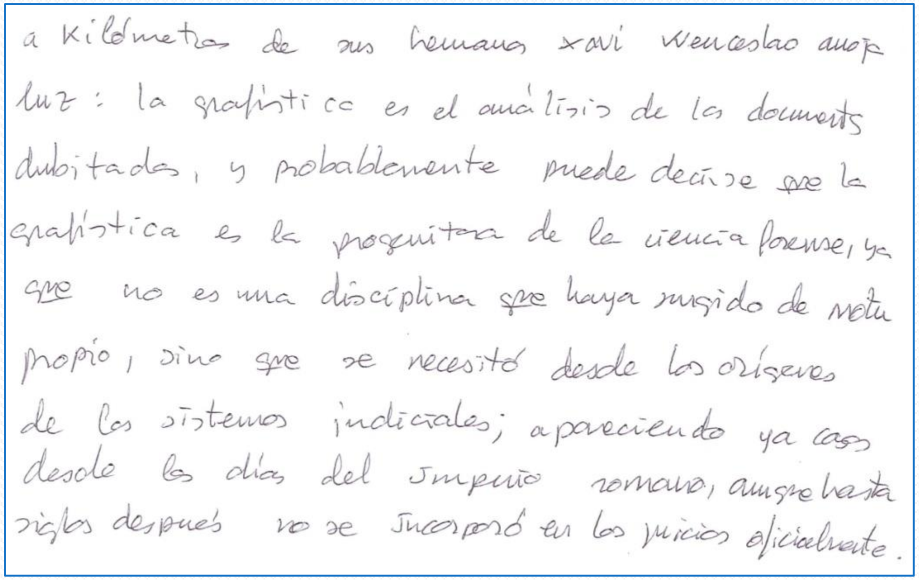
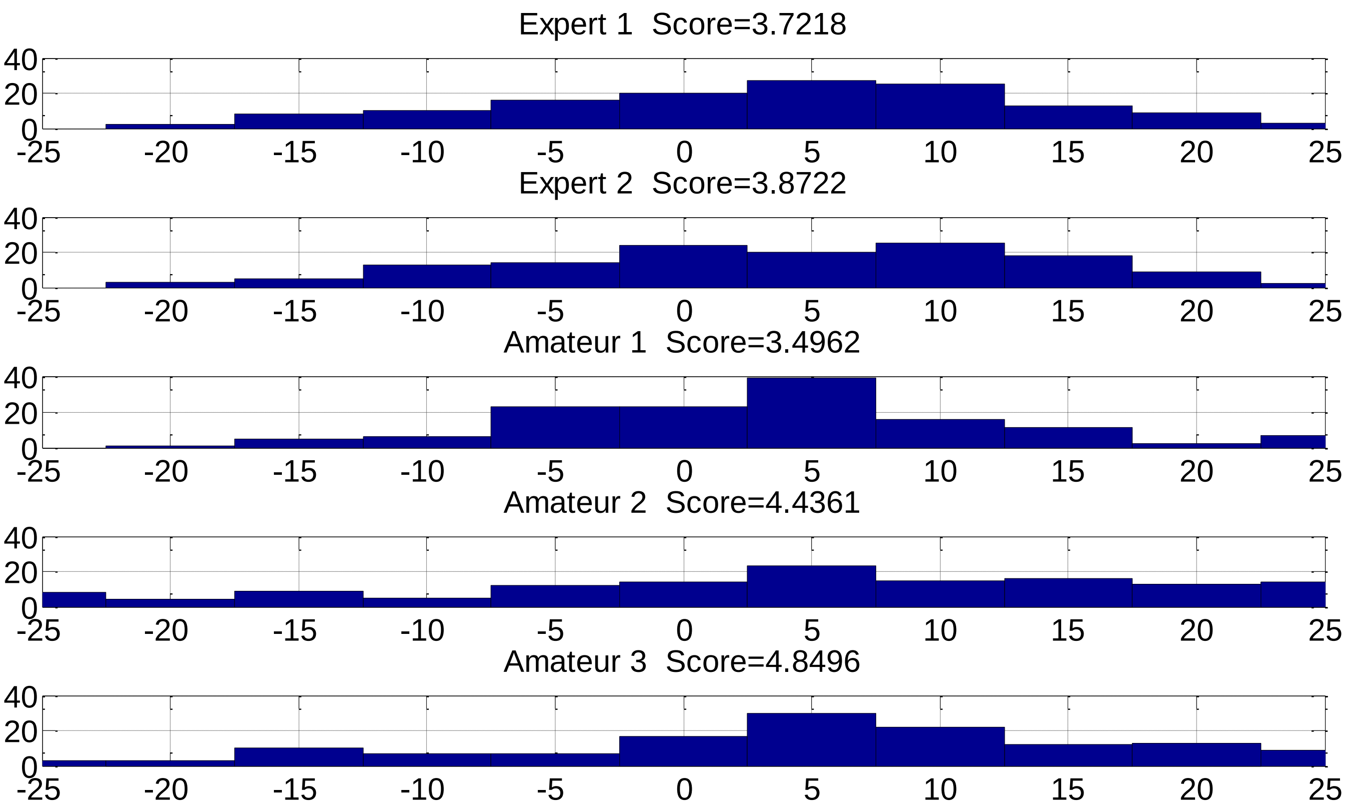
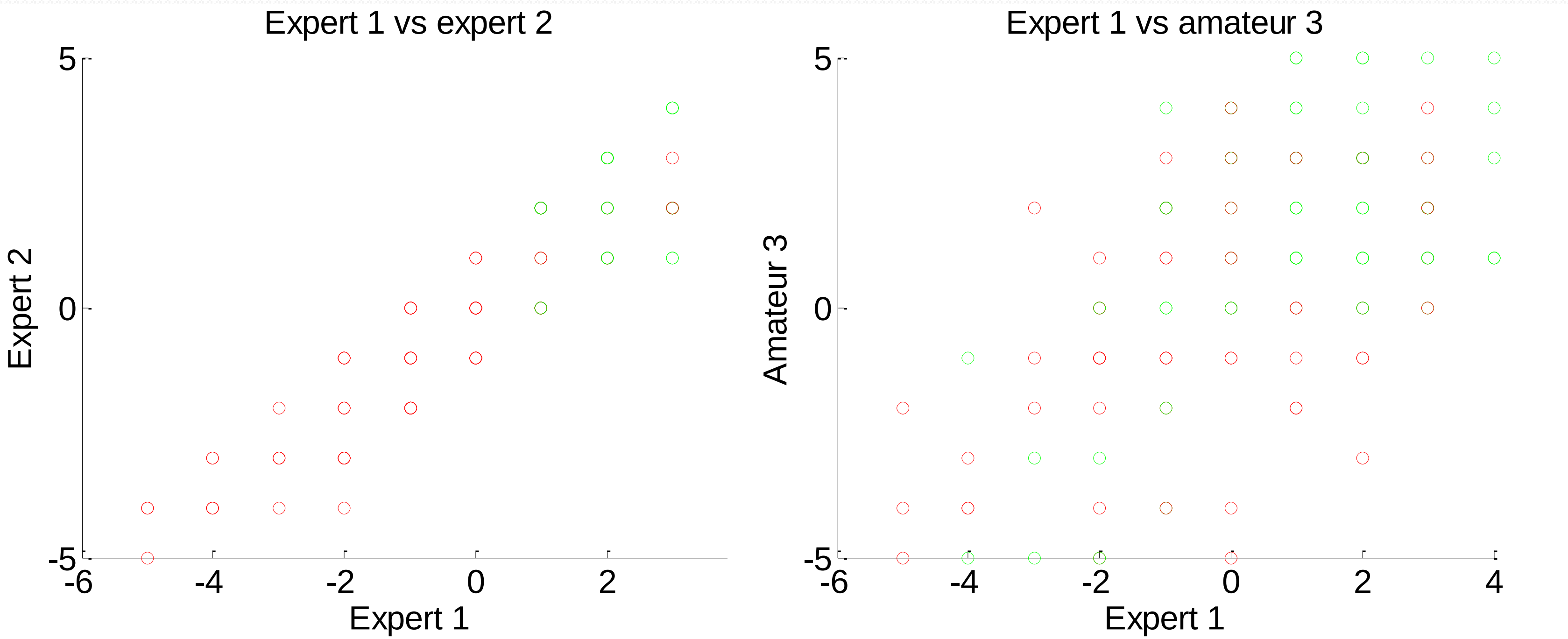


Clasificacion automatica vs manual

	Cursive letters					Capital letters				
			Identification rates					Identification rates		
classifier	FM	ρ	mean	male	female	FM	ρ	mean	male	female
machine						4,04	0,5033	76,00%	86,11%	62,26%
expert 1	4	0,3543	68,80%	72,22%	64,15%					
expert 2	4,2	0,3683	68,80%	72,22%	64,15%					
amateur 1	3,48	0,3969	68,00%	52,78%	88,68%	4,12	0,3792	66,40%	63,89%	69,81%
amateur 2	4,44	0,3100	64,80%	65,28%	64,15%	3,92	0,3316	60,00%	72,22%	43,40%
Amateur 3	5,28	0,3961	73,60%	84,72%	58,49%	6,12	0,3845	68,80%	77,78%	56,60%

Figure of merit for human classification




Expert 1 vs expert 2
Expert 2
Expert 1
5
0
-5
-6
-4
-2
0
2
Expert 1 vs amateur 3
Amateur 3
Expert 1
5
0
-5
-6
-4
-2
0
2
4

COST IC1206

De-identification for privacy protection in multimedia content

- De-identification in multimedia content can be defined as the process of concealing the identities of individuals captured in a given set of data (images, video, audio, text), for the purpose of protecting their privacy. This will provide an effective means for supporting the EU's Data Protection Directive (95/46/EC), which is concerned with the introduction of appropriate measures for the protection of personal data. The fact that a person can be identified by such features as face, voice, silhouette and gait, indicates the de-identification process as an interdisciplinary challenge, involving such scientific areas as image processing, speech analysis, video tracking and biometrics. This Action aims to facilitate coordinated interdisciplinary efforts (related to scientific, legal, ethical and societal aspects) in the introduction of person de-identification and reversible de-identification in multimedia content by networking relevant European experts and organizations.

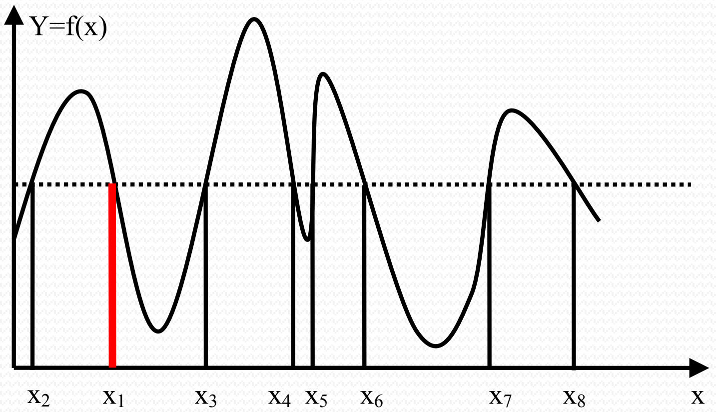
Security solutions

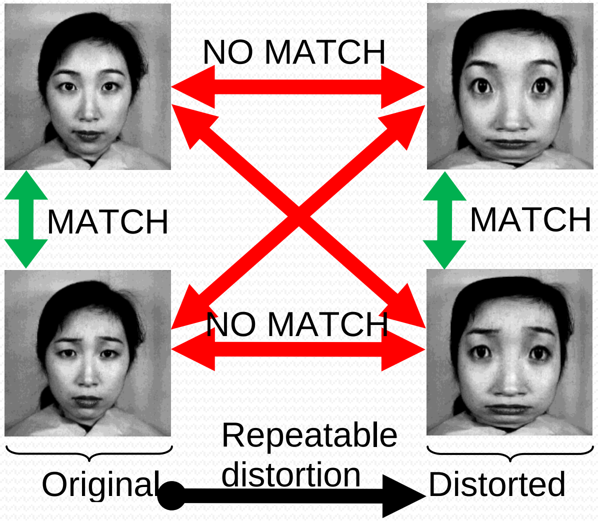
- Standard encryption techniques are not useful for securing biometric templates: While it is possible to decrypt the template and perform matching between the query and decrypted template, such an approach is not secure because it leaves the template exposed during every authentication attempt.
- The solutions proposed in the literature can be split into two categories :
  - Feature transformation.
  - Biometric Cryptosystems.

Feature transformation

A transformation function $Y = f(x)$ is applied to the biometric information and only the transformed template is stored in the database.

In salting $Y = f(x)$ is invertible. Thus, if a hacker knows the key and the transformed template, he can recover the original biometric template, and the security is based on the secrecy of the key or password. This is the unique approach that requires a secret information (key). This is not necessary in the other categories. The second group is based on noninvertible transformation systems. They apply a one-way function on the template and it is computationally hard to invert a transformed template even if the key (transform function) is known.





De-identification proposal for handwritten texts

- Transformation of X, Y coordinates, probably modifying the gender style.
- Reversible de-identification: invertible function
- Non reversible de-identification: non-invertible function