

Biometric recognition by means of online signature and handwriting

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Outline

- **Biometrics**
 - Definition & Comparison with classic systems
 - Main blocks
- **Signature**
 - Online/offline
 - Algorithms

Biometrics

- **Biometrics = “bios” (life) and “metrikos” (measure)**
- **Field of development of statistical and mathematical methods applicable to data analysis problems in the biological sciences.**

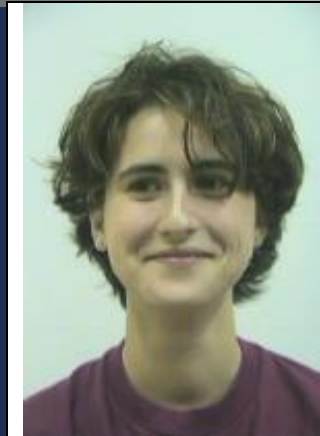
Biometrics: Applications

- Statistical methods for the analysis of data from agricultural field experiments to compare the yields of different varieties of wheat.
- Analysis of data from human clinical trials evaluating the relative effectiveness of competing therapies for disease.
- Security applications: analyze human characteristics for human verification or identification

Biometrics: security applications

Authentication method	Advantages	Drawbacks
Handheld tokens (card, ID, passport, etc.)	<ul style="list-style-type: none">▪ A new one can be issued.▪ It is quite standard, although moving to a different country, facility, etc.	<ul style="list-style-type: none">▪ It can be stolen.▪ A fake one can be issued.▪ It can be shared.▪ One person can be registered with different identities.
Knowledge based (password, PIN, etc.)	<ul style="list-style-type: none">▪ It is a simple and economical method.▪ If there are problems, it can be replaced by a new one quite easily.	<ul style="list-style-type: none">▪ It can be guessed or cracked.▪ Good passwords are difficult to remember.▪ It can be shared.▪ One person can be registered with different identities.
Biometrics	<ul style="list-style-type: none">▪ It cannot be lost, forgotten, guessed, stolen, shared, etc.▪ It is quite easy to check if one person has several identities.▪ It can provide a greater degree of security than the other ones.	<ul style="list-style-type: none">▪ In some cases a fake one can be issued.▪ It is neither replaceable nor secret.▪ If a person's biometric data is stolen, it is not possible to replace it.

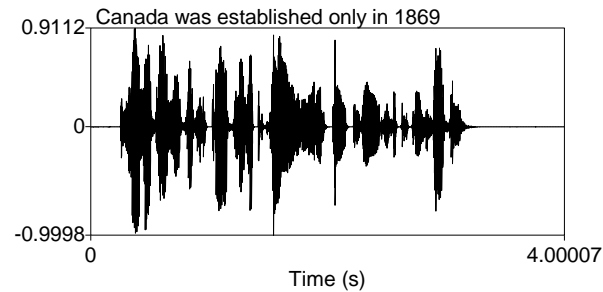
Biometric traits



Face acquired with digital camera



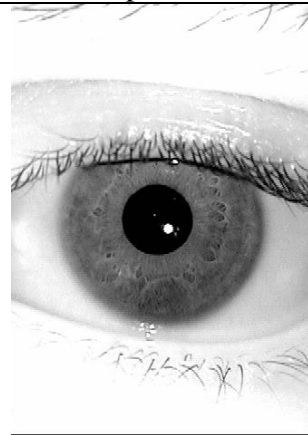
Fingerprint Acquired with optical sensor



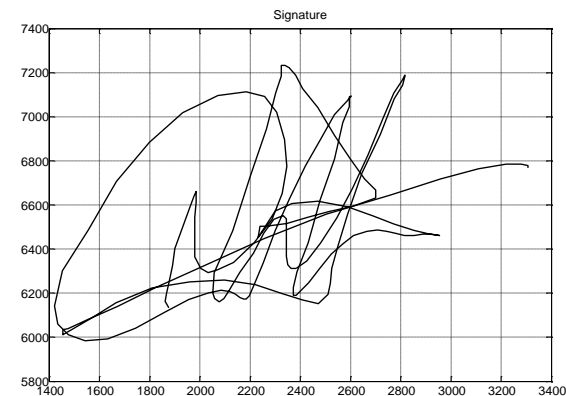
Speech
Acquired with a microphone



2D Hand geometry acquired with a document scanner

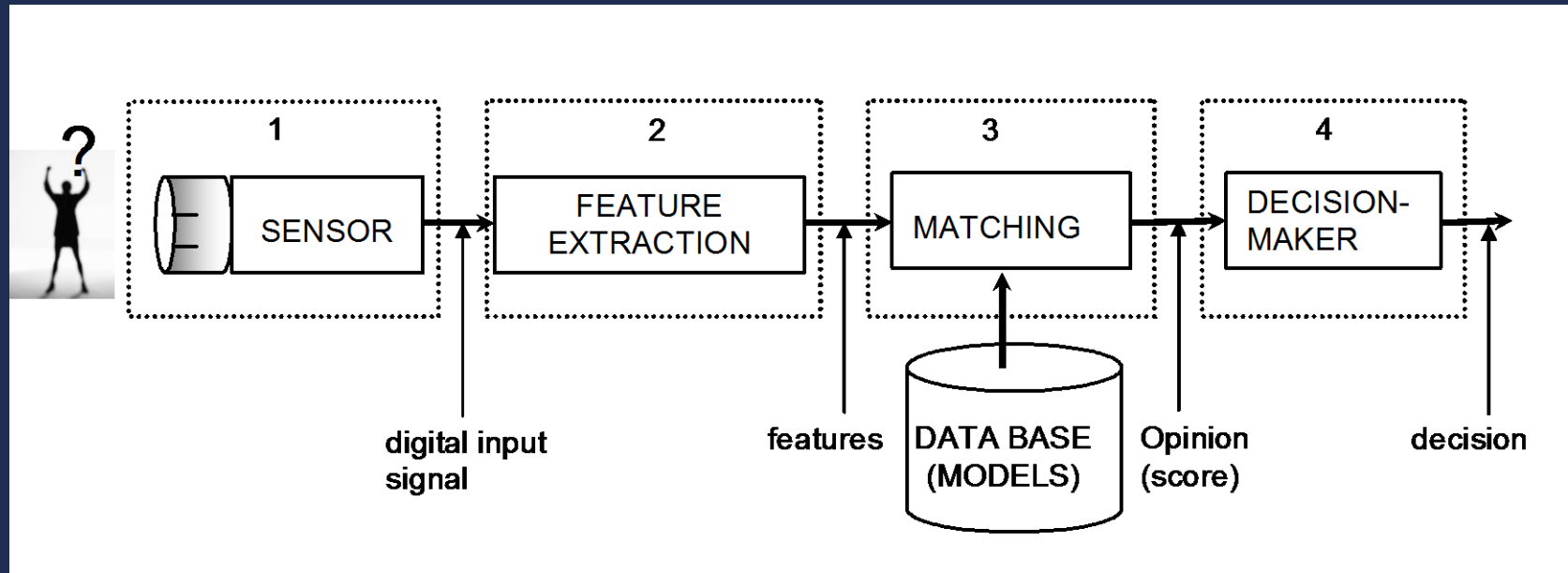


Iris acquired with a physical access device



Signature
Acquired with a graphics tablet

General Scheme for Biometric recognition



SENSOR

Biometric sensors



Webcam



Fingerprint optical scanner



Headset microphone for speech



3D Hand-geometry scanner



Iris Desktop camera

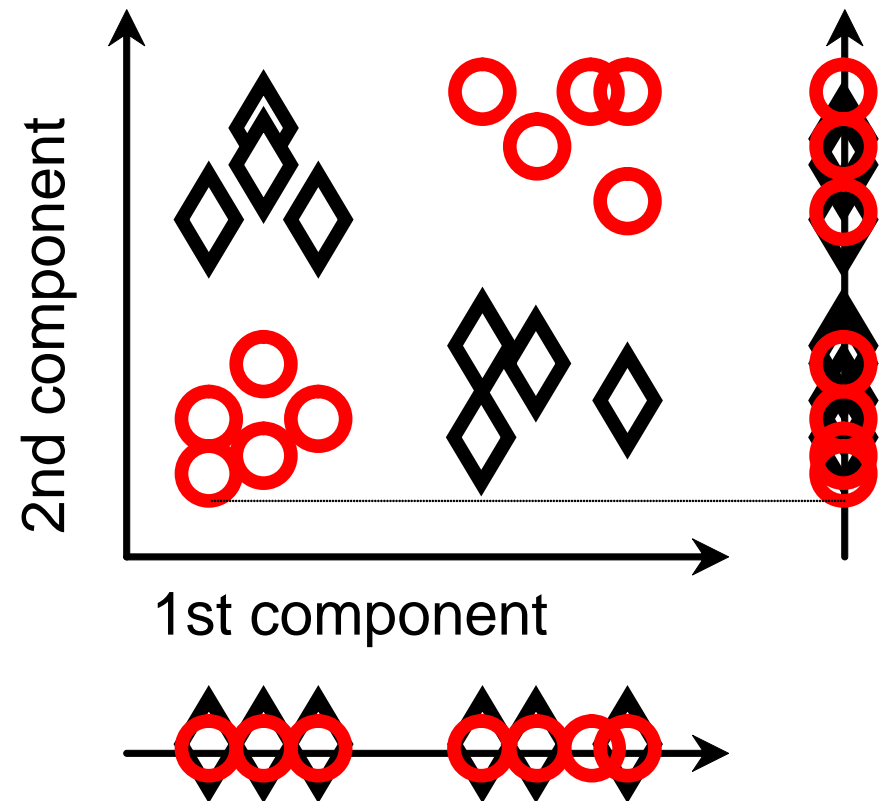
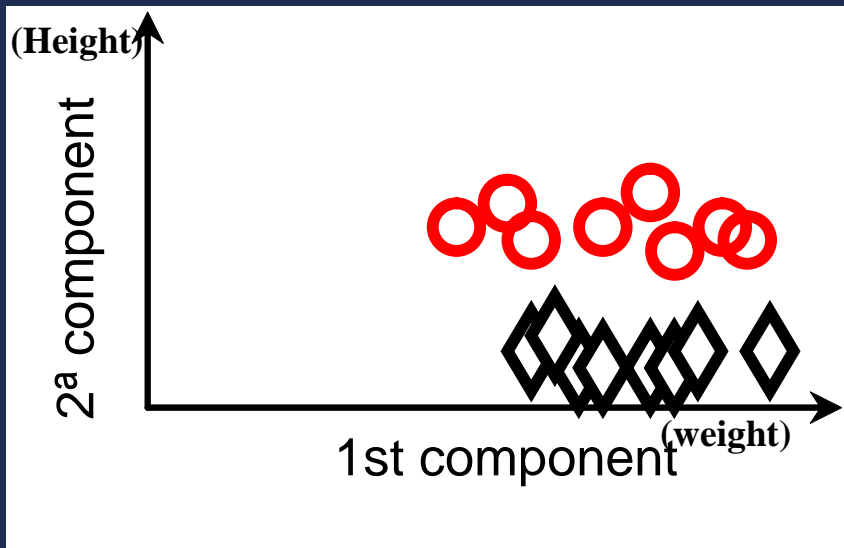


Graphics tablet for signature

FEATURE EXTRACTION

Feature extraction

- Feature selection



MATCHING

Biometrics vs. Passwords

- Password 1: RJ45tx
- Password 2: RJ46tx

- Face 1



- Face 2



Passwords must be identical

Biometric data won't be identical

Low computational burden algorithms?

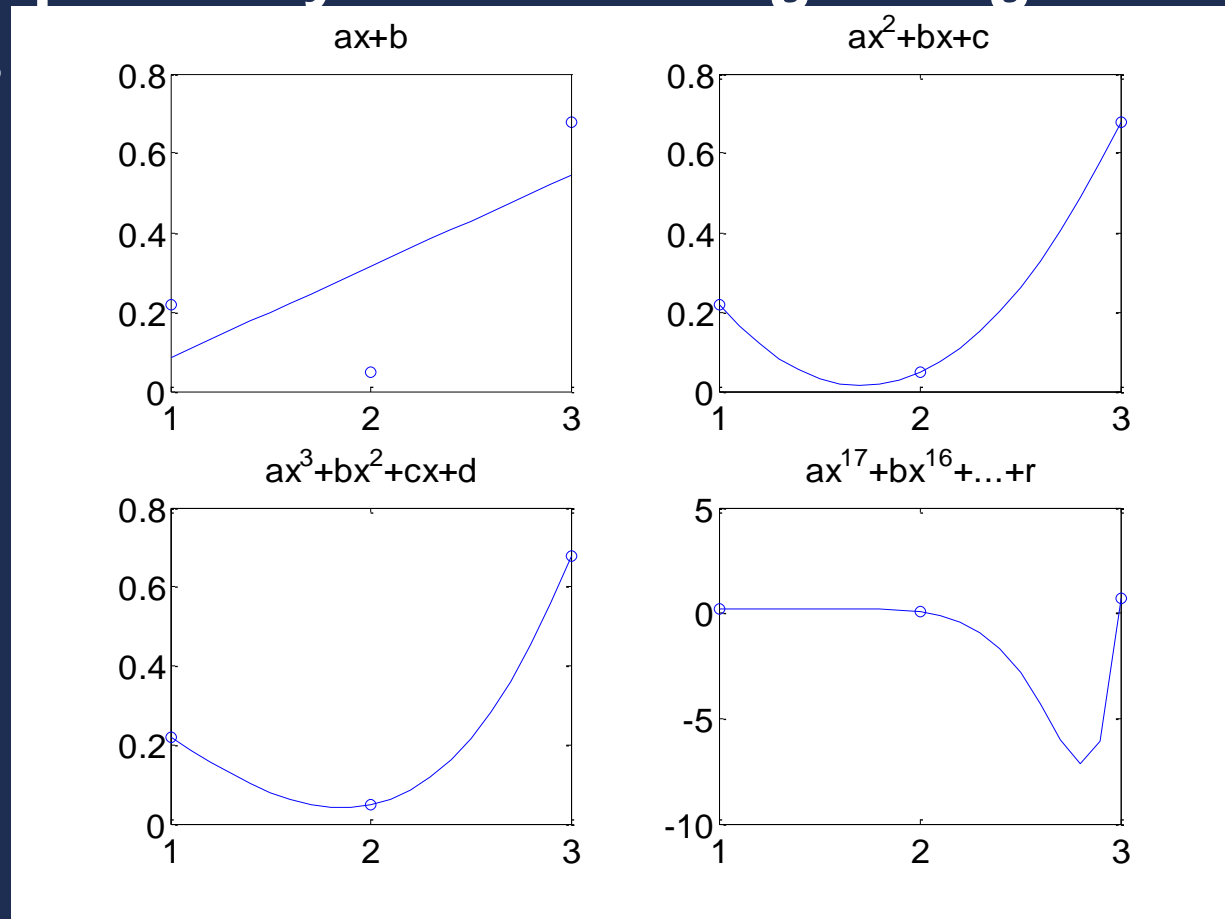
- **Cultural background:**
 - "Keep things simple!" **William of Occam**
 - "Make everything as simple as possible, but not simpler" **Albert Einstein**
- **Scientist/technician experience:**
 - Provide a very sophisticated and complicated paper plenty of mathematics and it will be accepted.

Pattern recognition

- **Example 1: OCR**
 - Few classes (p.e. 10 digits 0,1,..9).
 - Large amount of samples per class.
- **Example 2: Biometrics**
 - Large amount of classes (each person is one class).
 - Few amount of samples per class.

Low computational burden algorithms?

- Simple example: Polynomial fitting using three points



Training strategies (1/3)

- **Generative (informative):**
 - The classifier learns the class densities, examines the likelihood of each class to produce the measured features and assigns to the most likely class.
 - Because each class density is considered apart from the others, the model for each class is relatively easy to train. For biometrics, this corresponds to one model per person; only samples belonging to this person are used.
 - The main problem is the small number of available samples per user.

Training strategies (2/3)

- **Discriminative:**

- The classifier does not model the underlying class feature densities; it focuses on modeling the class boundaries or the class membership probabilities directly.
- For biometrics, this corresponds to training the classifier to differentiate one user from the others. This means that the algorithm requires samples from the given user but also samples belonging to the other ones.
- In this approach the number of samples is higher, but most of the samples are inhibitory

Training strategies (3/3)

- **Dichotomic classifier :**

- We train a single classifier to solve the dichotomy: Are these two features vectors from the same person? In doing this, we solve the problem concerning the number of training samples per class.
- As we do not need to train the classifier with the people present in the operational database, it will be capable of classifying in an open world situation.
- As a matter of fact, the biometric system, in contrast with the classical discriminative and generative algorithms, does not learn any specific model for each user, and it has a larger generalization capability.

•Joan Fabregas & Marcos Faúndez-Zanuy “Biometric dispersión Matcher”. Pattern Recognition. Elsevier. Pattern Recognition Vol. 41 (2008), Issue 11, pp. 3412-3426. Elsevier. ISSN: 0031-3203 Nov. 2008.

•Joan Fabregas and Marcos Faundez-Zanuy “Biometric Dispersion Matcher versus LDA” Pattern Recognition, Volume 42, Issue 9, pp. 1816-1823 Elsevier ISSN: 0031-3203 Sep. 2009

Training strategies: comparison

- n individuals and s samples per individual, using half of the samples for training and half for testing

Strategy	Samples per class for training	Samples per person for testing	
		genuine	impostor
Generative	$\frac{s}{2}$ genuine samples	$\frac{s}{2}$	$(n-1)\frac{s}{2}$
Discriminative	$\frac{s}{2}$ genuine samples $(n-1)\frac{s}{2}$ impostors	$\frac{s}{2}$	$(n-1)\frac{s}{2}$
Dispersion matcher	$n\frac{s(s-1)}{2}$ pairs genuine-genuine $n(n-1)s^2$ pairs genuine-impostor	$\frac{s}{2}$	$(n-1)\frac{s}{2}$

Training strategies: comparison

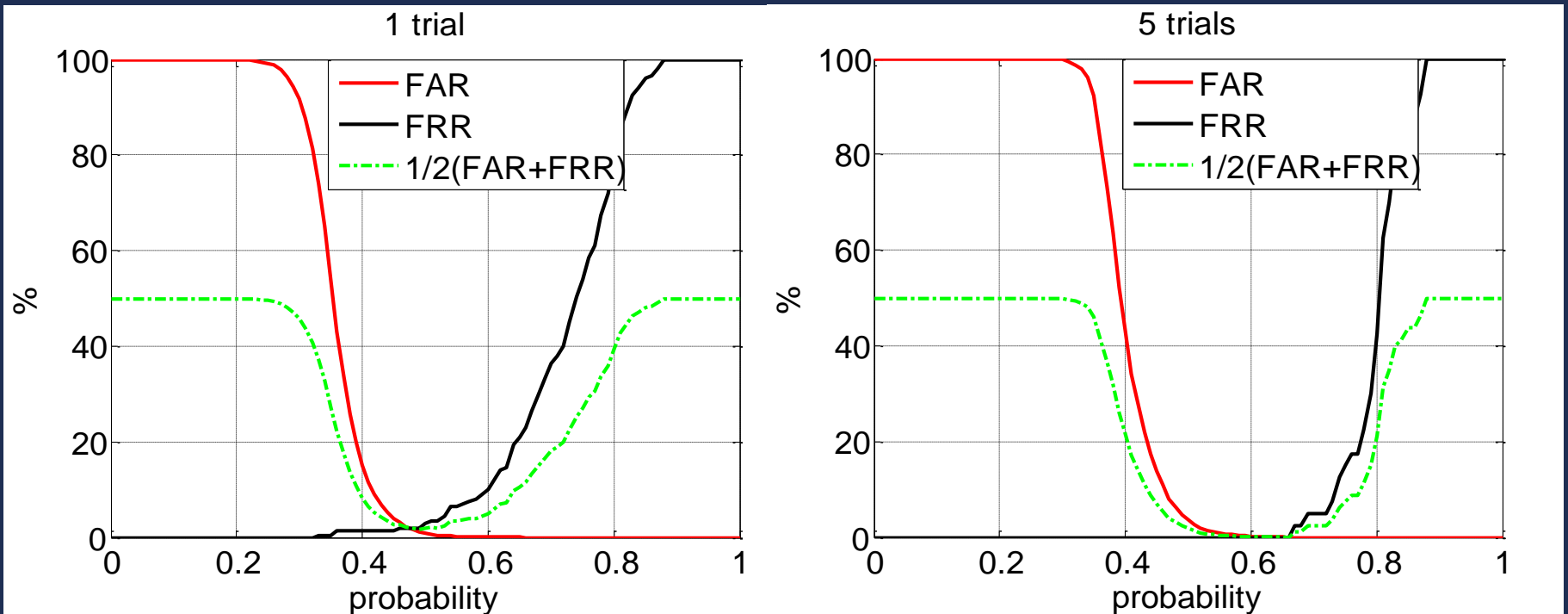
- **ORL** : 40 people, 10 images per person
- 5 For training 5 for testing

Strategy	Samples per class for training	Samples per person for testing	
		genuine	impostor
Generative	5 genuine samples	5	39*5
Discriminative	5 genuine samples + 39*5 impostors	5	39*5
Dispersion matcher	40*10 genuine pairs + 40*39*25 pairs genuine-impostor	5	39*5

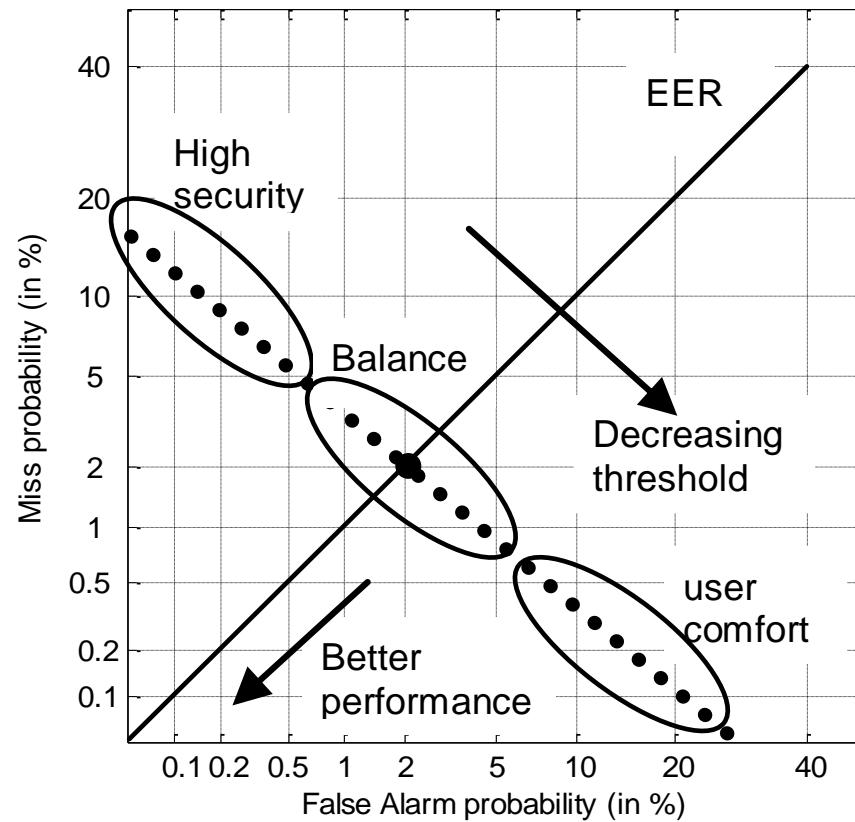
DECISION MAKER

Verification (1:1 comparison)

- FAR, FRR, EER

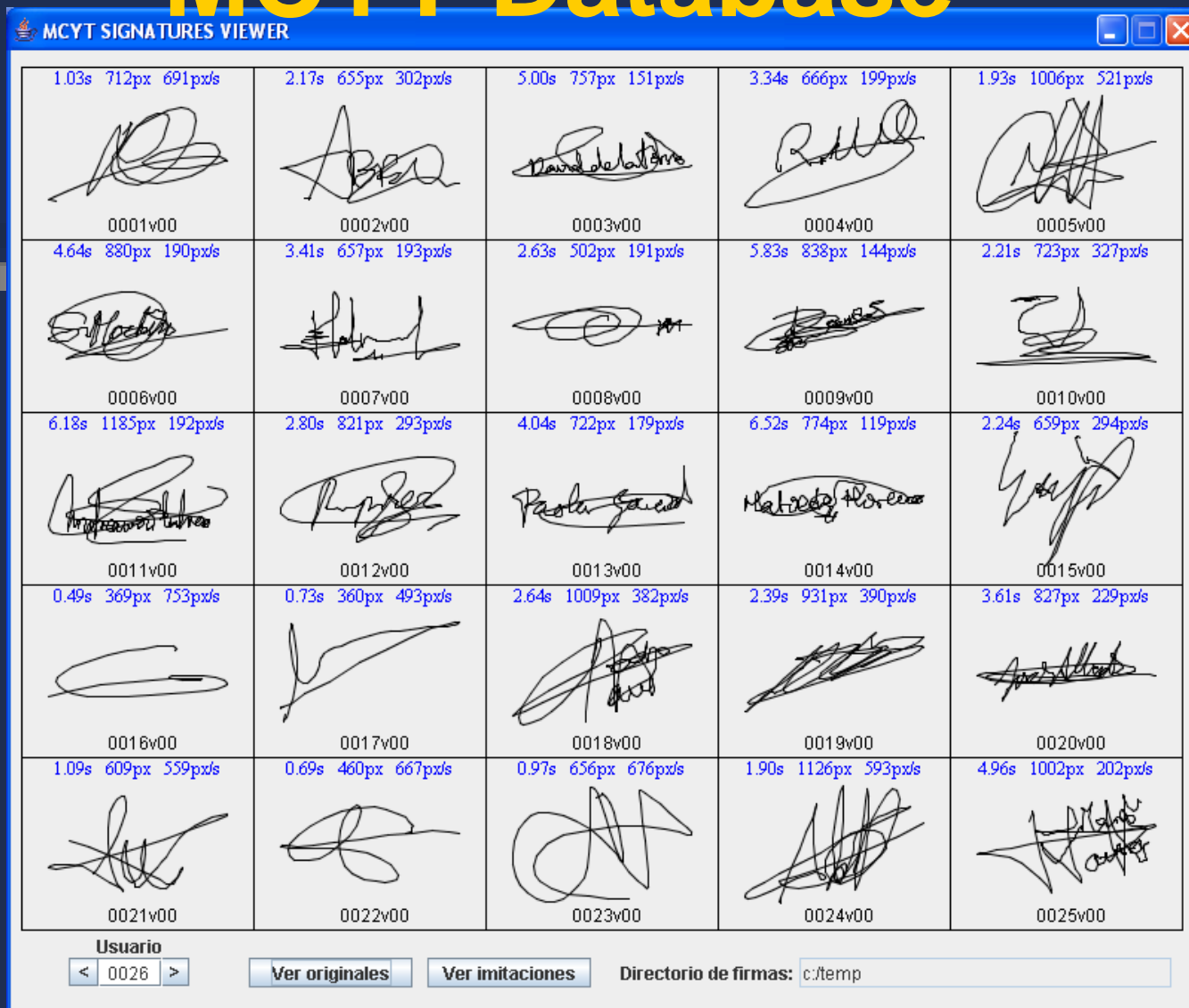


DET plot

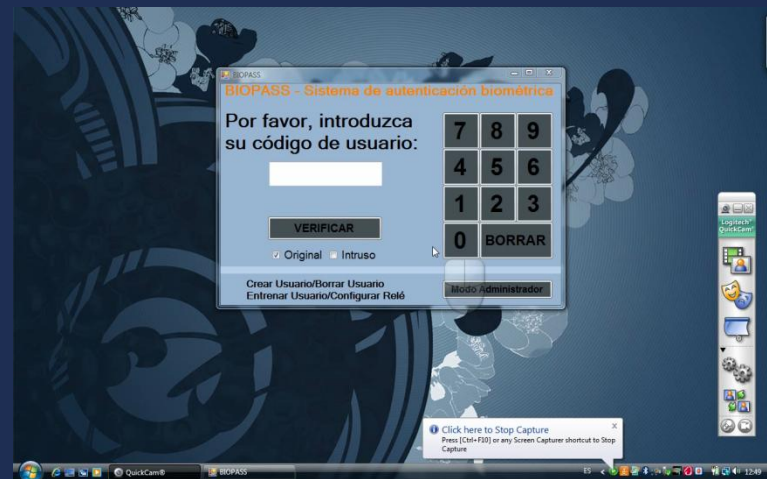


DATABASE

MCYT Database



Multimodal biometrics



• Marcos Faúndez-Zanuy, Julian Fierrez-Aguilar, Javier Ortega-Garcia and Joaquin Gonzalez-Rodriguez “Multimodal biometric databases: an overview”. IEEE Aerospace and electronic systems magazine. Vol. 21 n° 9, pp. 29-37, ISSN: 0885-8985, August 2006

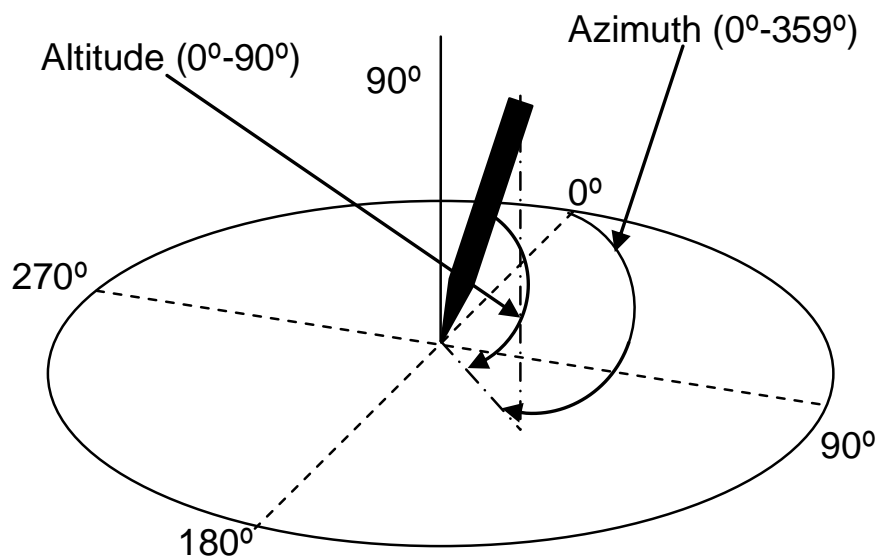
SIGNATURE BIOMETRICS

Static signature

- **Users write their signature on paper, digitize it through an optical scanner or a camera, and the biometric system recognizes the signature analyzing its shape. This group is also known as “off-line”**

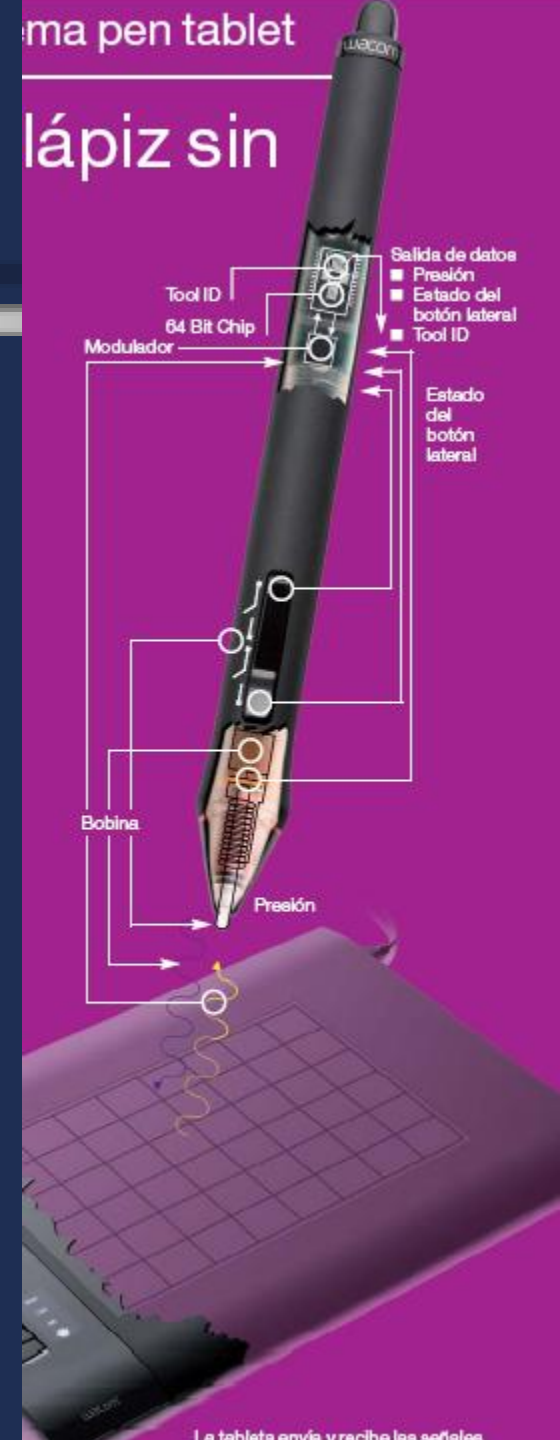
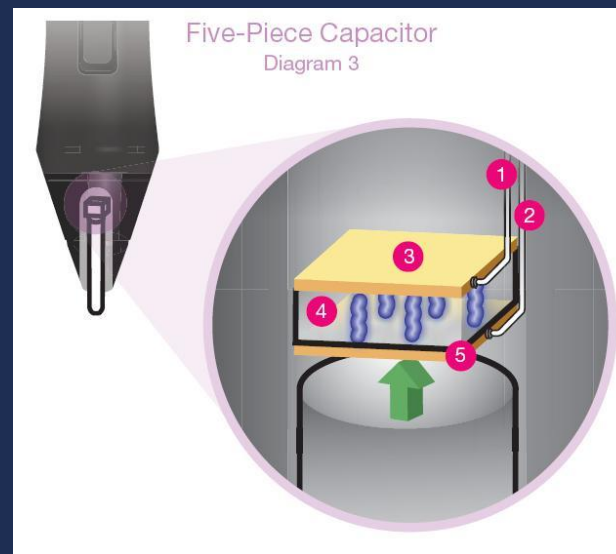
Dynamic signature

- Users write their signature in a digitizing tablet, which acquires the signature in real time.
 - Position in x-axis.
 - Position in y-axis.
 - Pressure applied by the pen.
 - Azimuth angle of the pen with respect to the tablet.
 - Altitude angle of the pen with respect to the tablet.

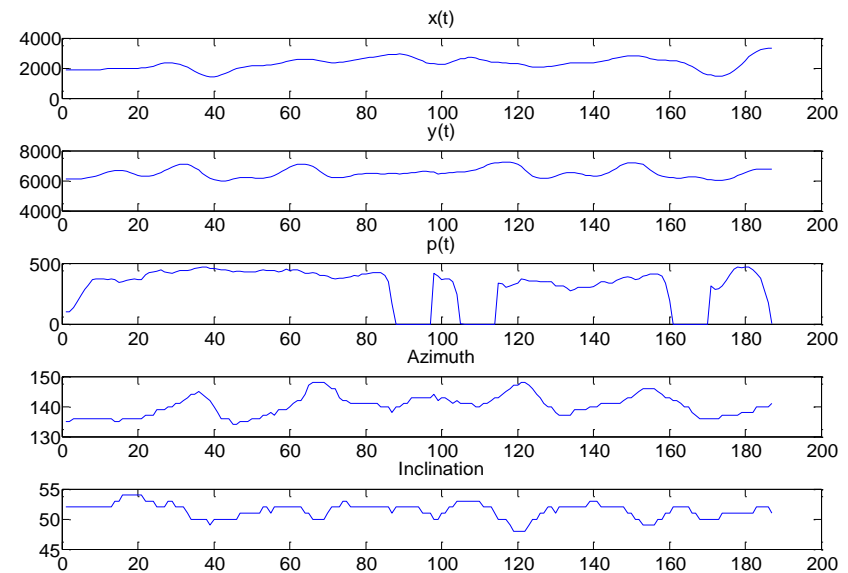
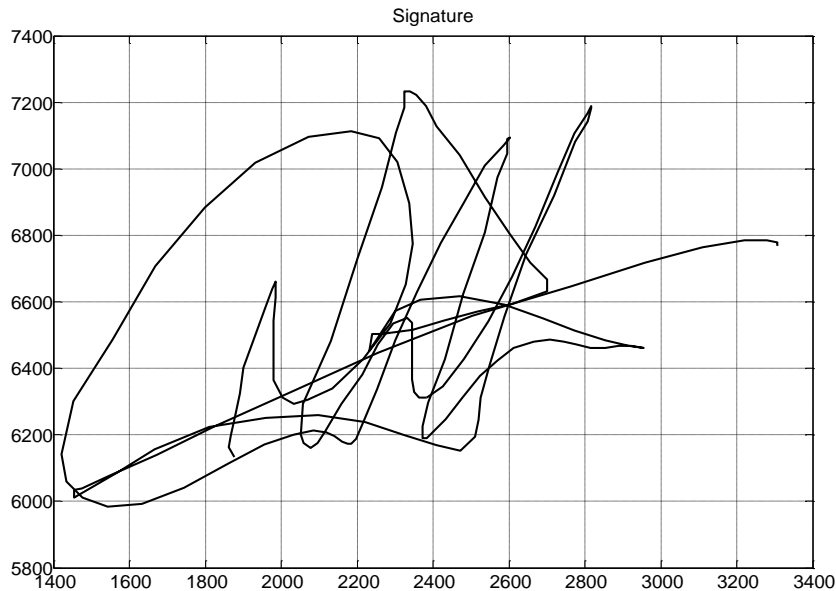


Intuos pen

- Looks and feels like a pen yet contains no batteries or magnets. Instead it takes advantage of electromagnetic resonance technology in which radio waves are sent to the stylus and returned for position analysis. In operation, a grid of wires below the screen alternates between transmit and receive mode about every 20 microseconds



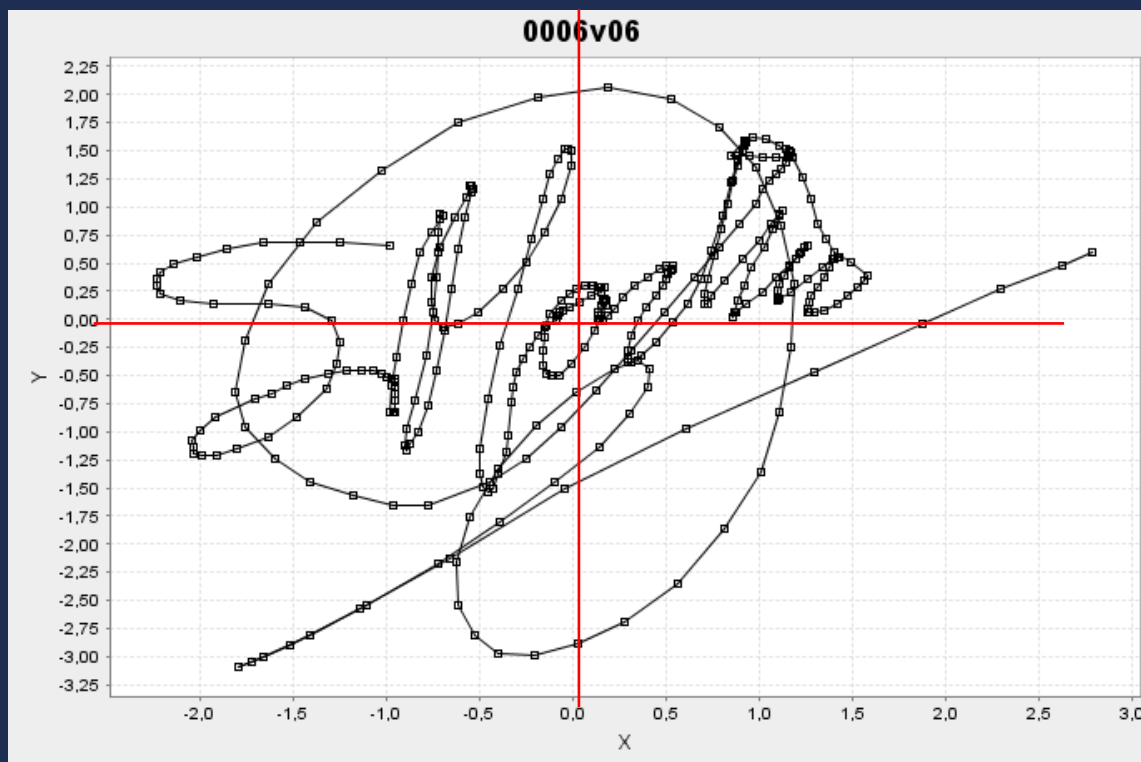
Example of online signature



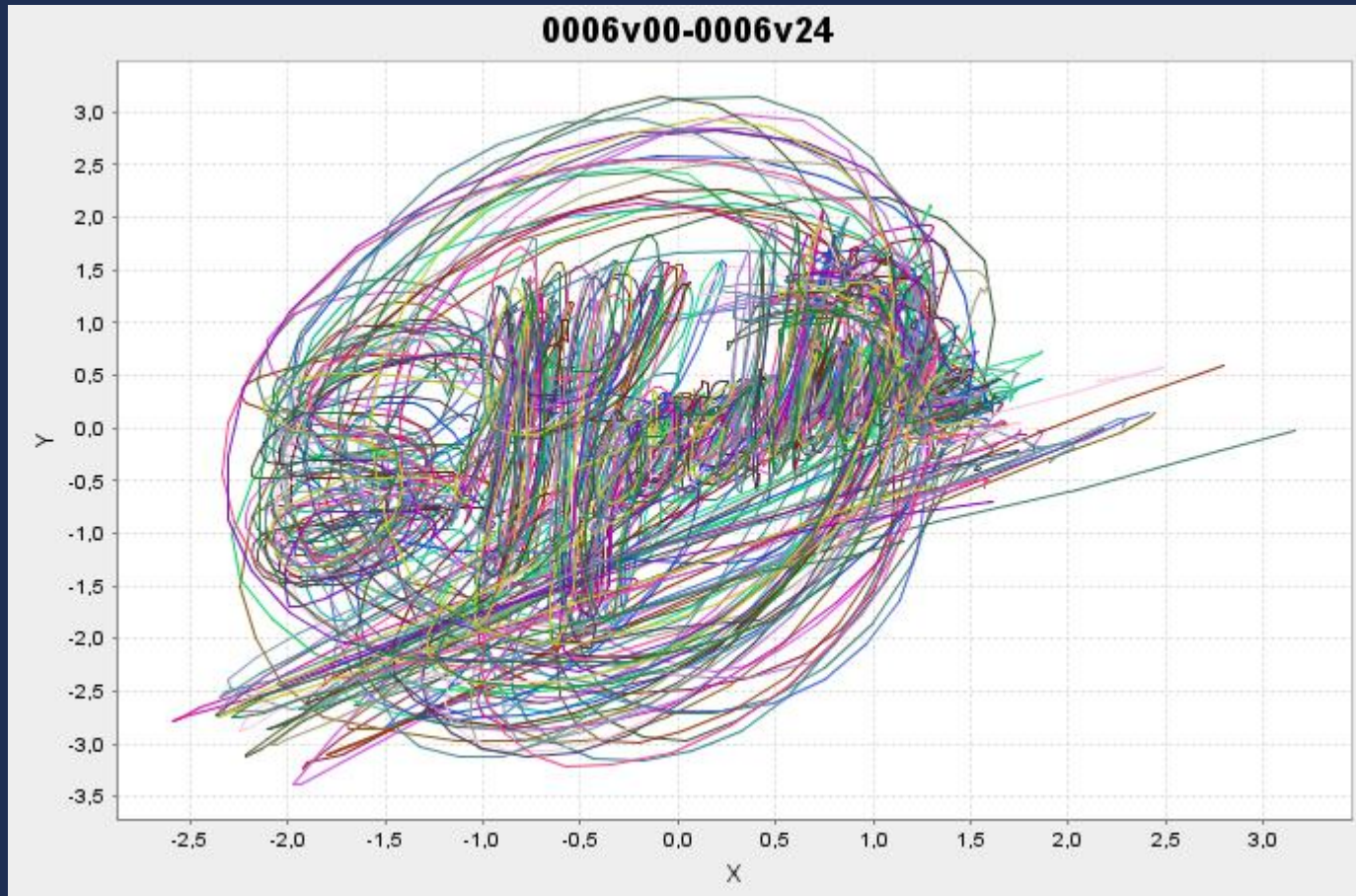
How many times rises the pen?

Normalization

- We have one sample each 10ms
- We can normalize the center of mass of the signature to the (0,0) position.



Example of variability for a given user



Advantages

- It is resistant to impostor attempts. Although, theoretically, a person could learn to sign in exactly the same manner as another person, in practice, it is very difficult to replicate the dynamic information (pressure, azimuth, altitude, etc.) for each digitized signature point (pixel), which cannot be ascertained from examining a written signature or by observing a person signing.
- It is accepted in many government, legal and commercial transactions as a method of personal authentication. Signatures have traditionally played the role of documents authentication. Thus, it is perceived as a noninvasive and non-threatening process, and can overcome some of the privacy problems.
- The user can change his/her signature. Biometrics presents a serious drawback when compared with classical methods passwords and tokens (while it is possible to obtain a new card number, it is not possible to replace any biometric data, which should last forever). However, signature is an exception, because users can change their signature.

Drawbacks

- **Some people exhibit a lot of variability between different realizations of their signature, mainly due to lack of habit.**
- **They evolve with time and are influenced by physical and emotional conditions of the signatories.**
- **Professional forgers can reproduce signatures in order to fool a biometric system. This is especially important for static signature recognition.**

Kinds of fake signatures

- **“Simple” forgery:** where the forger makes no attempt to simulate or trace a genuine signature.
- **“Substitution” or “Random” forgery:** where the forger uses his/her own signature as a forgery.
- **“Freehand” or “Skilled” forgery:** where the forger tries and practices imitating as closely as possible the static and dynamic information of the signature to be forged.

Dynamic signature verification

(1/3)

- **Sensor**: Online signatures are scanned with a graphic tablet.
- **Feature extraction**: Some features will exhibit more discriminatory capability than others. Thus, once extracted, some feature selection should be done. Two classes of features can be extracted in dynamic systems:
 - **Static features**: Extracted from the whole process of signing, such as maximum, minimum and average of writing speed, curvature measurements, ratio of long to short stroke, segments length, etc. The concatenation of all these measurements constitutes an N-dimensional feature vector, being N the number of measurements. These features are also known as parameters.
 - **Dynamic features**: These features are the evolution of a given parameter as function of time $f(t)$, such as the ones plotted in figure 3. Examples are position $x(t)$, $y(t)$, velocity $v(t)$, acceleration $a(t)$, pressure $p(t)$, tangential acceleration $ta(t)$, curvature radius $cr(t)$, normal acceleration $na(t)$, etc. These features are also named functions.

Dynamic signature verification

(2/3)

- **Matching:** Consists of measuring the similarity between the claimed identity model and the input features. Some kind of length normalization must be done, because different repetitions of a signature from a given person, will last differently.
 - Template matching methods: The input and model signatures are expressed as feature vectors and compared using a distance measure between them. Example: DTW
 - Stochastic models: The features extracted from the training signatures are used to work out a statistical model. During testing, the similarity of input and reference is established. Example: HMM
 - Neural Networks: For instance, a Multi-Layer Perceptron can perform as a classifier. In order to adapt to the dynamic characteristics, recurrent neural networks, time-delay neural networks, and hybrid networks can be used.

Dynamic signature verification

(3/3)

- **Decision:** Once a similarity (probability) measure, also known as opinion and score, is obtained, the decision implies the computation of a decision threshold. If the similarity is greater than a threshold, the decision is ACCEPT, otherwise it is REJECT. Contrarily, if the matching block produces a distance (dissimilarity) measure, the person is accepted if the distance is smaller than the threshold, and otherwise it is rejected.

DTW Algorithm

```
int DTWDistance(char s[1..n], char t[1..m]) {
    declare int DTW[0..n, 0..m]
    declare int i, j, cost

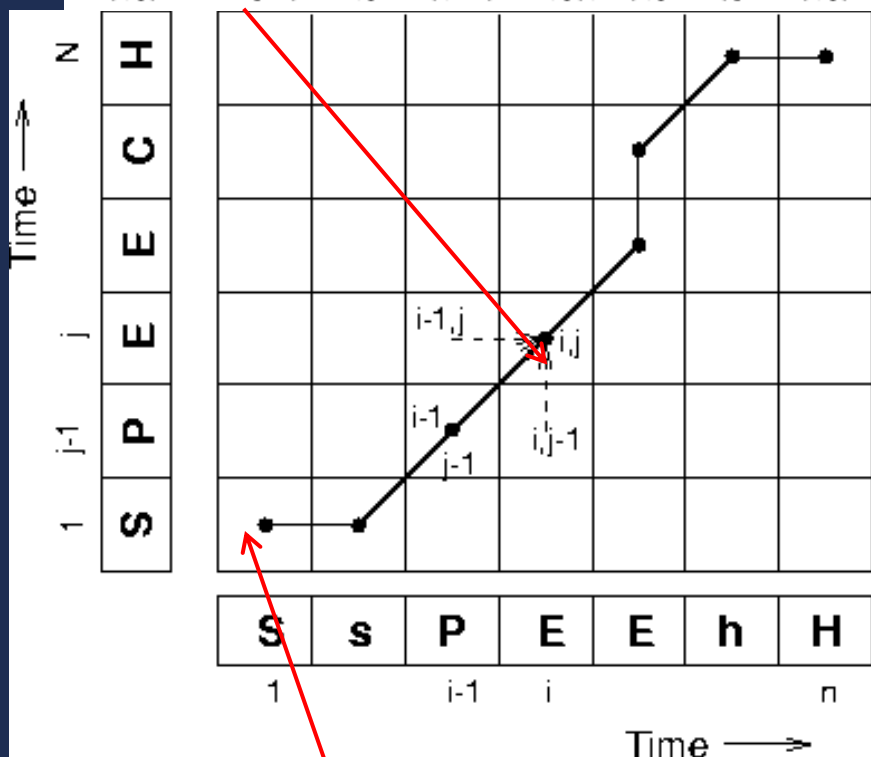
    for i := 1 to m
        DTW[0, i] := infinity
    for i := 1 to n
        DTW[i, 0] := infinity
    DTW[0, 0] := 0

    for i := 1 to n
        for j := 1 to m
            cost := d(s[i], t[j])
            DTW[i, j] := cost + minimum(DTW[i-1, j],           // insertion
                                         DTW[i, j-1],           // deletion
                                         DTW[i-1, j-1])          // match

    return DTW[n, m]
}
```

DTW

$$D(i, j) = \min[D(i-1, j-1), D(i-1, j), D(i, j-1)] + d(i, j) \quad (1)$$

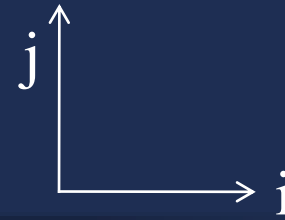


$$d(x, y) = \sqrt{\sum_i (x_i - y_i)^2}$$

<http://www.cnel.ufl.edu/~kkale/dtw.html>

$D(1,1) = d(1,1)$ (initial condition)

DTW



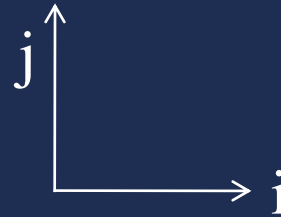
Iteration 1 (inicialization)

$D(1,1) = d(1,1)$ (initial condition)

—	∞						
T	∞						
A	∞						
C	∞						
—	$D(0,1)=\infty$	$D(1,1)=0$					
	$D(0,0)=0$	$D(1,0)=\infty$	∞	∞	∞	∞	∞
		—	C	A	A	T	—

DTW

Iteration 2



—	∞						
T	∞						
A	∞						
C	∞						
—	∞	—0—→	1				
	0	∞	∞	∞	∞	∞	∞
		—	C	A	A	T	—

$$D(2,1) = d(2,1) + \min\{D(1,0), D(1,1), D(2,0)\} = d(2,1) + D(1,1) = 1$$

$d(2,1) = d(c,-) = 1$ (example: equal $d=0$, different $d=1$)

DTW

Iteration 3

—	∞						
T	∞						
A	∞						
C	∞						
—	∞	—0—	→1—	→2			
	0	∞	∞	∞	∞	∞	∞
		—	C	A	A	T	—

DTW

Iteration 4

—	∞						
T	∞						
A	∞						
C	∞						
—	∞	—0—	→1—	→2—	→3→		
	0	∞	∞	∞	∞	∞	∞
		—	C	A	A	T	—

DTW

Iteration 5

—	∞						
T	∞						
A	∞						
C	∞						
—	∞	—0—	→1—	←2—	←3→	←4→	
	0	∞	∞	∞	∞	∞	∞
		—	C	A	A	T	—

DTW

Iteration 6

—	∞						
T	∞						
A	∞						
C	∞						
—	∞	—0—	→1—	←2—	←3—	←4—	←5—
	0	∞	∞	∞	∞	∞	∞
		—	C	A	A	T	—

DTW

Iteration 7

—	∞						
T	∞						
A	∞						
C	∞	\uparrow 1					
—	∞	0 \rightarrow	1 \rightarrow	2 \rightarrow	3 \rightarrow	4 \rightarrow	5 \rightarrow
	0	∞	∞	∞	∞	∞	∞
		—	C	A	A	T	—

DTW

Iteration 8

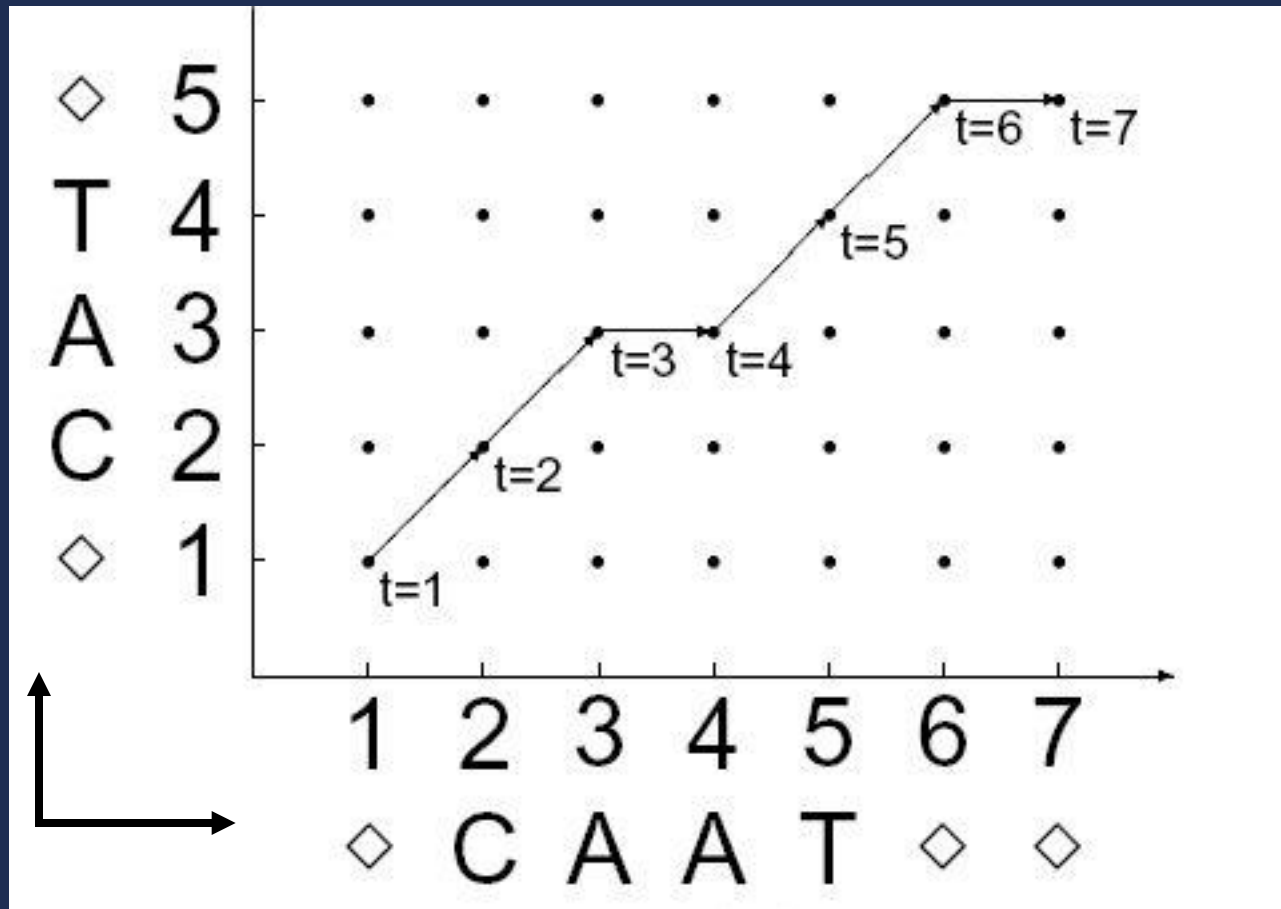
—	∞						
T	∞						
A	∞						
C	∞	↑ 1 ↗	0				
—	∞	0 →	1	2	3	4	5 →
	0	∞	∞	∞	∞	∞	∞
		—	C	A	A	T	—

DTW

Final iteration

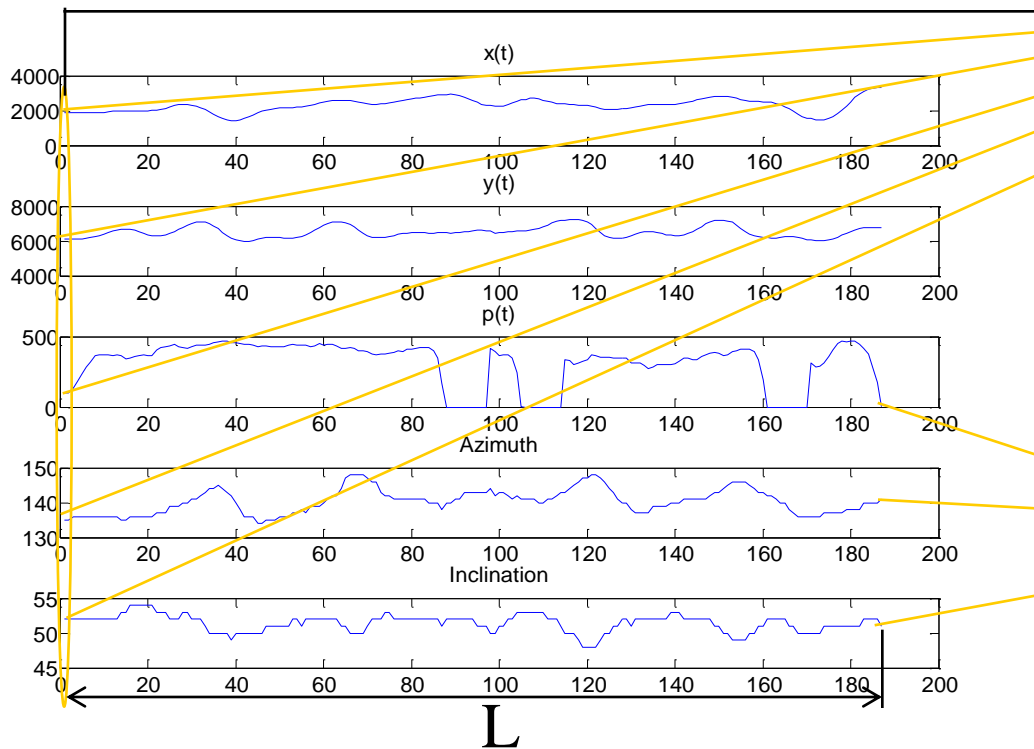
—	∞	\uparrow 4	\uparrow 3	\uparrow 2	\nearrow 2	\nearrow 2	\nearrow 1
T	∞	\uparrow 3	\uparrow 2	\uparrow 1	\nearrow 1	\nearrow 1	\rightarrow 2
A	∞	\uparrow 2	\uparrow 1	0	\rightarrow 1	\rightarrow 2	\rightarrow 3
C	∞	\uparrow 1	0	\rightarrow 1	\rightarrow 2	\rightarrow 3	\rightarrow 4
—	∞	0	\rightarrow 1	\rightarrow 2	\rightarrow 3	\rightarrow 4	\rightarrow 5
	0	∞	∞	∞	∞	∞	∞
		—	C	A	A	T	—

Template matching example: DTW



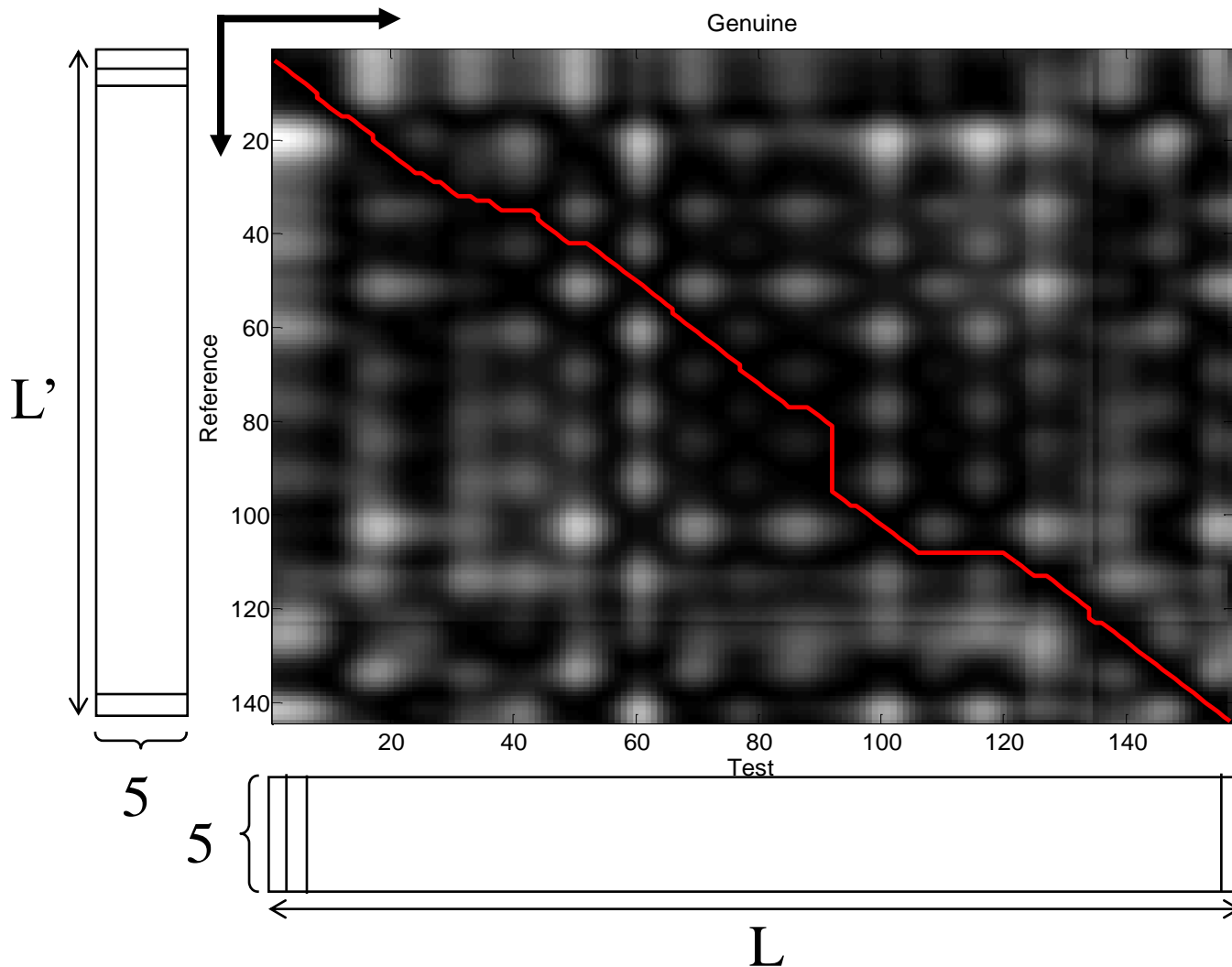
Vector sequence obtention

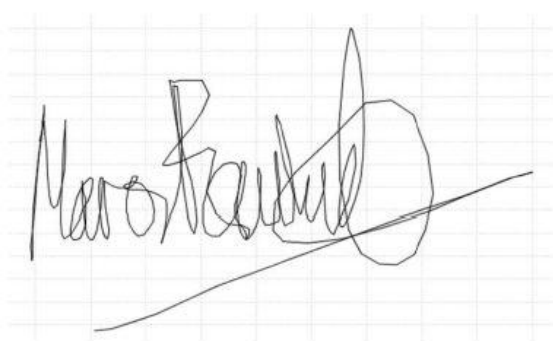
Firma 1 persona 1



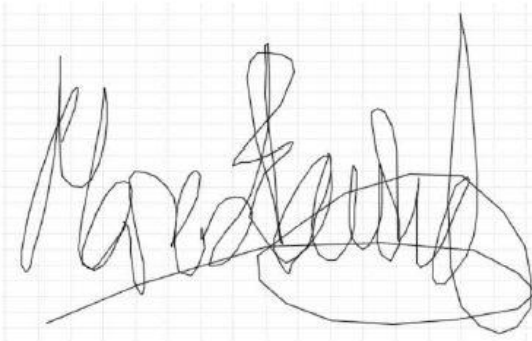
Sequence of L
vectors of 5
dimensions

Alignment example for genuine signature

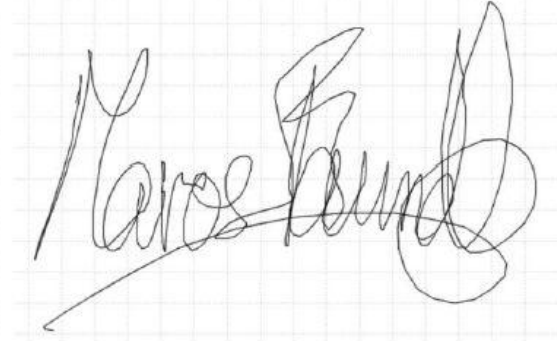




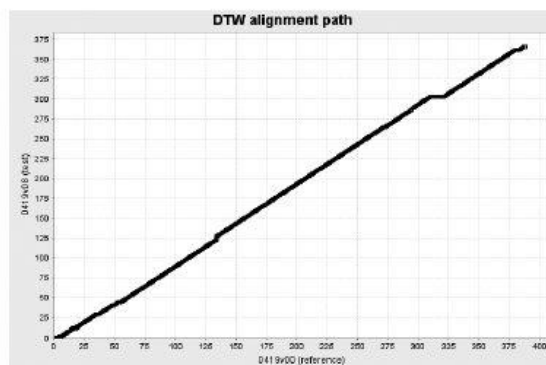
(a)



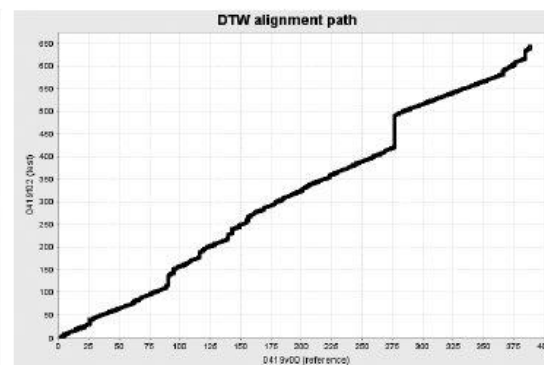
(b)



(c)



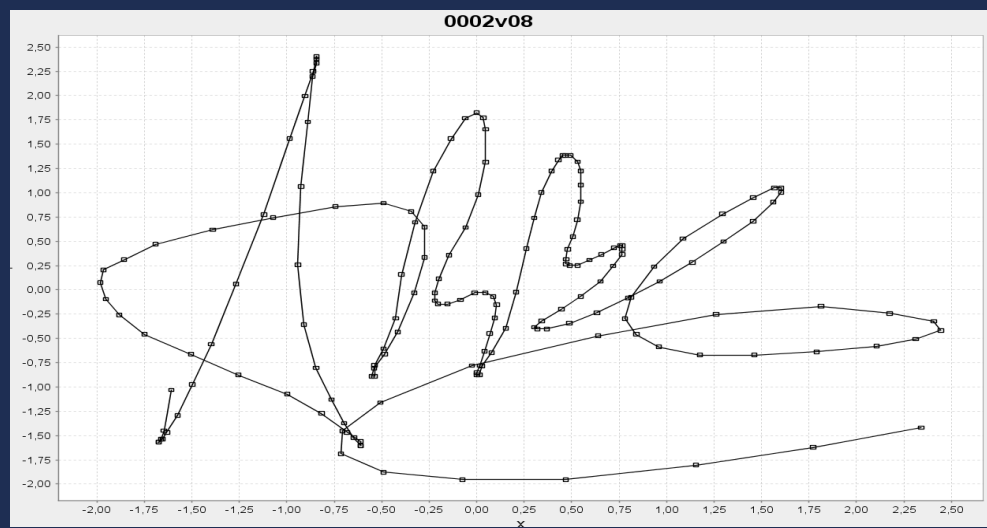
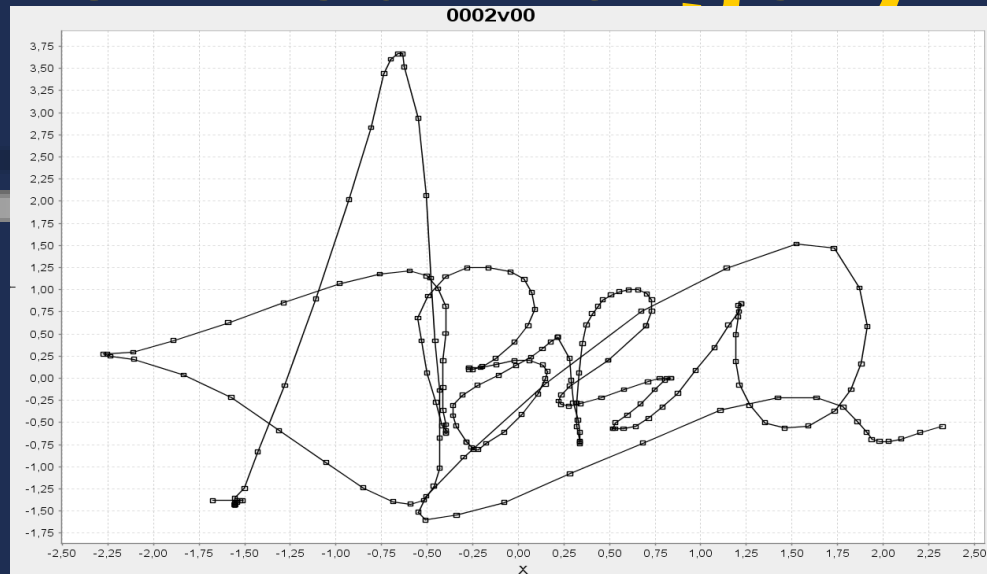
(d)

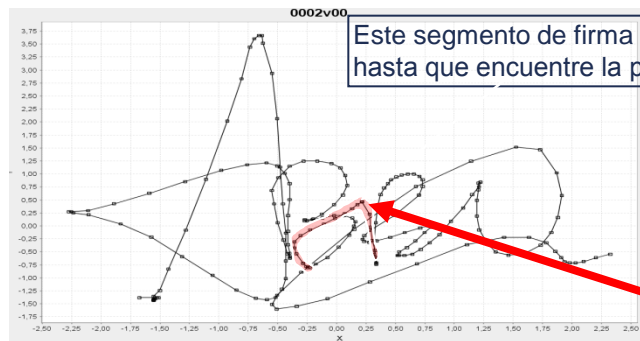


(e)

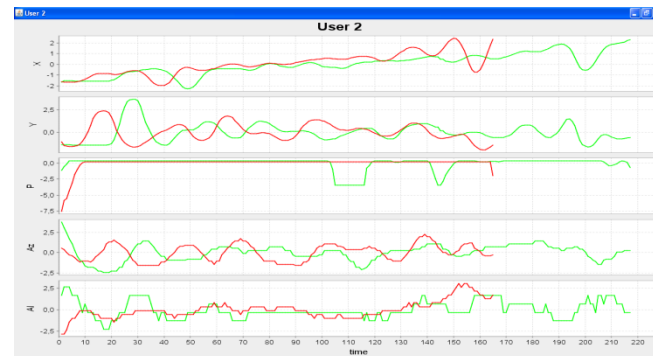
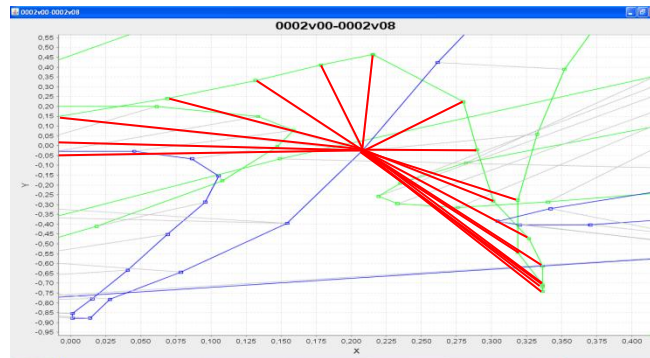
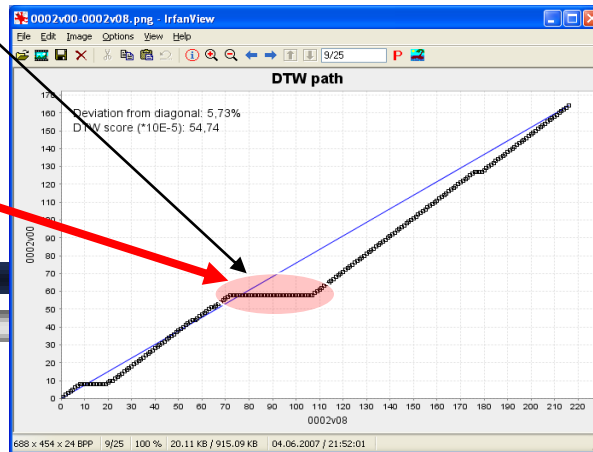
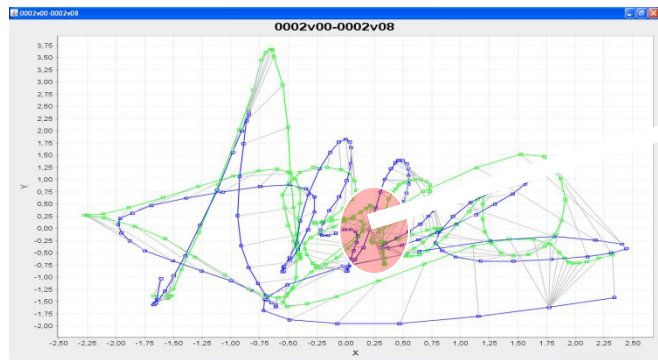
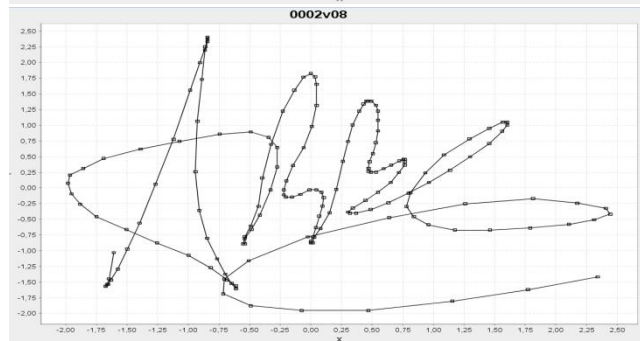
Fig. 1. Example of what is shown in the *final hypothesis*. Figures (a) and (b) show two original signatures and figure (c) shows a skilled forgery. Figure (d) shows the DTW alignment path for the original signatures, which is more diagonal than that followed when a signature is a forgery, figure (e).

“skilled” forgery



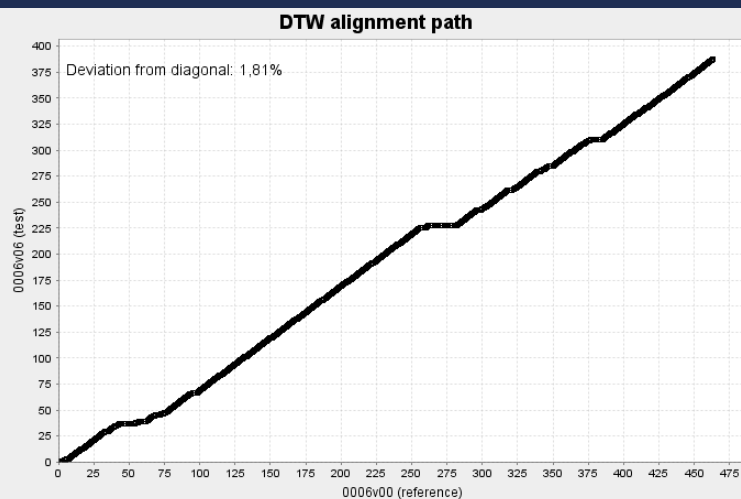
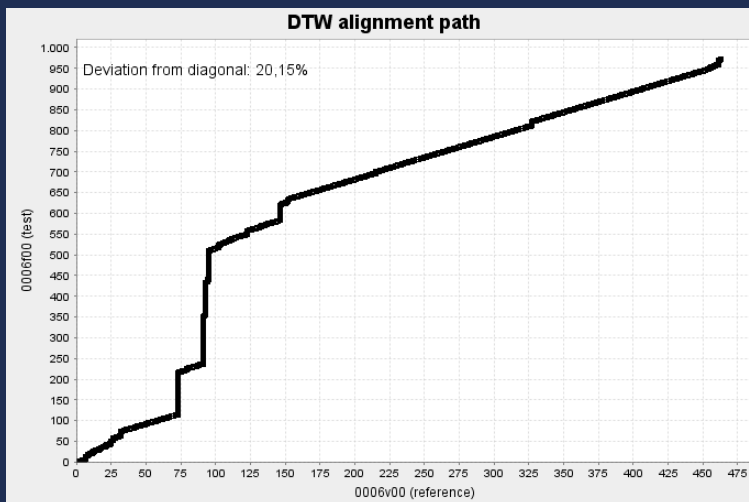


Este segmento de firma no aparece en la de abajo, por lo que el camino DTW tiene que “esperar” hasta que encuentre la próxima correspondencia.



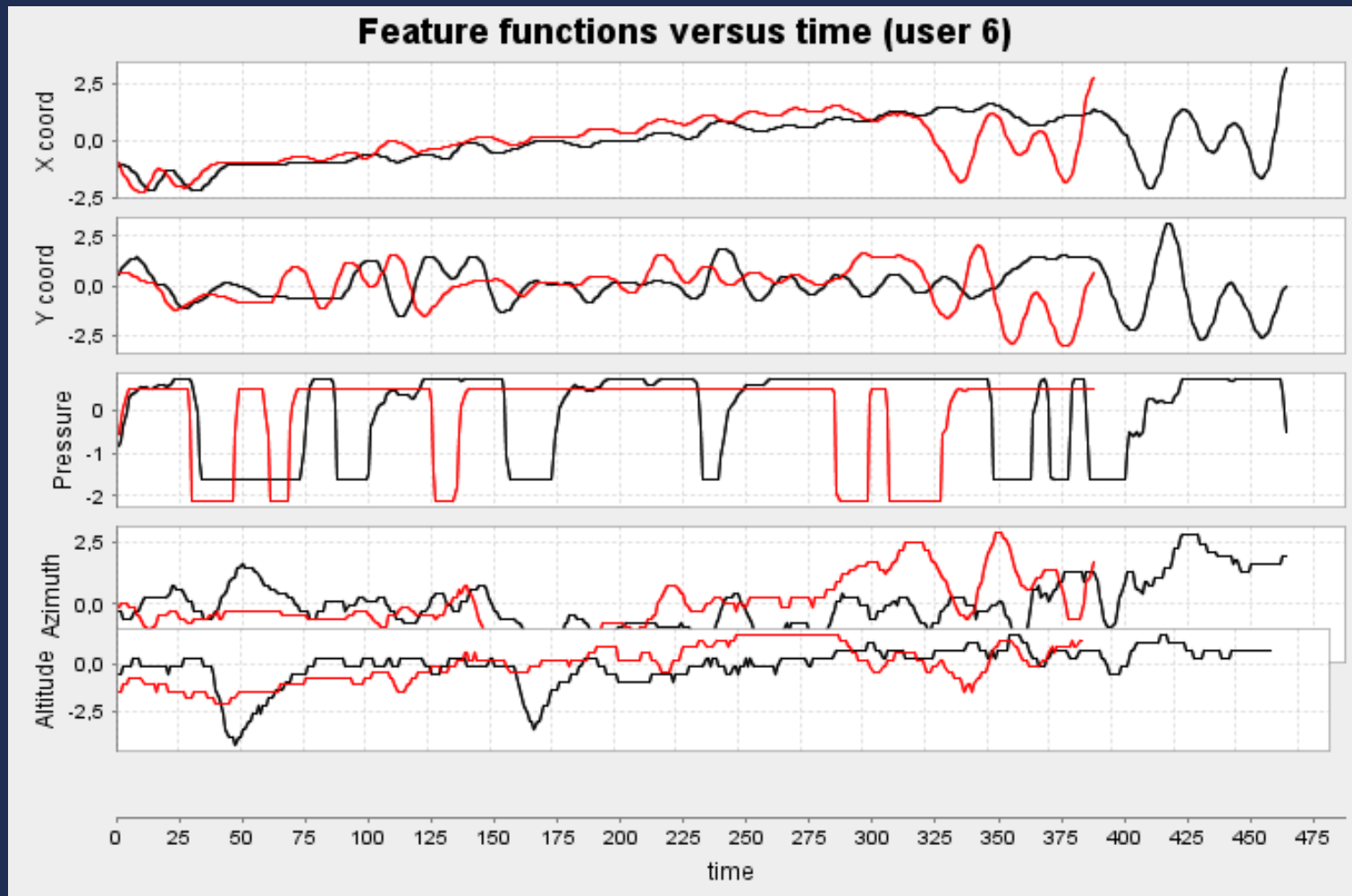
DTW alignment

- Different signatures last different.
- For genuine users the path tends to be more linear than for impostors.



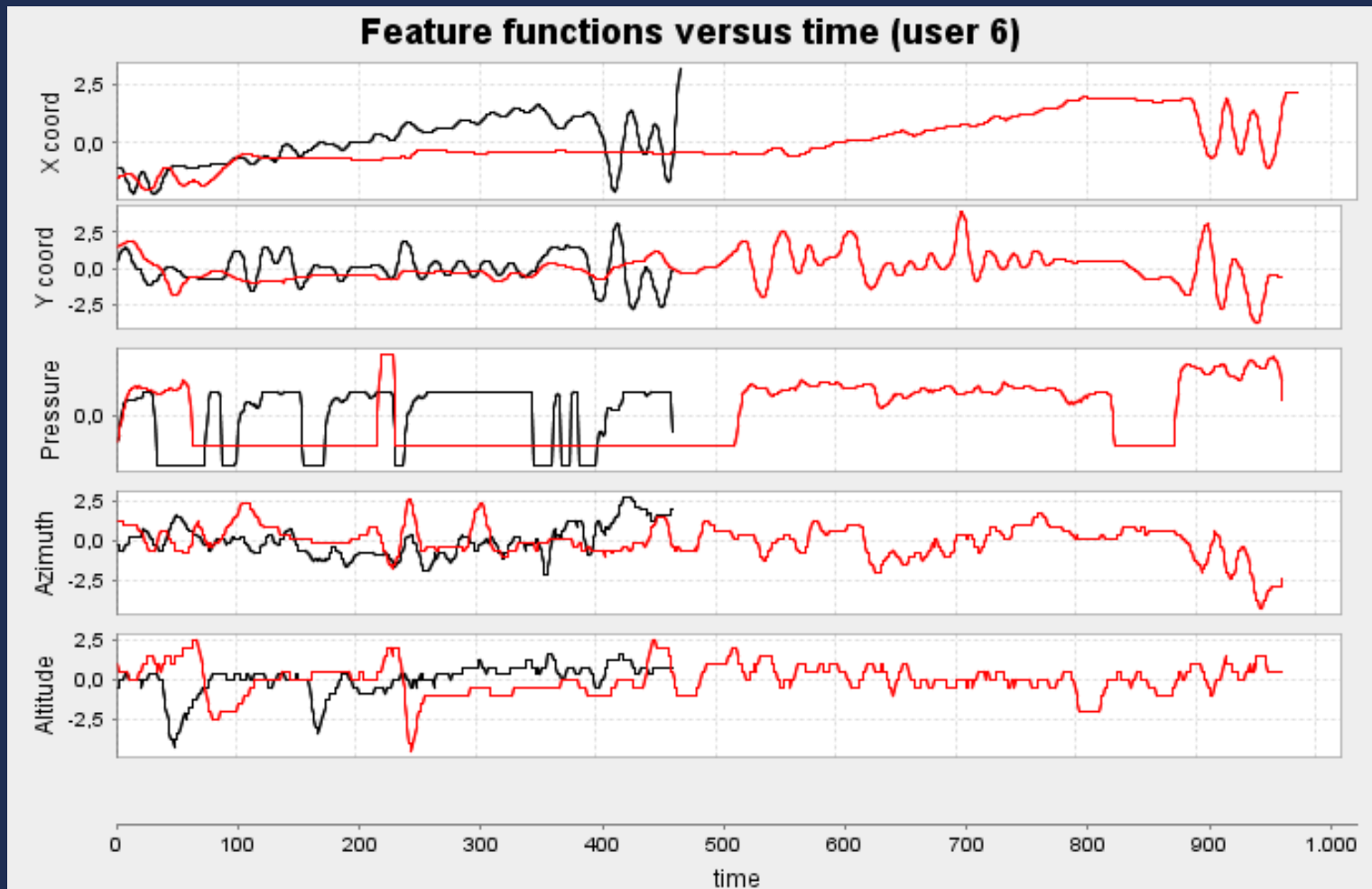
Dynamic information of two genuine signatures

“Black” signature is longer than “red” one



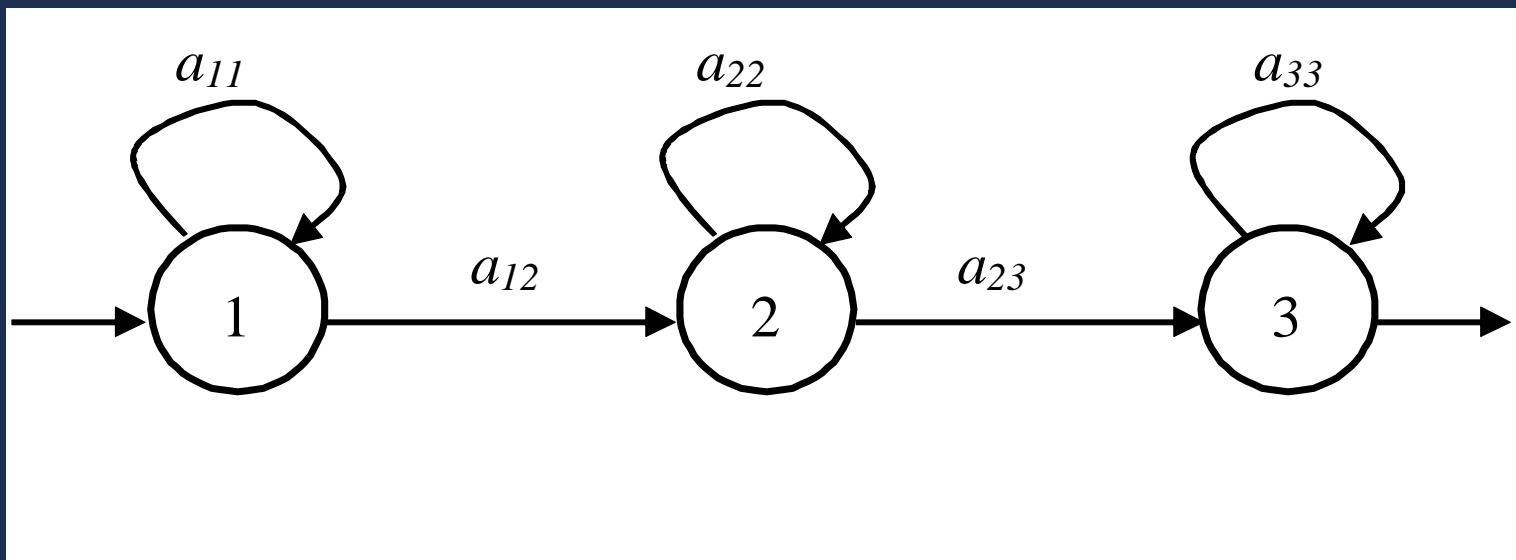
Dynamic information: original versus impostor

“red” signature lasts approximately double.



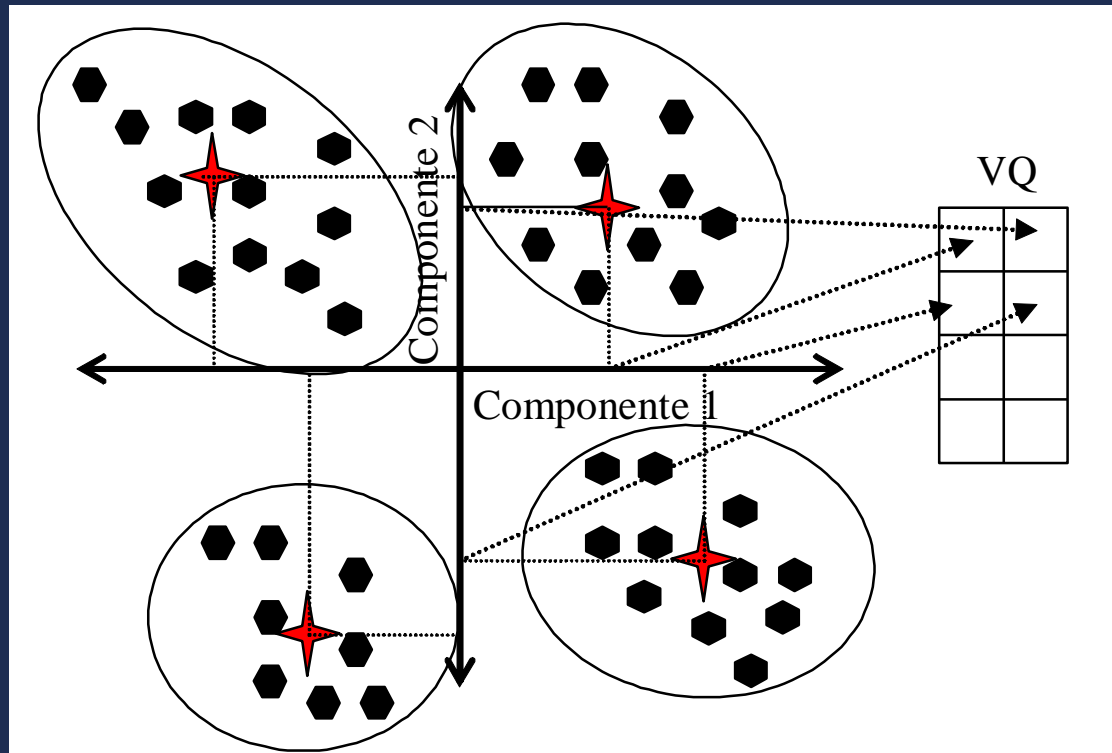
Example of statistical alignment: HMM

- An HMM is a finite state machine, where a probability density function is associated with each state. The states are connected by transition probability. The probability that a sequence of feature vectors was generated by this model can be found by Baum-Welch decoding. HMM have become very successful in speech recognition. It can manage signals of different time duration (utterances, signatures, etc.). Usually a left-to-right model is used.
- 1="C", 2="A", 3="T"

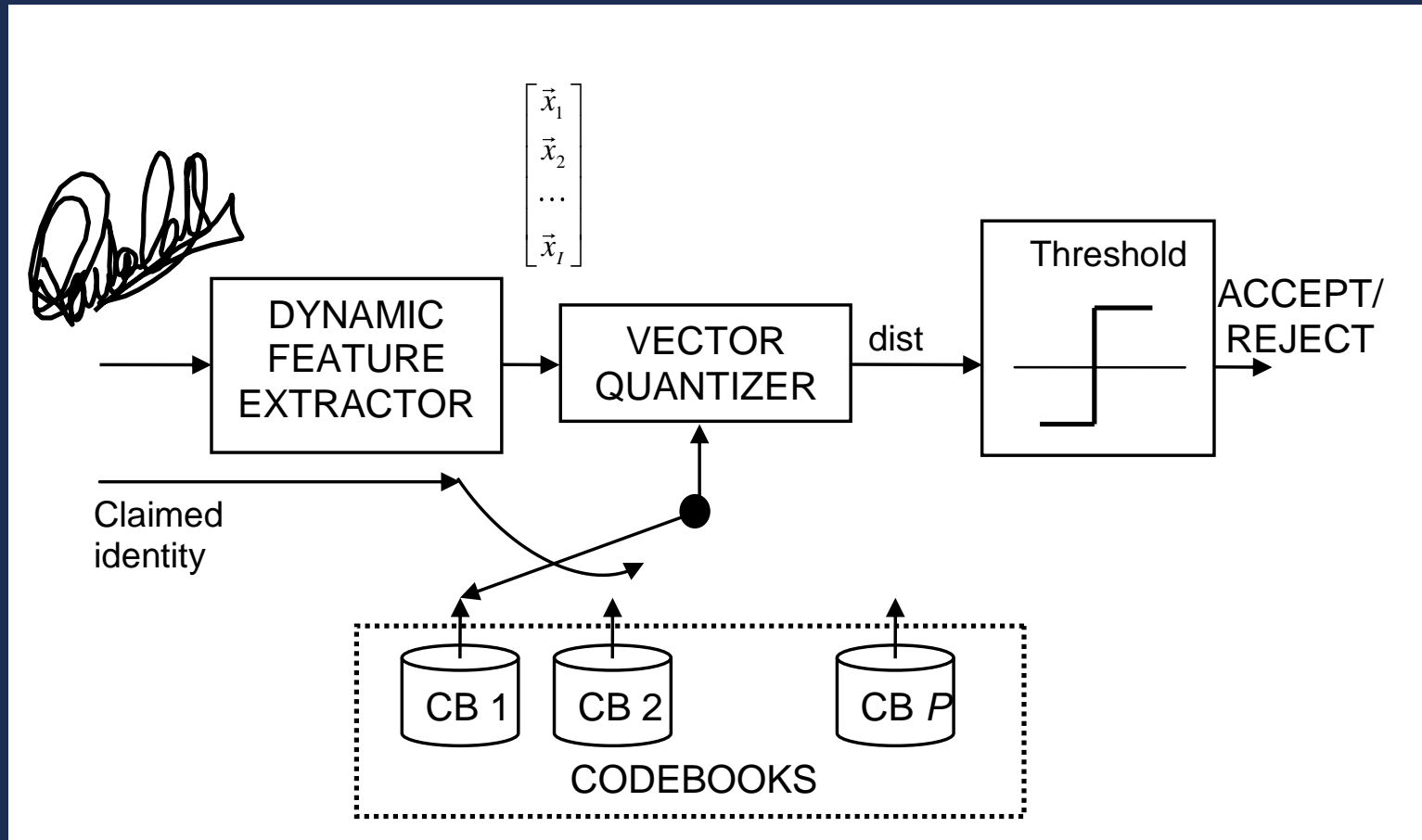


Vector Quantization (1/2)

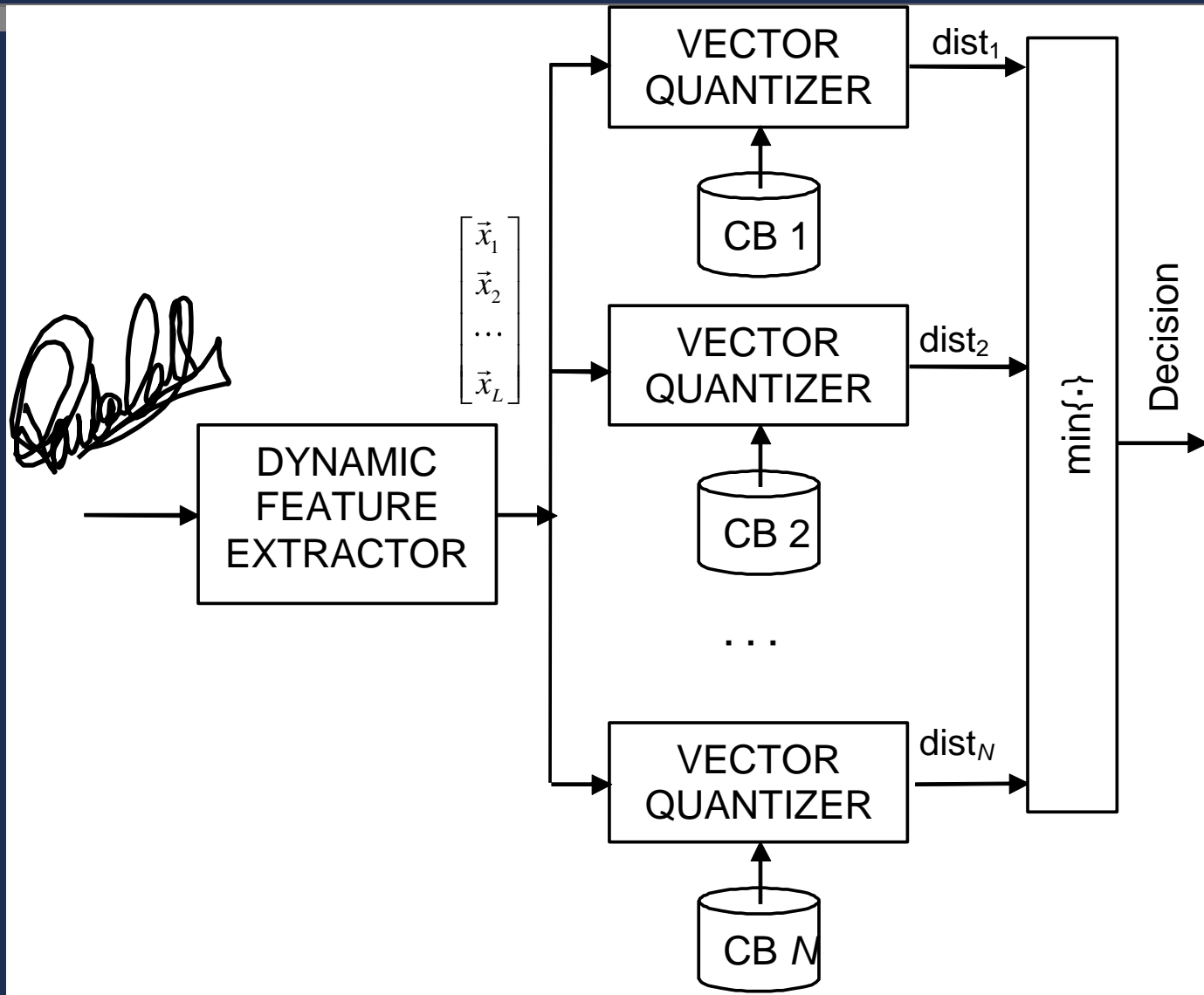
- Example: two dimensional vectors



Verification by means of VQ



Identification by means of VQ (2/2)



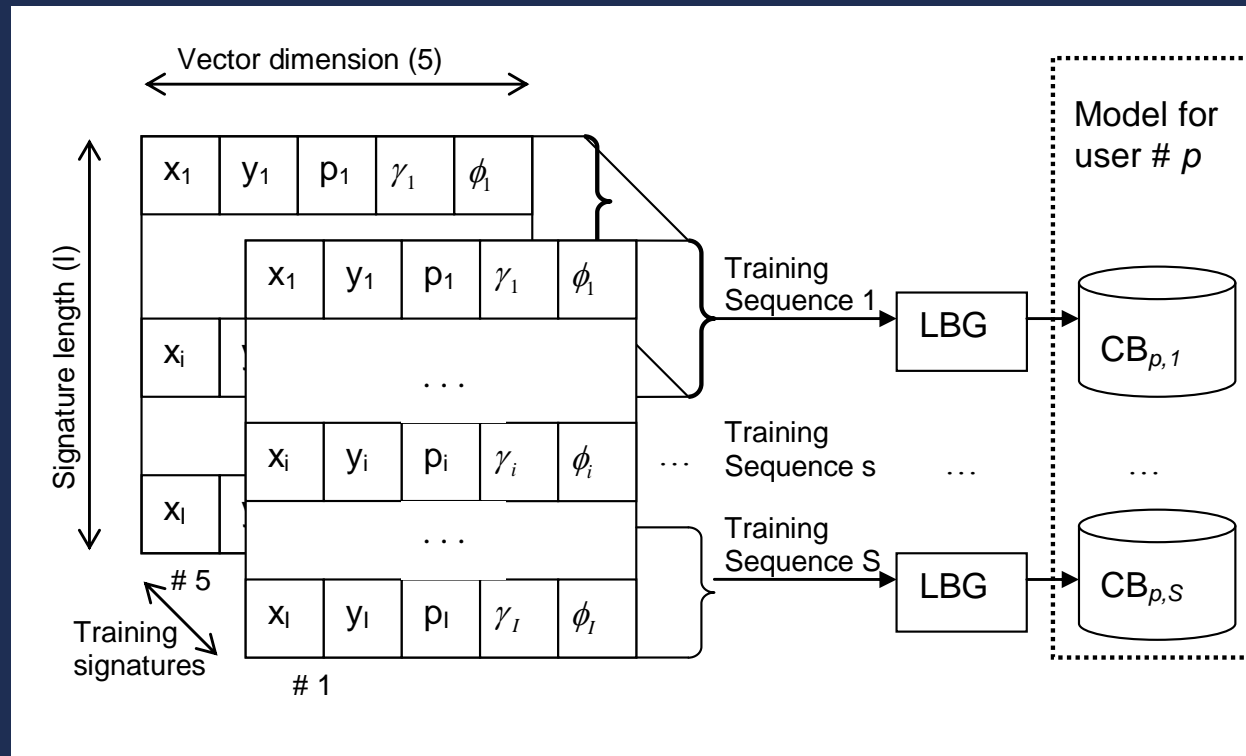
Experimental results (MCYT, 330 users)

Method	Parameters	Identification rate (%)	Minimum DCF (%)	
			substitution	skilled
VQ	1×5	11.36%	45.80%	46.15%
VQ	2×5	50.5%	29.16%	36.76%
VQ	4×5	79.79%	19.73%	28.72%
VQ	8×5	92.36%	10.97%	21.81%
VQ	16×5	96.21%	6.99%	16.64%
VQ	32×5	95.79%	5.56%	14.16%
VQ	64×5	96.07%	4.89%	12.43%
VQ	128×5	95.5%	4.34%	11.94%
VQ	256×5	94.43%	4.39%	11.87%
VQ	512×5	92.07%	4.77%	11.97%
HMM	Q=12,M=1	97.21%	5.38%	16.30%
DTW	Min {·}	98.71%	2.40%	8.94%
DTW	Mean {·}	96.86%	4.55%	11.27%
DTW	Median {·}	98.07%	3.23%	10.21%
VQ-DTW	1×5+DTW	98.64%	9.81%	18.16%
VQ-DTW	2×5+DTW	98.36%	6.16%	14.64%
VQ-DTW	4×5+DTW	98.71%	4.43%	12.18%
VQ-DTW	8×5+DTW	99.14%	3.23%	9.91%
VQ-DTW	16×5+DTW	99.36%	2.13%	7.94%
VQ-DTW	32×5+DTW	99.43%	1.62%	6.71%
VQ-DTW	64×5+DTW	99.5%	1.47%	6.26%
VQ-DTW	128×5+DTW	99.29%	1.41%	5.73%
VQ-DTW	256×5+DTW	99.29%	1.37%	5.43%
VQ-DTW	512×5+DTW	99.14%	1.32%	5.42%

Experimental results: MCYT & SVC

Model size	Identification rate		Verification errors (%)							
	MCYT	SVC	Substitution				skilled			
			MCYT		SVC		MCYT		SVC	
			DCF	EER	DCF	EER	DCF	EER	DCF	EER
1×5	10.24%	60%	45.65%	46.6%	48.14%	48.5%	45.62%	47.03%	45.56%	49.06%
2×5	48.67%	80%	29.21%	29.76%	33.74%	35%	36.21%	36.43%	42.44%	46.94%
4×5	77.21%	93%	19.49%	19.65%	24.53%	25.1%	28.3%	28.73%	38.56%	41.56%
8×5	91.27%	98%	10.81%	10.91%	14.62%	15.56%	21.2%	21.32%	31.56%	33%
16×5	95.27%	98%	6.94%	7.09%	11.16%	11.5%	15.98%	16.42%	23.75%	24%
32×5	95.58%	97.5%	5.37%	5.47%	8.29%	8.52%	13.17%	13.51%	19%	19.5%
64×5	95.52%	96.5%	4.8%	4.91%	6.37%	6.62%	11.72%	12%	16.38%	17%
128×5	95.21%	96.5%	4.31%	4.36%	5.13%	6%	11.39%	11.70%	14.5%	15.06%
256×5	94.24%	96%	4.39%	4.55%	5.01%	5.42%	11.39%	11.58%	13.5%	14%
512×5	91.82%	96%	4.8%	4.86%	5.14%	5.5%	11.46%	11.64%	13.25%	13.5%

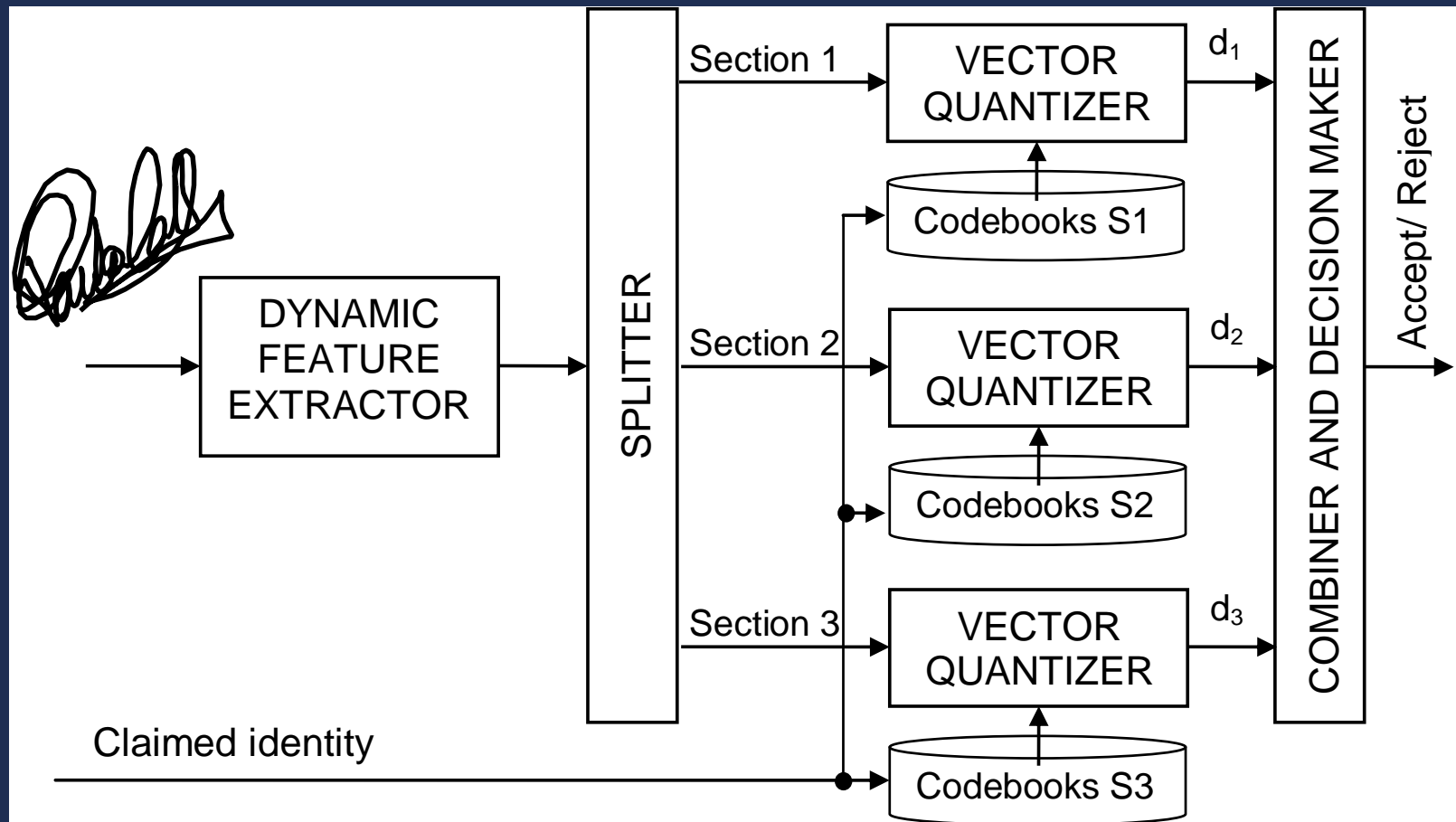
Multisection codebooks



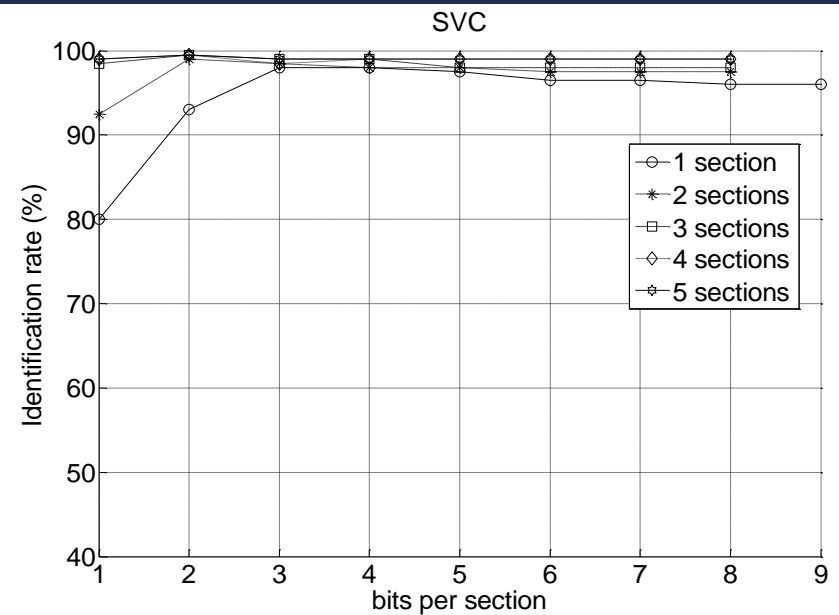
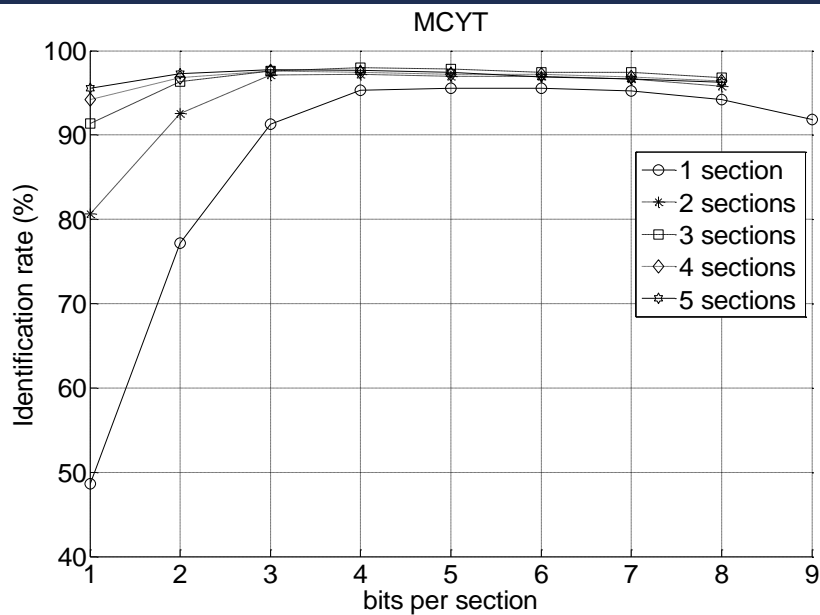
• Marcos Faúndez-Zanuy and Juan Manuel Pascual-Gaspar “Efficient On-line signature recognition based on Multi-section VQ” Pattern Analysis and Applications. Volume 14, Number 1 pp. 37-45, February 2011.

• Juan Manuel Pascual Gaspar, Marcos Faundez-Zanuy, Carlos Vivaracho “Fast On-line signature recognition based on VQ with time modelling”. Engineering Applications of Artificial Intelligence. Elsevier. Vol. 24 (2011) 368–377, March 2011

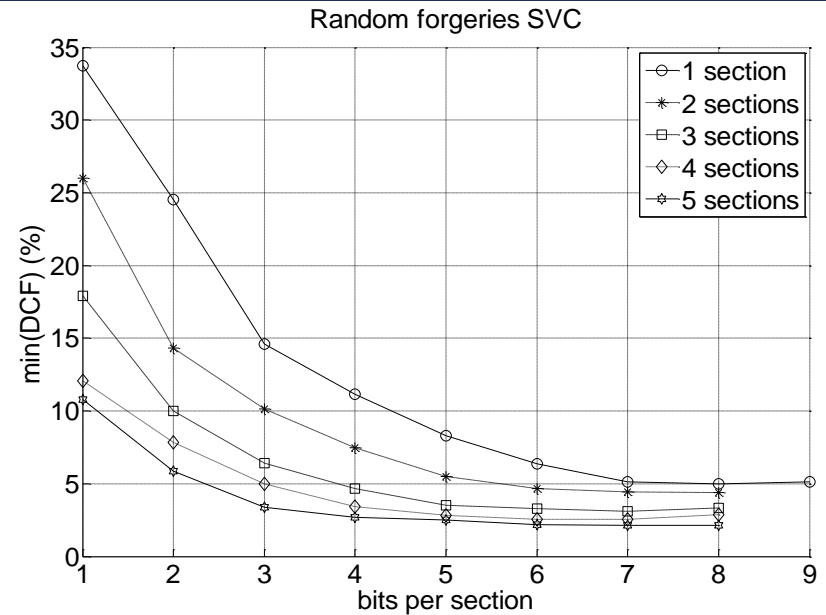
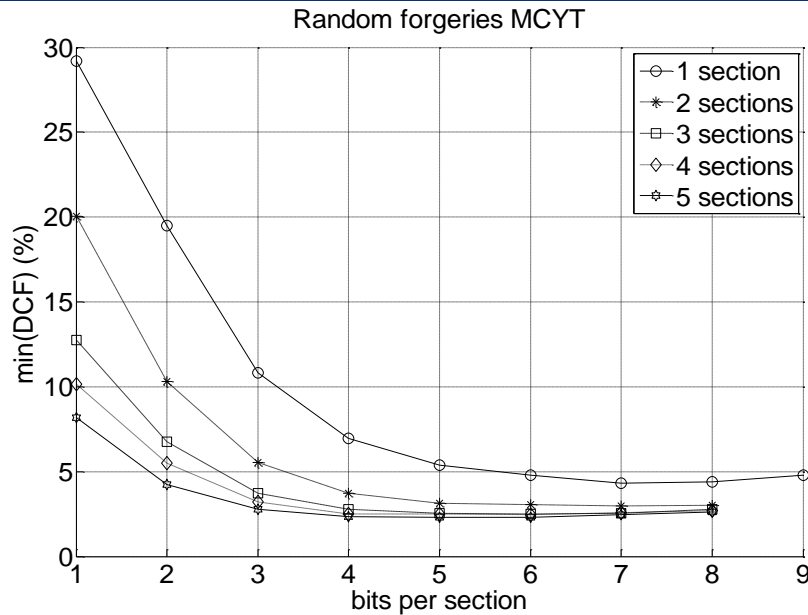
Signature verification: multisection codebooks



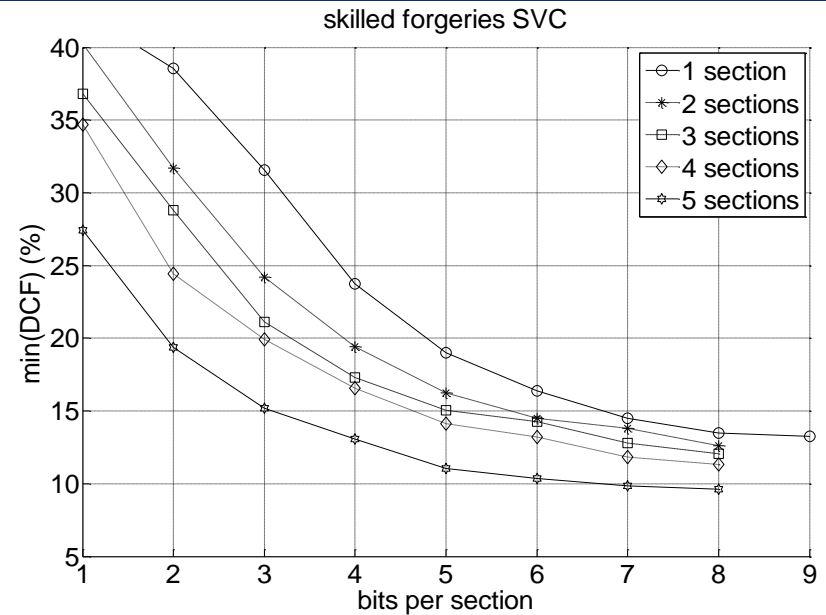
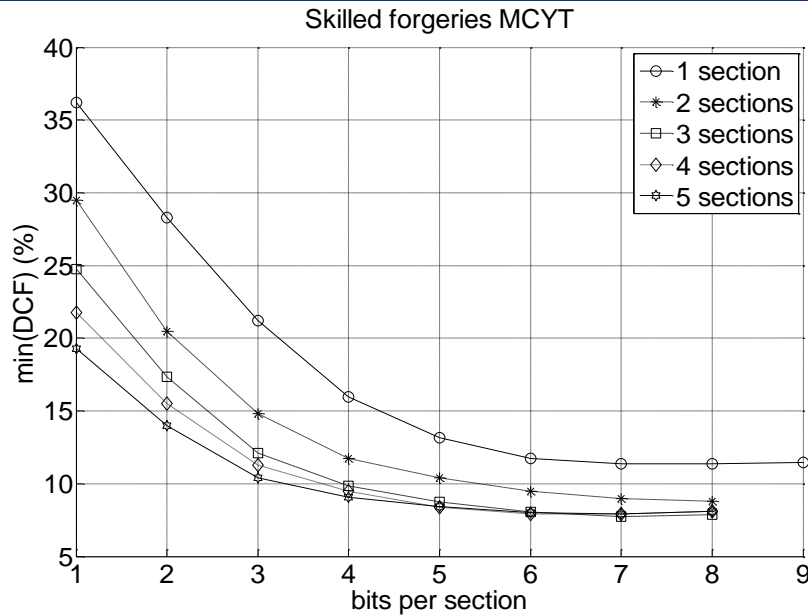
MSCB: identification results



MSCB: verification results (1/2)



MSCB: verification results (2/2)



HEALTH APPLICATIONS OF HANDWRITING

Alzheimer



- Sanitary cost for each patient and year is 35,000 USD in USA and 25,000 EUR in Spain.
- There are 800.000 Alzheimer patients in Spain. Only 4% receive treatment (32.000 patients)
- Early stage diagnose and better knowledge about the disease is basic.
- 1 of each 10 patients is younger than 60. The incidence is doubled for each 5 additional years of ageing after 65. After 85 betweed 1/3 and 1/2 of the population is affected by Alzheimer.

Pathology detection:

"MINI-EXAMEN COGNOSCITIVO"

Paciente Edad 73
 Ocupación Amasadora Escolaridad 6a. y 5a. Examinado por Fecha


ORIENTACION
 "Dígame el día 1 Fecha 30 Mes Febrero Estación Invierno Año 2000"
 "Dígame el Hospital (o al lugar) despacho Planta"
 Ciudad Barral Prov. San Juan Nación España

FIJACION
 "Repita estas 3 palabras: Peseta-Caballo-Manzana"
 (Repetirlas hasta que las aprenda) 2 (3)

CONCENTRACION Y CALCULO
 "Si tiene 30 pts. y me va dando de 3 en 3. ¿Cuántas le van quedando?" 5 (5)
 "Repita estos números: 5-9-2" (hasta que los aprenda) 2 (3)
 "Ahora hacia atrás"

MEMORIA
 "¿Recuerda las 3 palabras que le he dicho antes?" 2 (3)

LENGUAJE Y CONSTRUCCION
 Mostrar un bilingüa "¿Qué es esto?" Repetirlo con el reloj 2 (2)
 "Repita esta frase": "En un árbol había cinco perros" 2 (1)
 "Una manzana y una pera son frutas ¿Verdad? ¿Qué son el rojo y el verde?" 2 (2)
 "¿Qué son un perro y un gato?"
 "Coja este papel con la mano derecha, dóblelo y póngalo encima de la mesa" 2 (3)
 "Lea esto y haga lo que dice", **CIERRE LOS OJOS** 1 (1)
 "Escriba una frase" ganaron 1 (1)
 "Copie este dibujo":

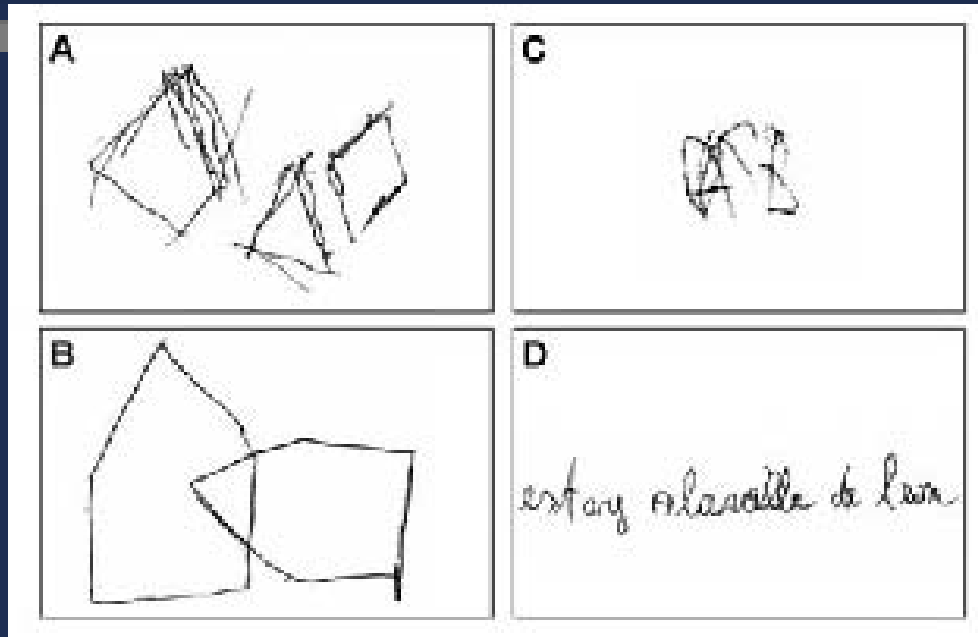


PUNTUACION TOTAL 33 (35)
 Nivel de conciencia (Marcar)

Alerta, Obnubilación, Estupor, Coma

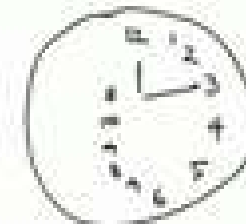
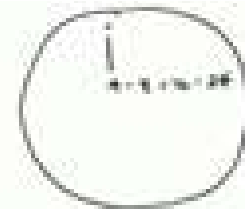
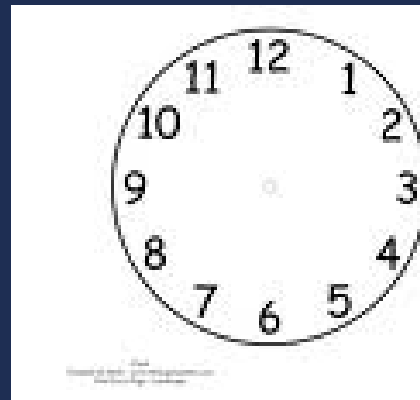
Lobo y colaba, 1979-85.

Hidrocefalia



Copia de los pentágonos del Mini Mental (MMSE) y escritura de un paciente con hidrocefalia crónica del adulto. En A y C, antes de la colocación de un sistema de derivación de líquido cefalorraquídeo. En B y D, 6 meses después del tratamiento quirúrgico

Clock test (1/2)



MMSE 26/30



MMSE 23/30



MMSE 23/30



MMSE 25/30



MMSE 27/30

Clock test (2/2)

Figure 1

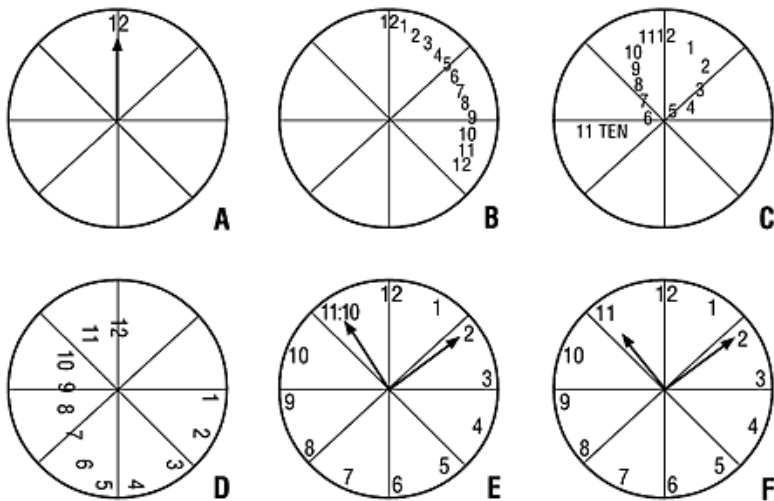


Figure 1. Scoring: **A.** Score = 0. **B.** The number 1 is in the correct position; score = 1. **C.** Numbers 1 and 2 are in the correct positions; score = 2. **D.** Numbers 7, 8, 10, and 11 are in the correct positions; score = 4. **E.** Numbers 1, 2, 4, 5, 7, 8, 10 and 11 are in the correct positions; score = 8. No points for hands of approximately equal length regardless of position. **F.** Numbers 1, 2, 4, 5, 7, 8, 10 and 11 are in correct position for 8 points. The little hand is on the 11 (1 point) and the big hand is on the 2 (1 point); score = 10 points (modified from Manos PJ and Wu, 1994)

Table 1

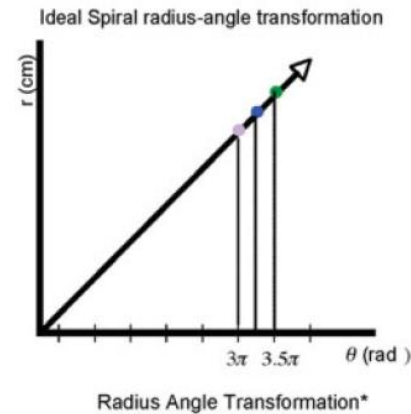
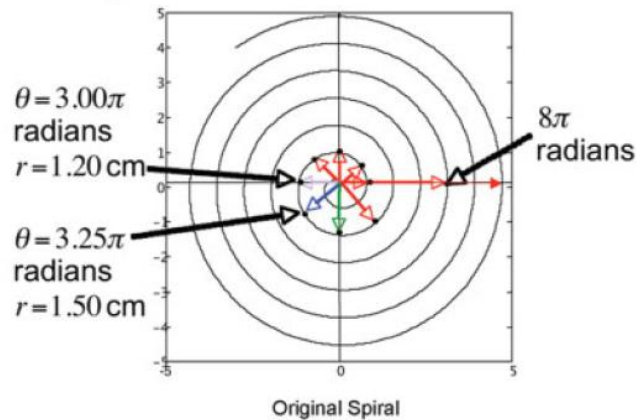
A Partial Frequency Distribution of Ten-Point Clock Test Scores by Diagnosis in a Series of Patients Referred for Psychiatric Consultation

Diagnosis	% of Patients with Score = 10	% of Patients Score < 8	% of Patients Score < 5
Delirium	0	92	40
Dementia	0	90	70
Opioid Intoxication	10	70	40
Cognitive Disorder NOS (not otherwise specified)	14	64	39
Major Depression	58	25	0
Alcohol Dependence	40	13	0
Adjustment Disorder	57	5	0

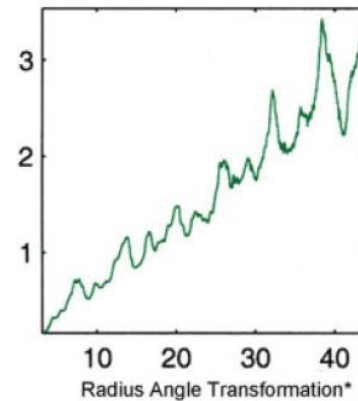
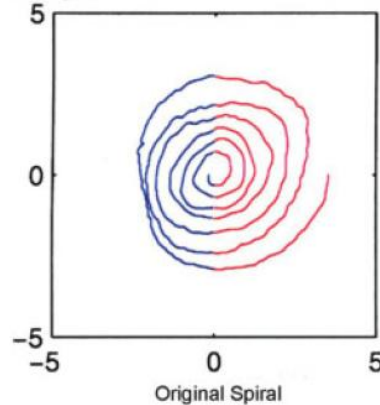
(modified from Manos PJ, 1997)

Archimedes spiral

A. Ideal Spiral



B. Parkinson's Spiral



Security implications (1/2)

FIRMAS INDUBITADAS 1986

LOS - VARIACIONES = numero = var

Claudia Hernandez

Claudia Hernandez

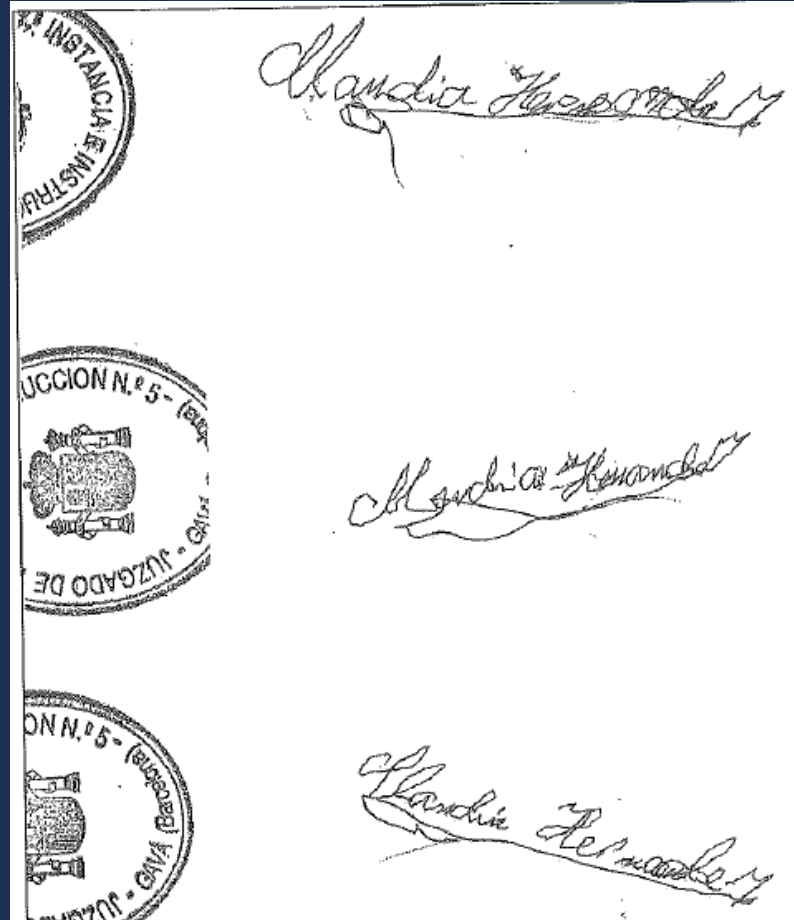
D^a CALUDIA HERNANDEZ ALTABELLA

FIRMA DUBITADA (fotocopia inicial) 1985

Claudia Hernandez

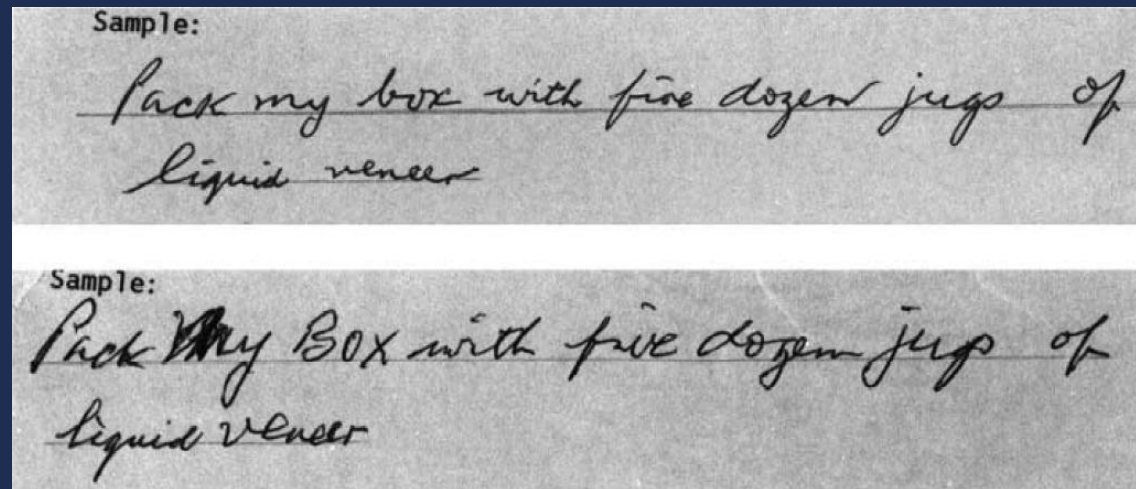
FIRMA DUBITADA nueva
(original aportado a los autos) 1985

Claudia Hernandez



Security implications

- [Walton 1997] analyzes 200 patients of Parkinson and a control group of the same ages and he finds some changes on the handwriting similar to forgeries, although a deeper analysis shows differences.



En la parte superior se muestra la escritura de un enfermo de Parkinson de 72 años de edad. En la parte inferior, la misma frase escrita por la misma persona al cabo de 5 años. Se observa fácilmente el deterioro en la grafía.

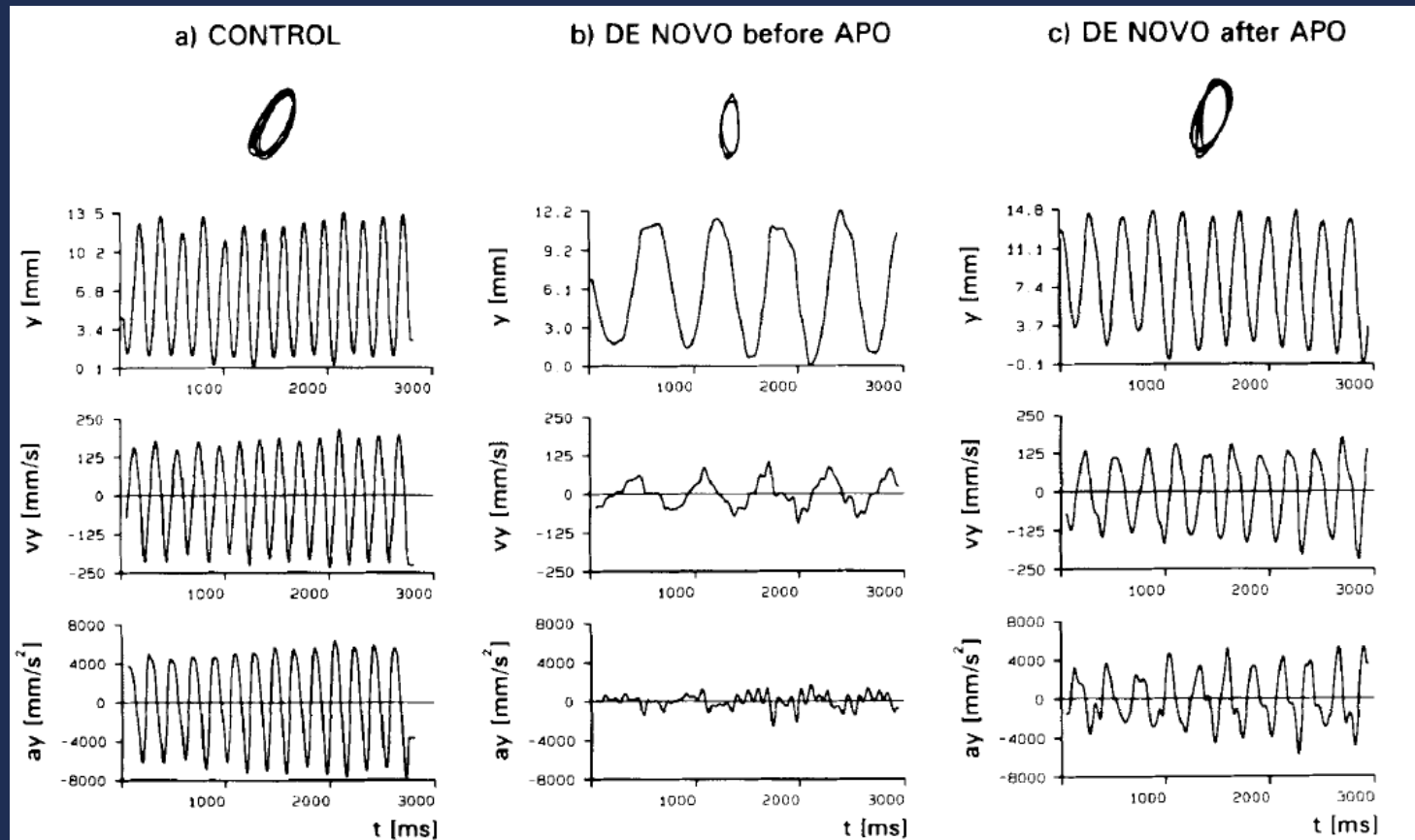
Relevant facts

- A human examiner is affected by subjectivity. Specially if the medical expert does not have graphological background.
- The results provided by a human examiner are more qualitative than quantitative.
- Pathology detection is probably done in a late stage.
- Some problematics such as pauses and tremors are more difficult to see once the handwriting has already been done.
- The speech is also relevant and probably less studied because it is more difficult to be acquired (PC sound cards are relatively new) and difficult to be analyzed by a medical doctor.

Writing loops

Demo: <http://www.youtube.com/watch?v=FMjRBjsWYAU>

Example: relevance of apomorphine of Parkinson's disease



Summary

- Biometric recognition of people is a subset of biometric applications.
- Biometrics offers some advantages (and also drawbacks) when compared with classic methods.
- Biometrics differs from classical pattern recognition applications in some aspects (small amount of training samples).
- Signature and handwriting offers some nice properties: you can ask the user for a specific task, you can replace the signature.

QUESTIONS?