Stic-AmSud Project

Research at UFPR/PUCPR - Brazil

Luiz Eduardo S. Oliveira

Santiago, Jun 2014

About UFPR

- Universidade Federal do Paraná
  - Curitiba, PR
  - About 30,000 students
  - 112 under-grad courses
  - 89 graduate programs
  - 3500 professors
  - 7 campi
  - 2 hospitals

About DInf

- Department of Informatics
- Created in 1971
- 40 permanent professors
- Graduate program in Computer Science (PPGInf)
  - Created in 1996
  - 25 professors, 100 master and 50 PhD students
  - > 300 alumni

Research Areas

- Computational Intelligence
  - Artificial Intelligence
  - **Pattern Recognition & Machine Learning**
  - **Image Processing**
  - Algorithms
  - Bio-inspired computation
- Information Technology
  - Databases
  - Software Engineering
- Distributed Systems and Networks
  - Distributed systems
  - Operating systems
  - Wireless networks

Vision, Robotics, and Imaging Lab

- Created in 2010
- Part of the Department of Informatics of the Federal University of Parana
  - Pattern Recognition
  - Machine Learning
  - Image Processing
  - Robotics
  - Computer Vision
- 4 faculty members
- 3 associated members
- 6 PhD students, 11 master students

About myself

- BSc in Computer Science, 1996 - UP Curitiba
- MSc in Informatics, 1998 - UTFPR Curitiba
- PhD in Engineering, 2003 - ETS, Montreal, Canada
- Associated Professor @ PUC-PR 2004-2009
- Associated Professor @ UFPR since 2009
  - Head of the Graduate program (2010-2012)
  - Adjunct Head of the Graduate program (2013-2014)
  - CNPq Researcher - Level 1D

Brazilian Researchers

- Prof. Luiz Eduardo S. Oliveira
  - UFPR
- Prof. Alceu Souza Britto JR,
  - PUCPR
- Prof. Alessandro Koerich
  - PUCPR, ETS-Canada (Oct 2014)

On Going Research

- Forest Species Recognition
- Genre Music Classification
- Writer Identification
- Alarm detection in Distribution Networks
- Breast Cancer Classification
- Dynamic Selection of Classifiers
- Adaptation in Signature Verification

Forest Species Recognition

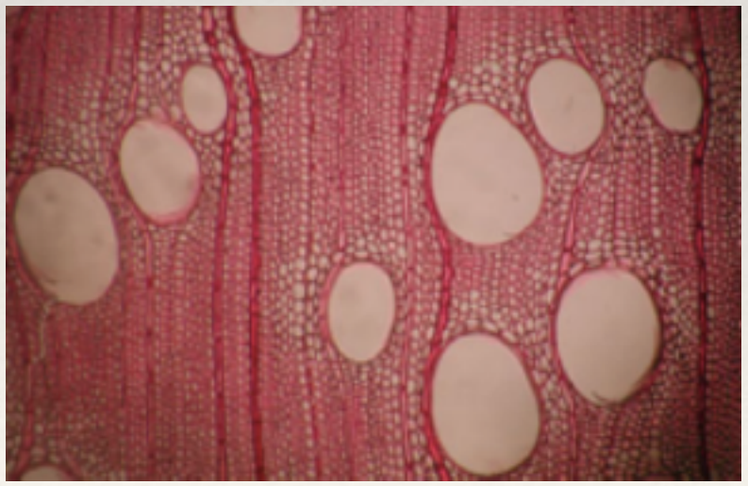
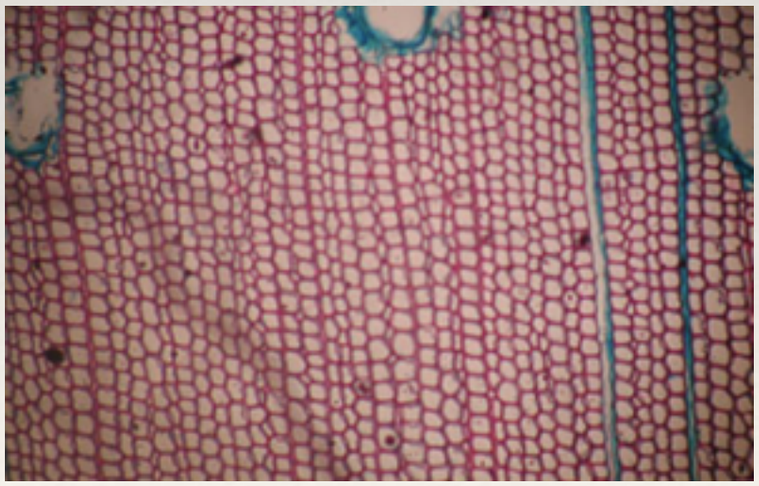
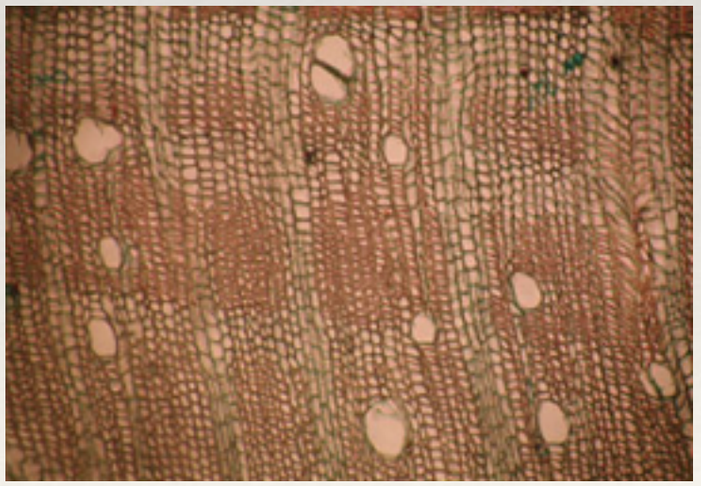
- Important issue for the safe trade of logs an timber
- But how to classify the wood outside the forest
  - No leaves, flowers, or fruits.
- Task that is usually performed by well-trained specialists.
  - Lack of specialised people

Forest Species Recognition

- Lack of public data
  - Most of works use databases with few classes and samples
  - With help of the Laboratory of Wood Anatomy of the UFPR we have built two datasets, which are available for research purposes.
    - Microscopic database
    - Macroscopic database

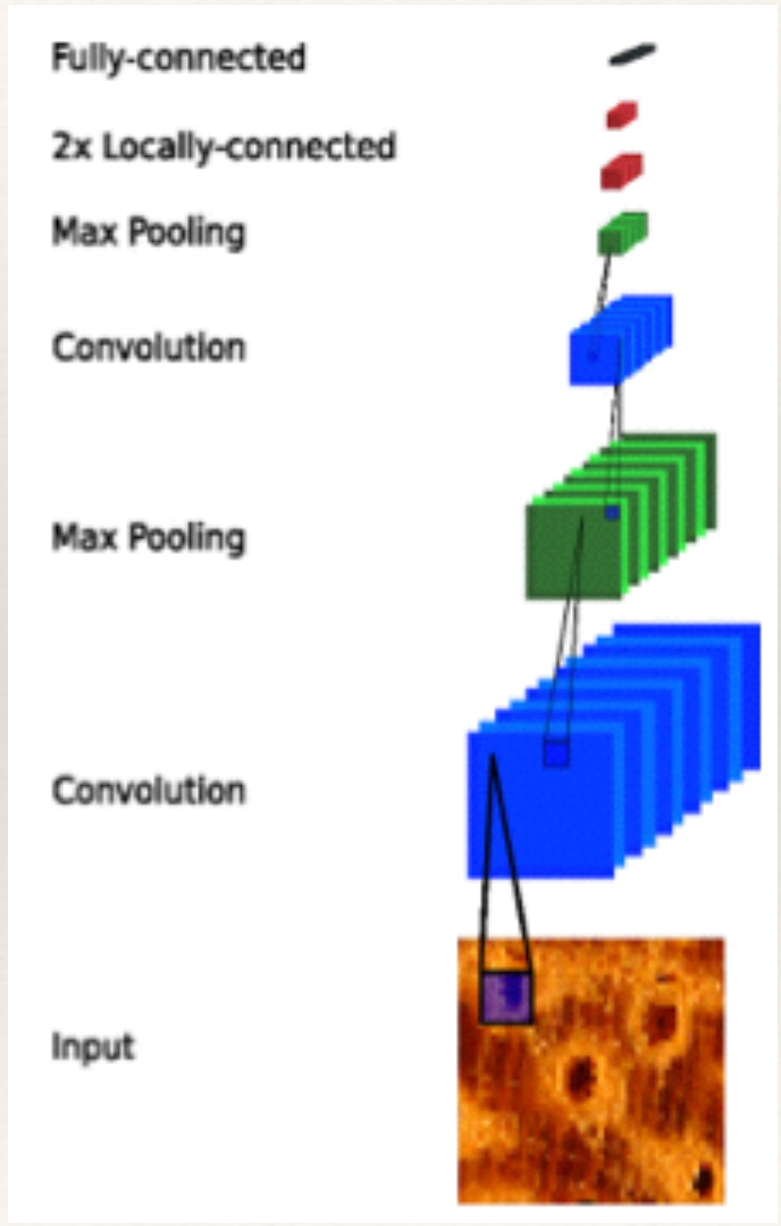
Forest Species Recognition

- Microscopic database [MVA 2012]
  - 112 classes
  - 20 samples per class

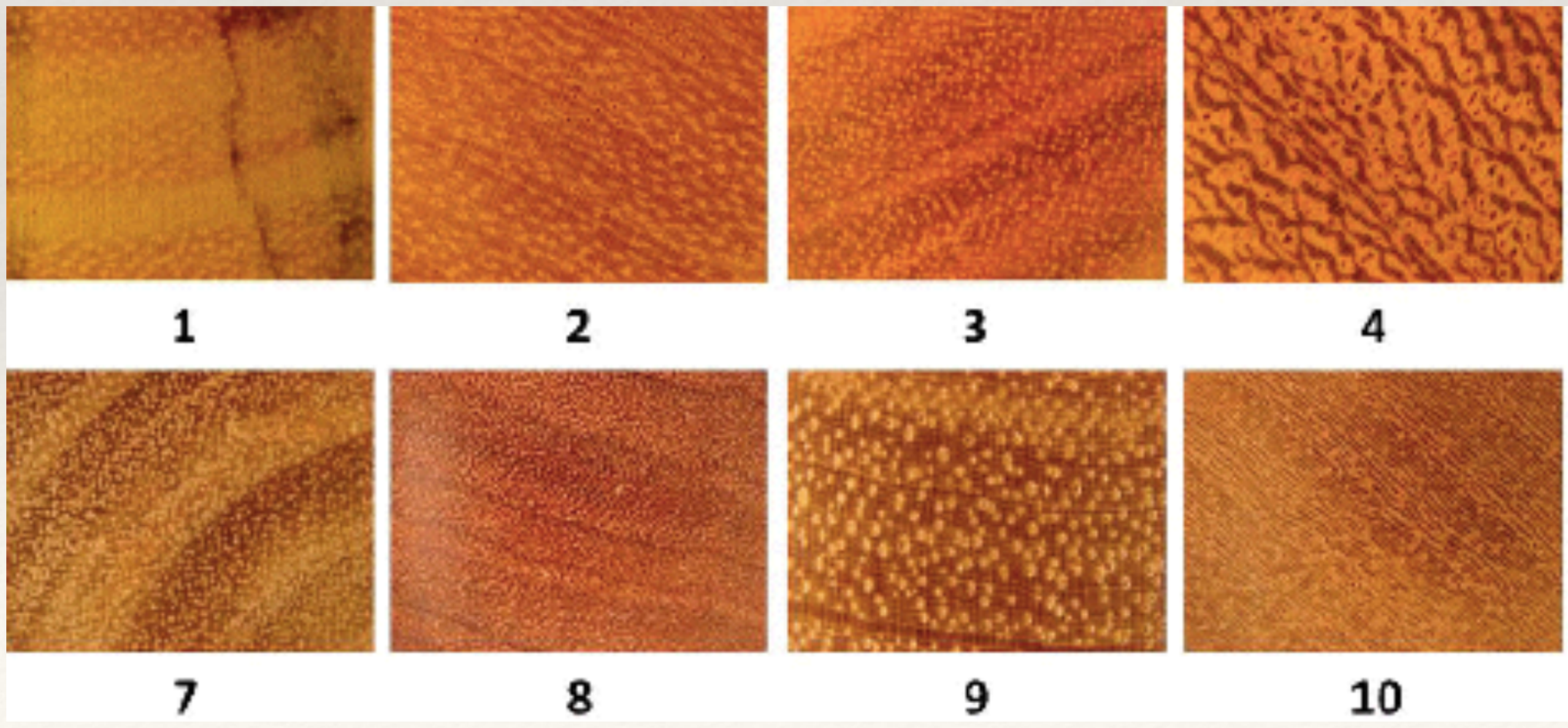
Forest Species Recognition

- Some results
  - QuadTree and LPQ (SVMs): 93.0% [SAC2013]
  - LPQ+LPQ Blackman+LPQ Guassian (SVMs): 95.6% [IJCNN2014]
  - Convolutional Neural Networks: 97% [ICPR2014]



Forest Species Recognition

- Macroscopic database [MVA 2014]
  - 41 classes
  - ~ 70 samples per class (2941 images)



Forest Species Recognition

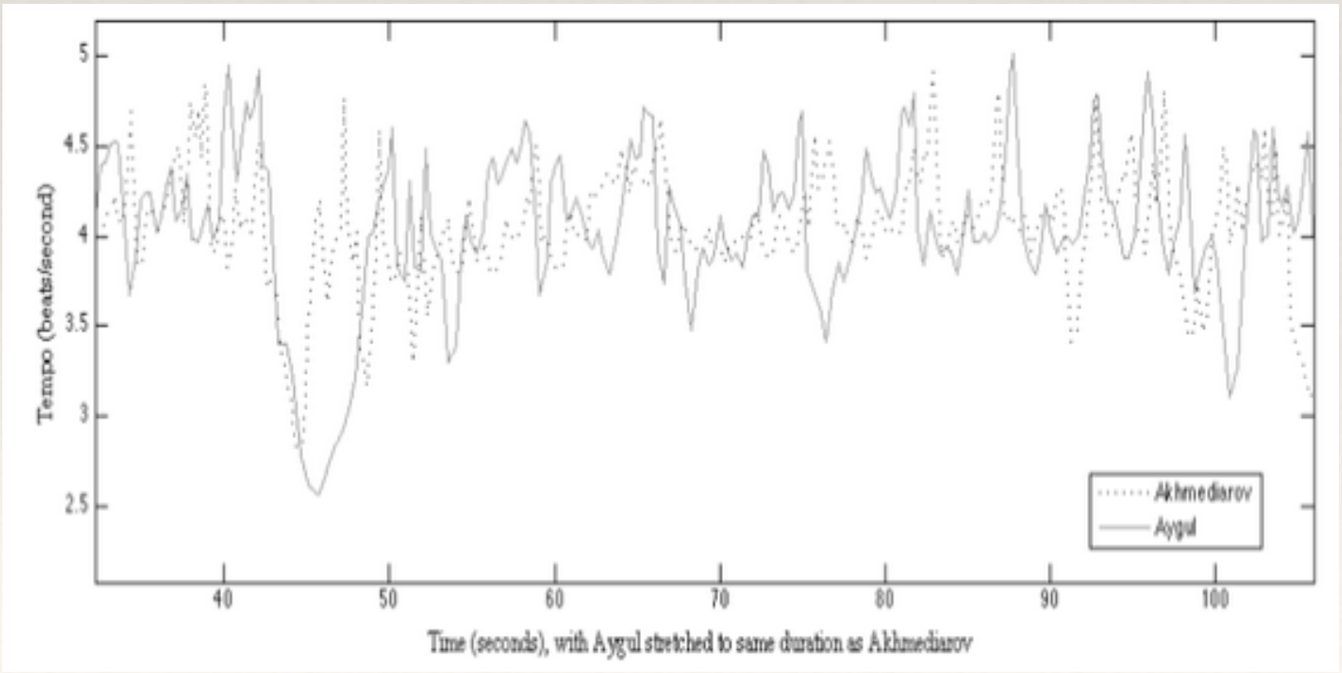
- Some results
  - GLCM+Color: 80% [ICPR2010]
  - Completed LPB: 96.2% [MVA 2014]
    - Two combination levels
      - Different classifiers (SVM) and different pieces of image (25 sub images)
- Convolutional Neural Nets: 95.7% [ICPR 2014]

Genre Music Recognition

- International cooperation CAPES/FCT-Portugal
- Organize the huge amount of data that becomes available on the internet
- Focus on music
- One way to organize music libraries is to assign a genre to each piece of music.
  - e.g, jazz, rock, pop, etc…
- Literature shows that the performance of a human in this task is around 76%

Genre Music Recognition

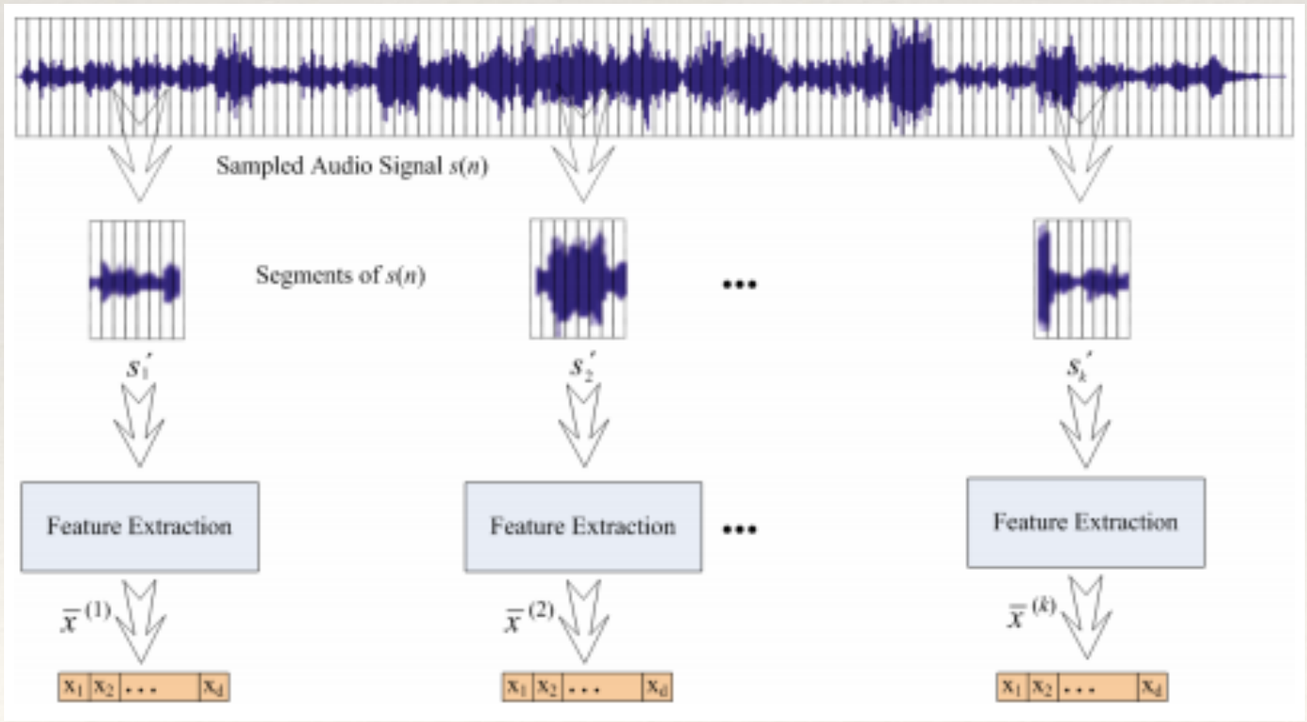
- MARSYAS (Music Analysis, Retrieval and Synthesis for Audio Signals)
  - Framework widely used for feature extraction
  - Timbral, Spectral, Chroma, Rolloff, etc..



Should we extract features from the entire music?

Genre Music Recognition

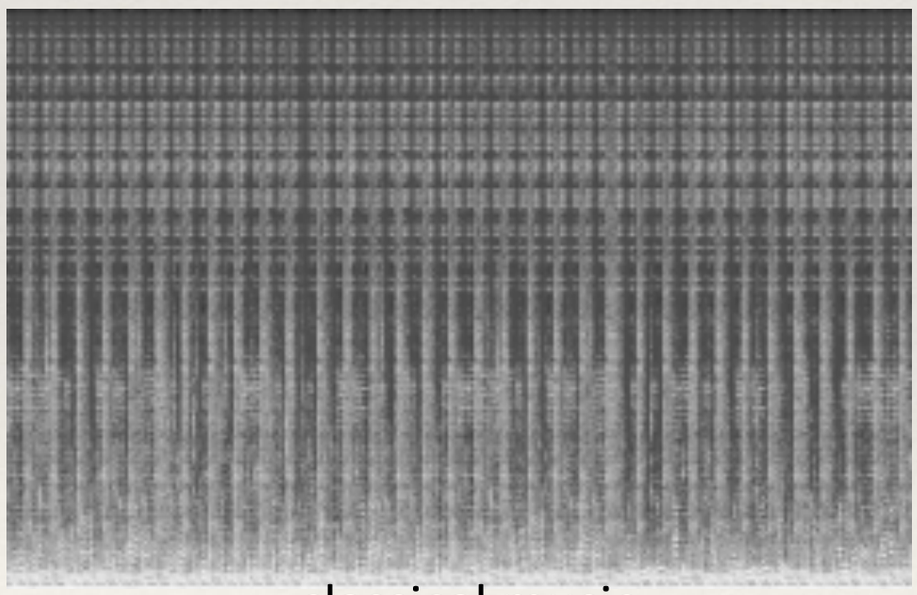
- Select some segments of the music and combine them to get a decision
  - How to select the segments?
  - How many segments?



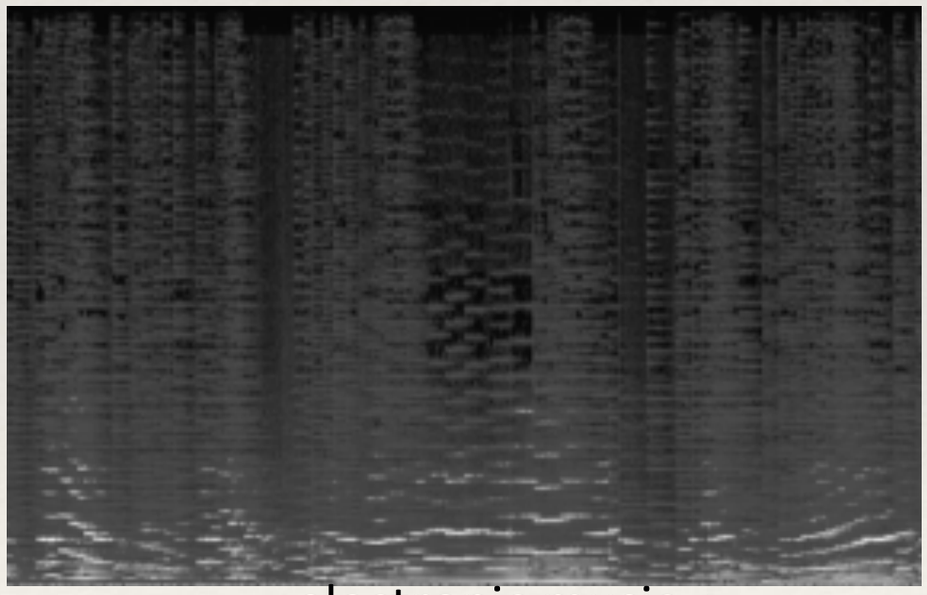
Performance on the LMD database (10 classes): 60% [ICPR 2010]

Genre Music Recognition

- Change the perspective
  - Instead of using the traditional MARSYAS features, we converted the segments of music into spectrograms
  - Texture problem



classical music



electronic music

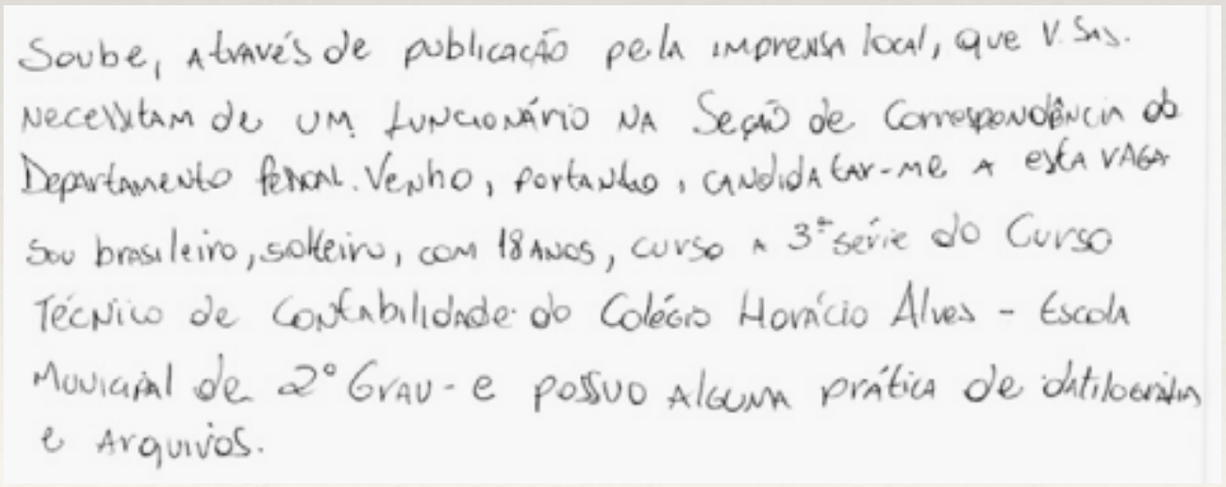
Performance using LBP descriptor: 82% (LMD), 80% (ISMIR) [Sig Processing 2012]

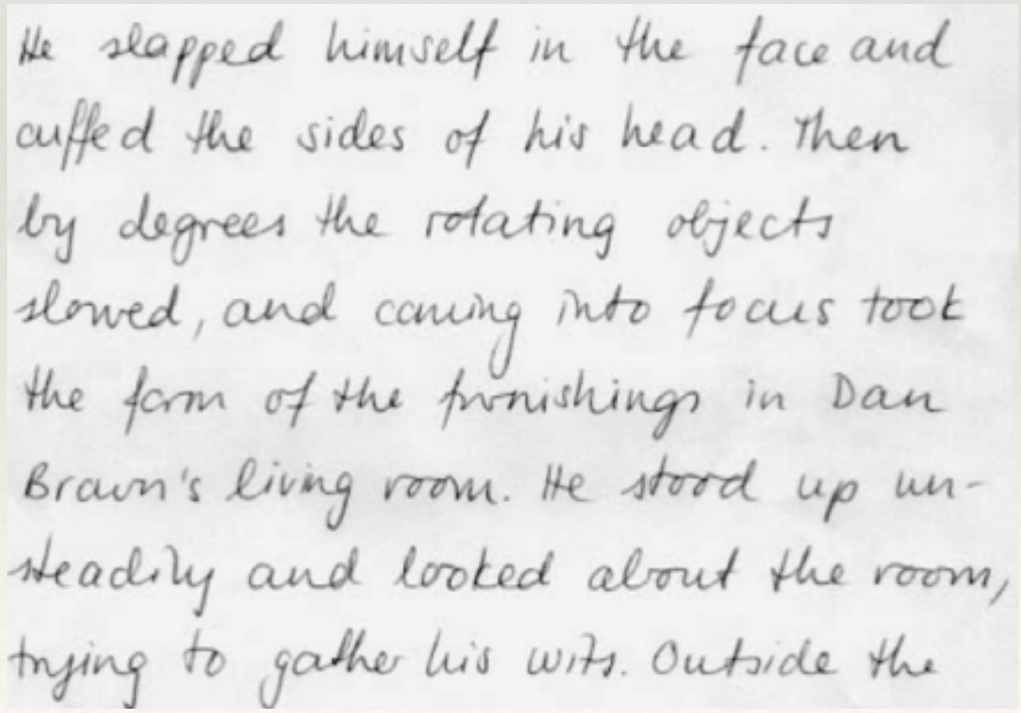
Genre Music Recognition

- Challenges
  - How many segments to use?
  - Different frequencies to create the spectrograms
  - Million Song Database
    - http://labrosa.ee.columbia.edu/millionsong/

Writer Identification

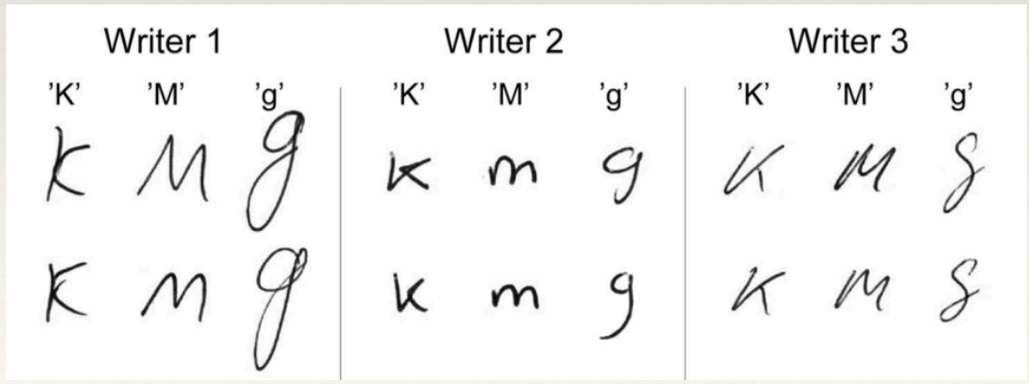
- Similar to signature in the sense that it contains handwriting information
- In this case one wants to know who wrote a given document.
- Documents may be written in any language


Soube, através de publicação pela imprensa local, que V. Sas. necessitam de um funcionário na Seção de Correspondência do Departamento federal. Venho, portanto, candidatar-me a esta vaga. Sou brasileiro, solteiro, com 18 anos, curso a 3ª série do Curso Técnico de Contabilidade do Colégio Horácio Alves - Escola Municipal de 2º Grau - e possuo alguma prática de datilografia e Arquivos.


He slapped himself in the face and cuffed the sides of his head. Then by degrees the rotating objects slowed, and coming into focus took the form of the furnishings in Dan Braun's living room. He stood up unsteadily and looked about the room, trying to gather his wits. Outside the

Writer Identification

- Classical approach to address this problem is to extract features from the handwriting
- Features used to recognise characters
  - Loops, concavities, contours, etc…
- Features used by forensic experts
  - How does the subject write a given letter(s)
  - Very effective, but it needs segmentation

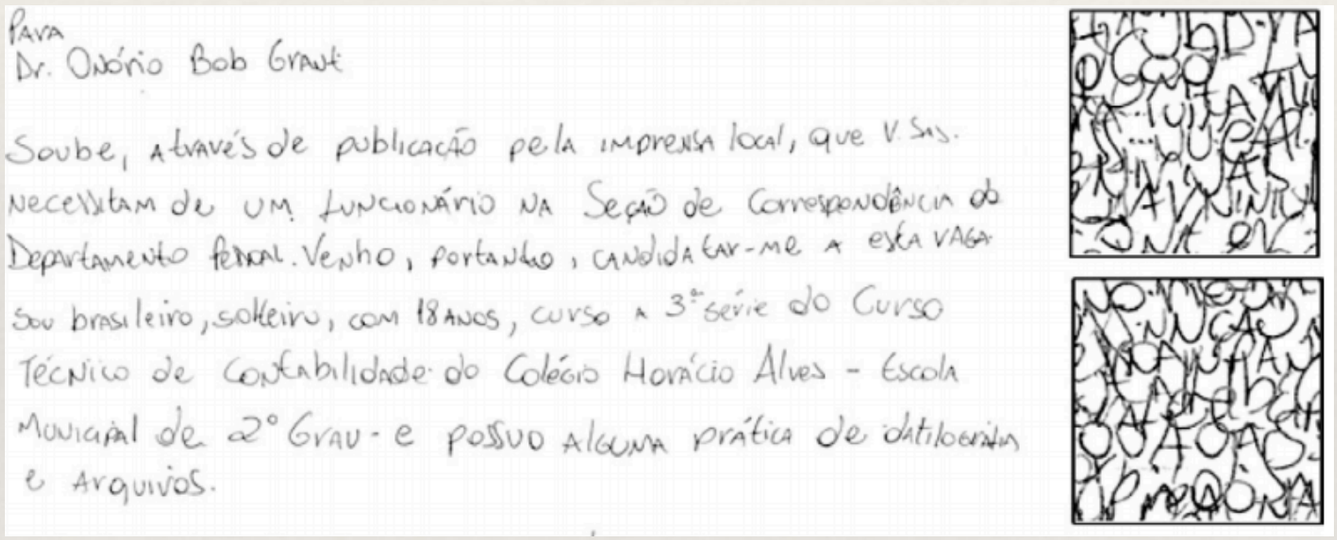


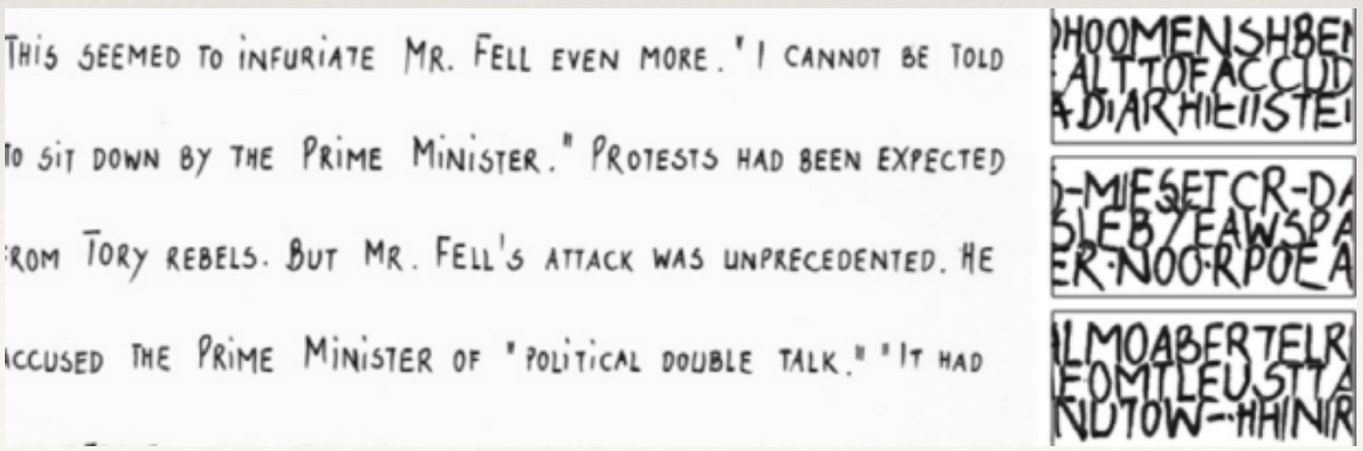
Writer Identification

- In order to skip segmentation we have to take a holistic approach
- In other words, we must see the whole, not the parts
- In this sense, we formulate the writer identification problem as a texture classification problem
  - Texture: Innate property of virtually all surfaces

Writer Identification

- Creating texture from the handwriting
  - No need of segmentation

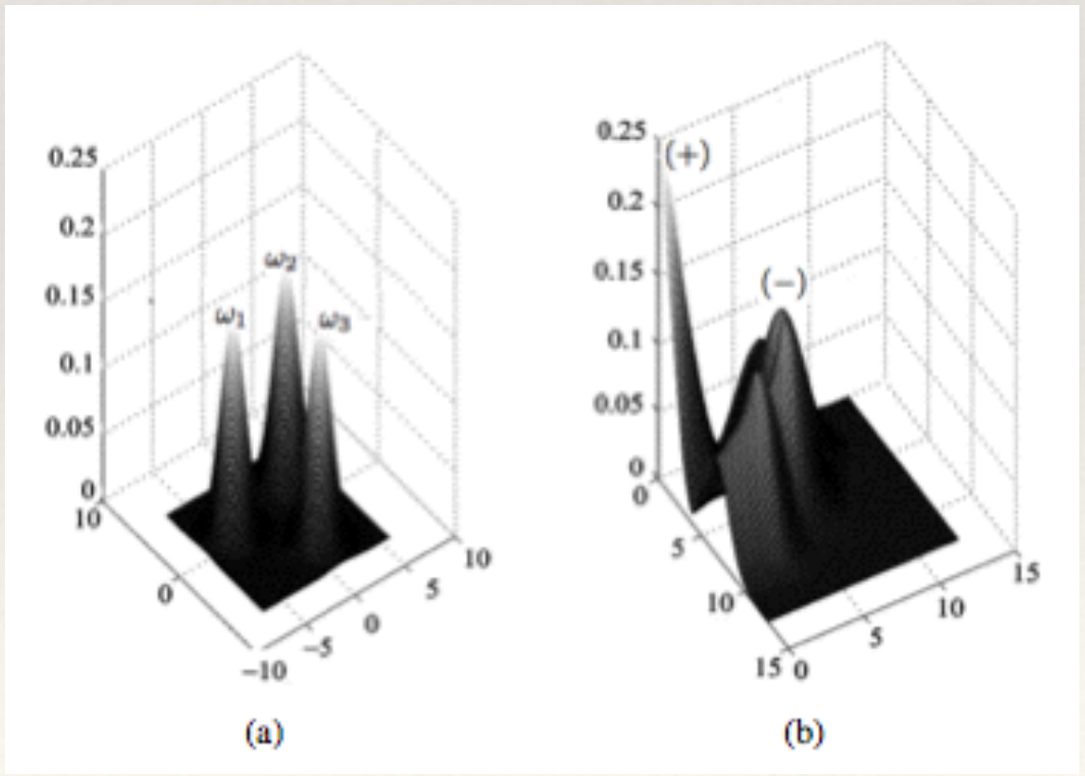




1. Detect all the connected components
2. Put them all together in a new image
3. Define how close the components may be
   1. Coarse of soft texture

Writer Identification

- Then we may use any textural descriptor
- Protocol used is based on the dissimilarity feature representation
  - Transform a n-class pattern recognition problem into a 2-class problem.
  - Dissimilarity vectors from the same class tend to have components close to zero



Writer Identification

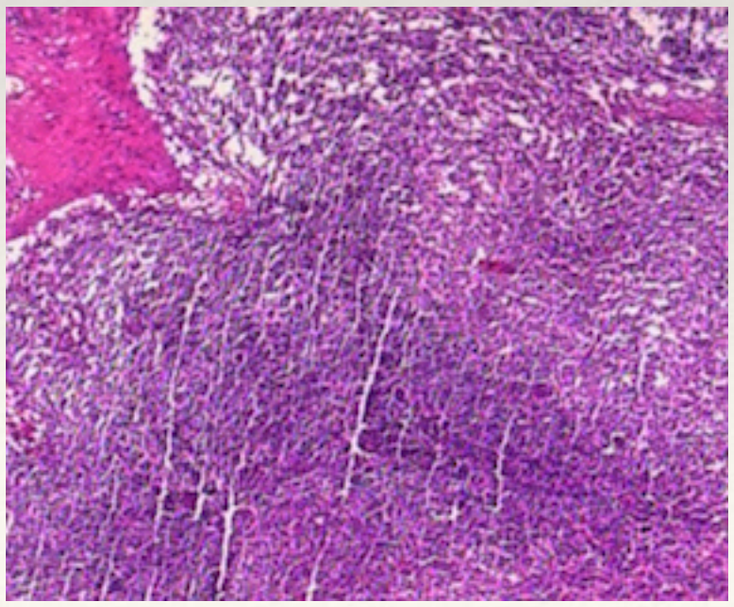
- Some results
  - GLCM [IJDAR 2012]
    - 350 writers (Brazilian Forensic Letters): Error rate: 3.9%
  - LBP and LPQ [ESwA 2013]
    - 650 writers (IAM): Error rate: 3.3%
- Forged text [ICPR 2014]
  - Firemaker: Error rate: 6%

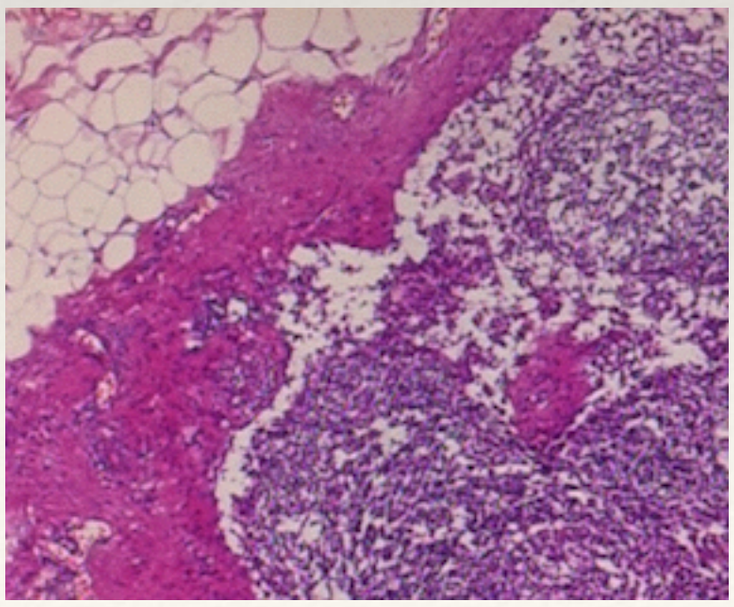
Writer Identification

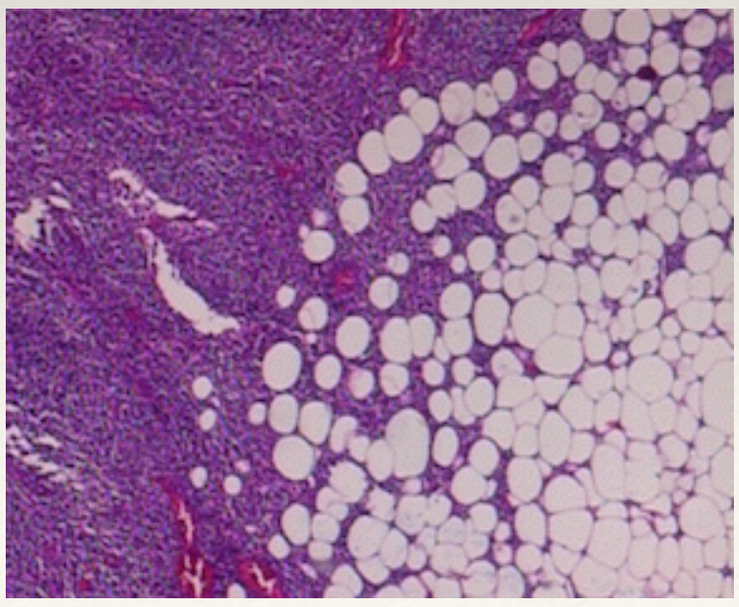
- Open issues
  - Is this texture good enough? Can we do better?
  - Which are the best writers to build a robust dissimilarity model?
    - Preliminary experiments show that we do not need all of them.
    - Better performance using selected writers.

Breast Cancer Classification

- 8-class problem.
  - One class (Ductal in situ) concentrates 95% of the data.
- Project just starting
- Data acquisition almost finished.
  - Great intra-class variability
- One class classification may be useful.







Dynamic Selection of Classifiers

- Survey recently published on Pattern Recognition
  - It is interesting but works better for more complex problems.
  - We found evidence of a relation between the observed performance contribution and the complexity of the classification problem.


Contents lists available at ScienceDirect

Pattern Recognition

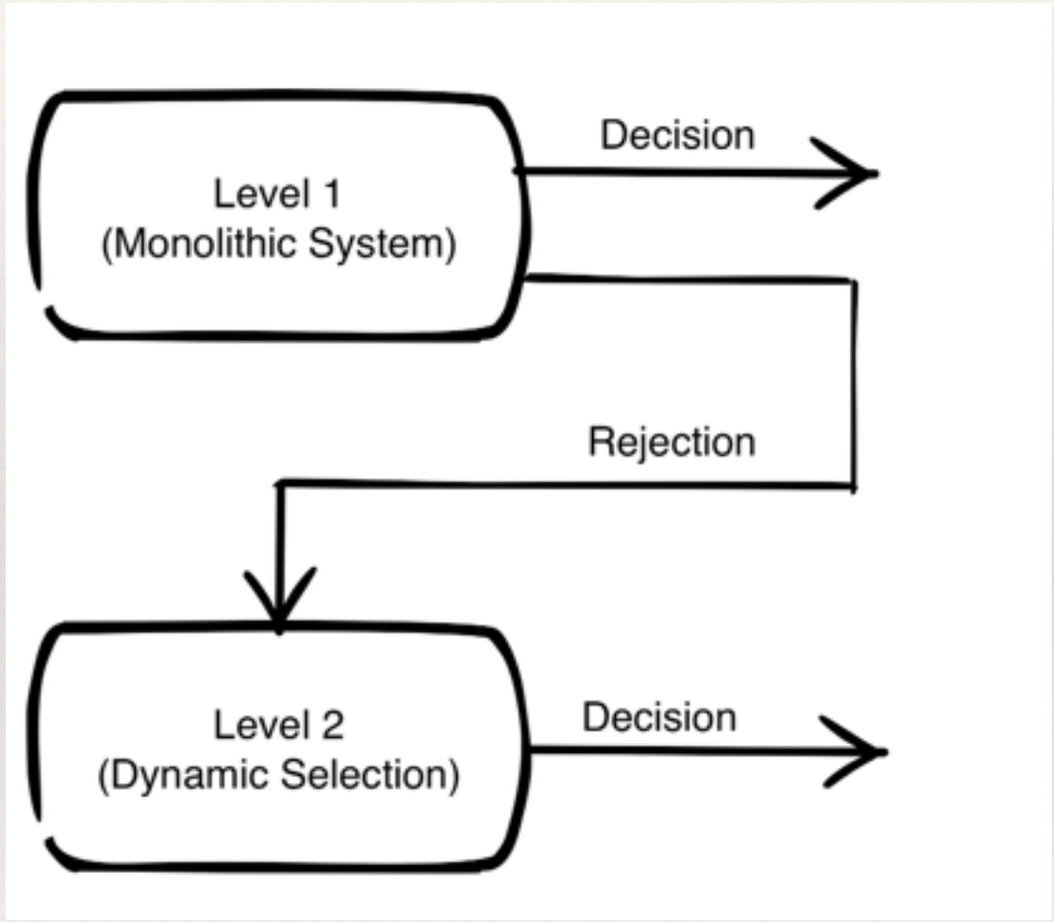
journal homepage: www.elsevier.com/locate/pr

Dynamic selection of classifiers—A comprehensive review

Alceu S. Britto Jr.[a,b,*], Robert Sabourin[c], Luiz E.S. Oliveira[d]

Dynamic Selection of Classifiers

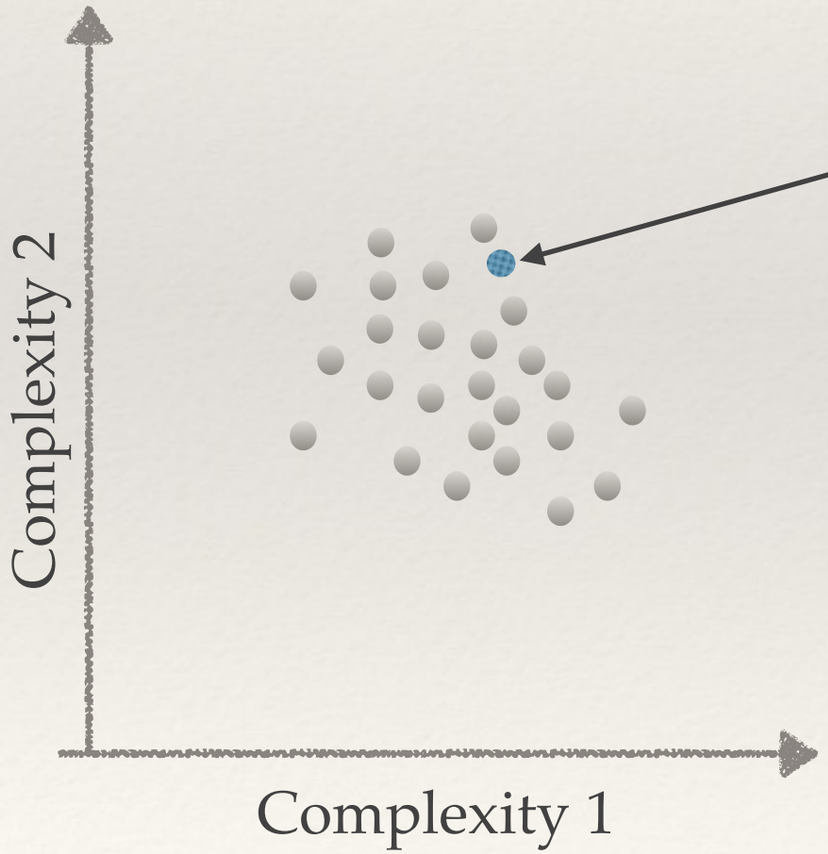
- Cascade approach
  - Solve easy cases on the first level
  - Define a robust rejection mechanism to send complex cases to the second level
    - Incongruence
- DSC in the second level to solve hard cases.



Dynamic Selection of Classifiers

- Complexity-based DSC (Macià et al [PR 2013])

Data generated artificially
fitness: Complexity measures

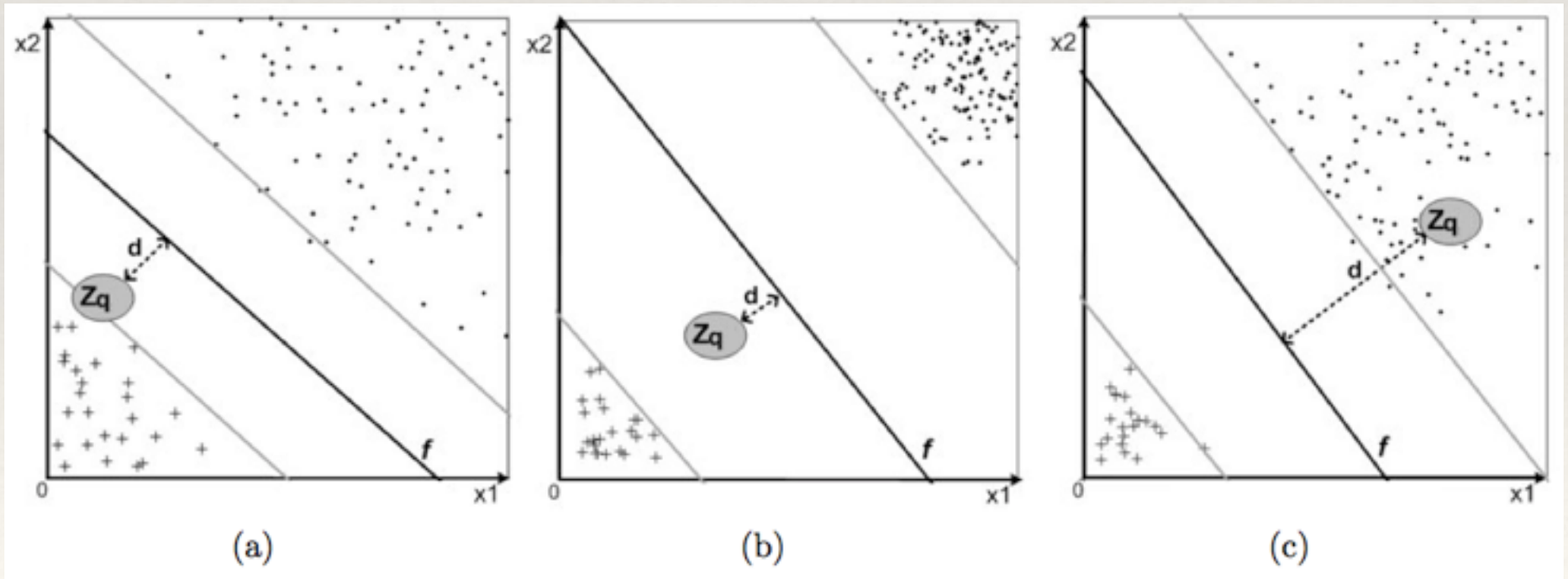


Real data projected onto
the complexity space

Select the classifiers related to data
with similar complexity

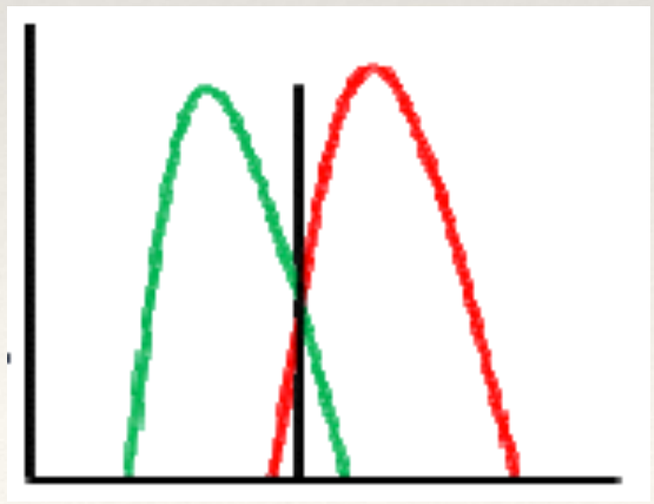
Dynamic Selection of Classifiers

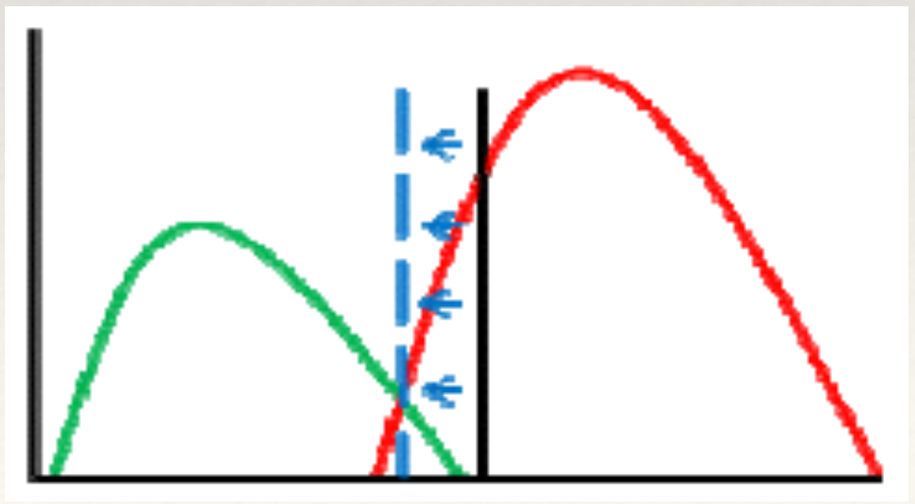
- Select Classifiers in the Dissimilarity Space
  - Extract some information from
    - the geometry of the dissimilarity space
    - the boundaries of the classifiers



Adaptation in Signature Verification

- How to adapt signature verification systems based on dissimilarity representation to the arrival of new data?
  - What is the best scenario?
    - Update the model
    - Create new models





“Thanks”