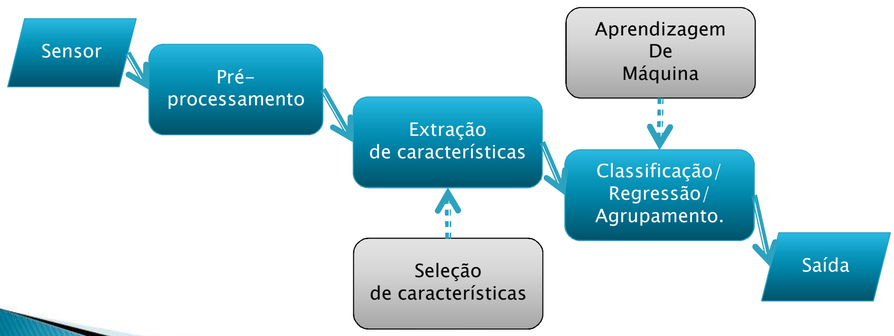
Aprendizagem de Máquina (AM) Introdução

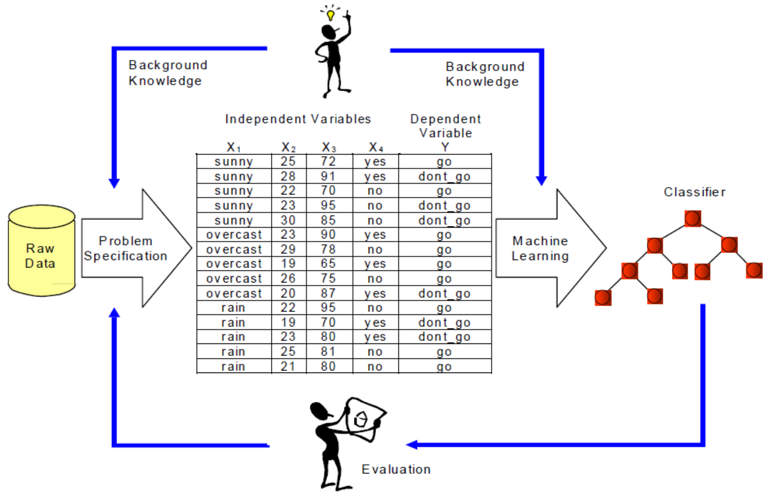
Prof. Dr. Alceu de Souza Britto Jr.
PPGIa/PUCPR

Aprendizagem de Máquina (AM)

- Reconhecimento de Padrões
- Ensinar a máquina via indução (obter um modelo a partir de dados ou exemplos)



Aprendizagem de Máquina



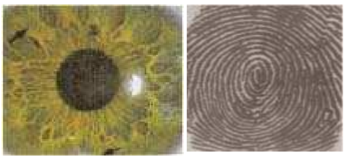
X_1	X_2	X_3	X_4	Y
sunny	25	72	yes	go
sunny	28	91	yes	dont_go
sunny	22	70	no	go
sunny	23	95	no	dont_go
sunny	30	85	no	dont_go
overcast	23	90	yes	go
overcast	29	78	no	go
overcast	19	65	yes	go
overcast	26	75	no	go
overcast	20	87	yes	dont_go
rain	22	95	no	go
rain	19	70	yes	dont_go
rain	23	80	yes	dont_go
rain	25	81	no	go
rain	21	80	no	go

Source: Reviewing some Machine Learning Methods and Concepts (ICMC) - Baranauskas & Monard, 2000

Áreas Correlacionadas

- Visão Computação, Mineração de Dados, Processamento de Linguagem Natural, Ciência de Dados, Big Data, Matemática, Estatística, dentre outras.
- Tarefas comuns
  - Classificação
  - Regressão
  - Agrupamento
  - Descrição
  - Associação.

Onde encontramos AM?

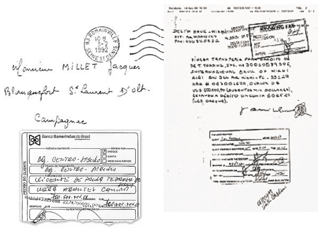


Biometría

Segurança e Controle de Acesso

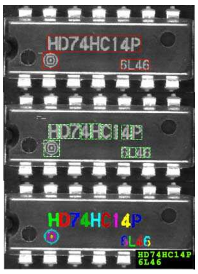
Terminais Bancários

Vigilância

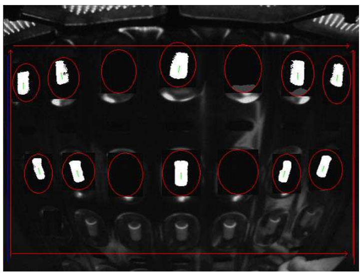


Processamento de Documentos / GED

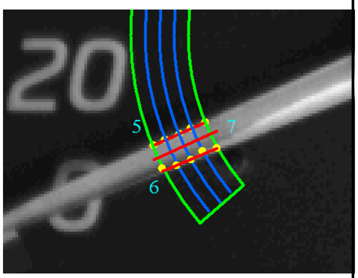
Onde encontramos AM?



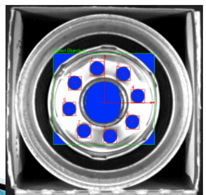
OCV



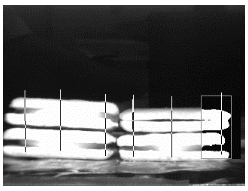
Presença / Ausência



Calibração / Aferição



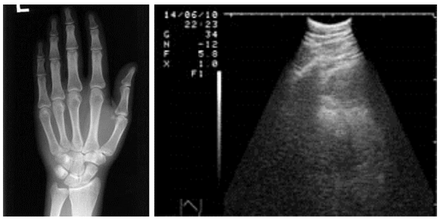
Metrologia



Conformidade

OCR

Onde encontramos AM?



Medicina / Diagnóstico

Supervisão de Trânsito

Alguns de meus projetos na área

- Reconhecimento de expressões faciais
- Determinação da idade através da face
- Classificação de vaga em estacionamento
- Identificação de espécies florestais
- Reconhecimento de gestos
- Identificação de pássaros (som e imagem)
- Classificação de gêneros musicais
- Monitoramento de ambientes
- Reconhecimento de manuscritos
- Seleção dinâmica de classificadores

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Contents lists available at SciVerse ScienceDirect
Expert Systems with Applications
journal homepage: www.elsevier.com/locate/eswa

Fusion of feature sets and classifiers for facial expression recognition

Thiago H.H. Zavaschi [a], Alceu S. Britto Jr. [a], Luiz E.S. Oliveira [b], Alessandro L. Koerich [a,b,*]

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[b] Federal University of Paraná, R. Cel. Francisco H. dos Santos, 100, Curitiba, PR 81531-990, Brazil

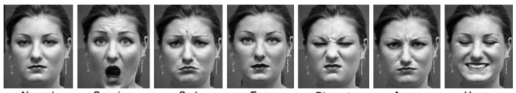

Table 4
Comparison with different approaches on JAFFE database.

Reference	Accuracy (%)	Features
Zhang et al. (1998)	90.1	Geometry and Gabor
Bashyal and Venayagamoorthy (2008)	90.2	Gabor and LVQ
Koutlas and Fotiadis (2008)	92.3	Gabor filters
Liu and Wang (2006)	92.5	Gabor filters
Oliveira et al. (2011)	94.0	2DPCA with feature selection and SVM
Shih et al. (2008)	94.1	2D-LDA and SVM
Liao et al. (2006)	94.5	LPB, Tsallis entropies, global appearance
Cheng et al. (2010)	95.2	Gaussian process
Zhi and Ruan (2008)	95.9	2D locality preserving projections
Proposed approach	96.2	Ensemble based on Gabor and LBP

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Contents lists available at ScienceDirect
Pattern Recognition
journal homepage: www.elsevier.com/locate/pr

A flexible hierarchical approach for facial age estimation based on multiple features

Jhony K. Pontes [a], Alceu S. Britto Jr [b], Clinton Fookes [a], Alessandro L. Koerich [c,*]

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[c] Department of Software and IT Engineering, École de Technologie Supérieure, Montréal, Québec, Canada

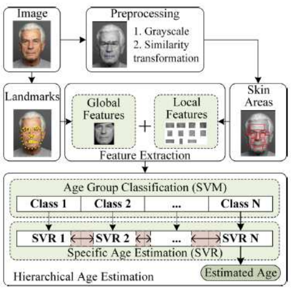

Fig. 1. An overview of the proposed age estimation approach.

Table 9
Comparison of the proposed approach to the previous works reported on the FG-NET Aging dataset.

Methods of age estimation	*MAE*	Methods of age estimation	*MAE*
WAS [29]	8.06	Duong et al. [14]	4.74
AGES [18]	6.77	Choi et al. [9]	4.65
RUN [42]	5.78	PLO [31]	4.82
Ranking [41]	5.33	CA-SVR [7]	4.67
LARR [19]	5.07	HC-SVR [32]	5.28
SVR [19]	5.66	ST + CSOHR [5]	4.70
Luu et al. [33]	4.37	**Human age estimation**	**6.52**
MTWGP [44]	4.83	**Flexible overlapped** & AAM + $LPQ_{7\times}7$	**4.50**
OHRank [6]	4.85	**Flexible overlapped** & AAM + $LPQ_{7\times}7$ (LOPO)	**4.78**

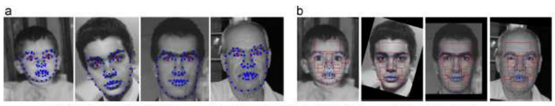

Fig. 2. Sample images from FG-NET: (a) grayscale conversion and the 68 landmarks and (b) after normalization and the eleven skin areas.

Machine Vision and Applications (2014) 25:1019–1031
DOI 10.1007/s00138-014-0592-7

ORIGINAL PAPER

Forest species recognition using macroscopic images

Pedro L. Paula Filho · Luiz S. Oliveira ·
Silvana Nisgoski · Alceu S. Britto Jr.

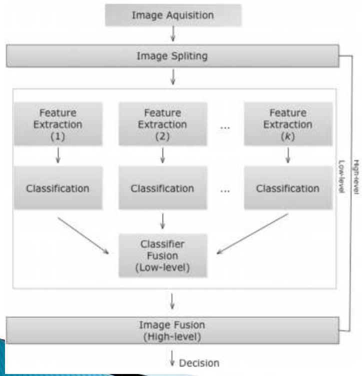

Table 7 Performance of the best ensembles using $n = 25$

Number of classifiers	Feature sets	Rec. rate %
6	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, Gabor, $LBP_{8,2}$, Fractals	97.77
4	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, $LBP_{8,2}$	97.71
4	$CLBP\_SMC_{24,5}$, Color RGB, Gabor, $LBP_{8,2}$	97.64
6	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, $LBP_{8,1}$, $LBP_{8,2}$, Fractals	97.64
6	$CLBP\_SMC_{16,3}$, $CLBP\_SMC_{24,5}$, Color RGB, Gabor, $LBP_{8,1}$, $LBP_{8,2}$, Fractals	97.64

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

ELSEVIER

PKLot – A robust dataset for parking lot classification

Paulo R.L. de Almeida [a], Luiz S. Oliveira [a], Alceu S. Britto Jr. [b,*], Eunelson J. Silva Jr. [b]
Alessandro L. Koerich [b,c]

[a] Federal University of Parana, Department of Informatics, R. Cel. Francisco H. dos Santos, 100, Curitiba, PR 81531-990, Brazil
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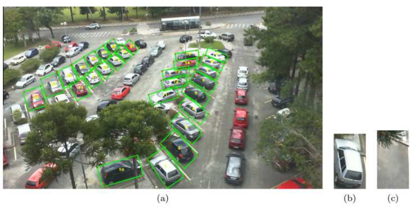

Fig. 4. Segmented image: (a) 28 delimited spaces, (b) occupied sub-image, and (c) empty sub-image.

Table 12
Comparison to related works reported in the literature.

Reference	Features	Number of parking spaces	Error rate (%)
Wu et al. (2007)	Color	1100	6.5
Sastre et al. (2007)	Gabor filters	12,150	2.2
Bong et al. (2008)	Color	80	7.0
Huang et al. (2008)	Color	2600	2.5
Ichihashi et al. (2009)	PCA	54,000	2.0
Huang and Wang (2010)	Color	6912	1.2
Proposed method	Texture	(UFPR04) 49,335 (UFPR05) 82,516 (PUCPR) 211,776	0.4 0.7 0.4

IJDAR (2003) 5: 102–117
Digital Object Identifier (DOI) 10.1007/s10032-002-0085-5

International Journal on Document Analysis and Recognition IJDAR
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The recognition of handwritten numeral strings using a two-stage HMM-based method

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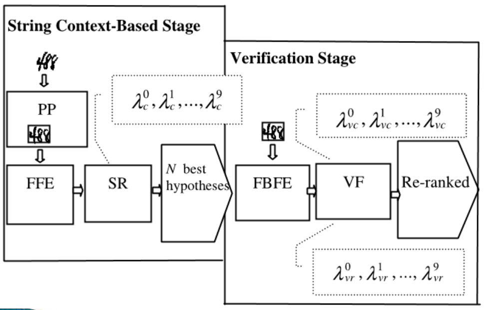
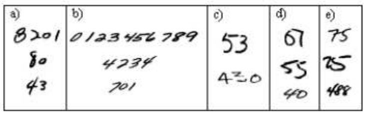




Class	Top (1)	Top (2)	Top (3)	Top (4)	Top (5)
2_digit	94.8	97.1	97.9	98.0	98.1
3_digit	91.6	94.6	95.0	95.0	95.0
4_digit	91.2	94.2	94.8	94.9	94.9
5_digit	88.3	92.1	92.6	92.7	92.8
6_digit	89.0	92.8	93.5	93.5	93.6
10_digit	86.9	90.3	90.3	90.4	90.4
Global	90.6	93.8	94.4	94.5	94.5
TDPs	88.9	93.5	94.8	95.3	95.7

2012 IEEE International Conference on Systems, Man, and Cybernetics
October 14-17, 2012, COEX, Seoul, Korea

Music Genre Classification using Dynamic Selection of Ensemble of Classifiers

- 10 classes base LMD (Latin Music Database)

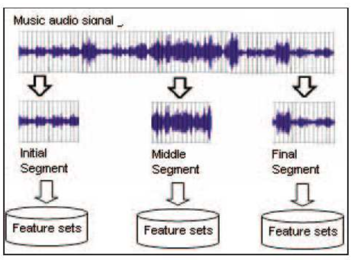


Figure 1. Feature extraction from 3 segments of the music signal adapted from [2].

TABLE V. BEST RESULTS OF THE DYNAMIC SELECTION METHOD AND THE CORRESPONDING K VALUE

Selection scheme	# of classifiers selected	# of votes	Accuracy (%)
Experiment 1 (E1) Oracle = 100%			
KE ($k = 1$)	72	72	59.66
KU ($k = 10$)	249	709	70.31
Experiment 2 (E2) Oracle = 100%			
KE ($k = 1$)	43	43	57.02
KU ($k = 13$)	143	573	64.94

2014 IEEE 26th International Conference on Tools with Artificial Intelligence

An HMM-based Gesture Recognition Method Trained on Few Samples

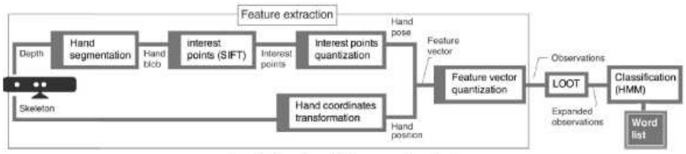
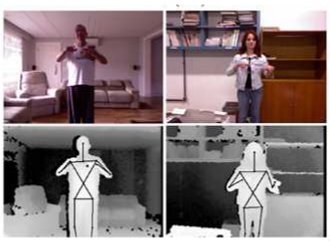


Fig. 2: Overview of the proposed method

# of training samples (for each word)	LRM without LOOT			LRM with LOOT			LRE with LOOT		
	top1	top2	top3	top1	top2	top3	top1	top2	top3
1	23.7	24.8	25.9	23.7	25.4	26.5	29.0	29.6	33.3
3	24.3	25.9	28.1	25.9	28.7	30.3	46.9	49.4	50.6
5	34.8	41.4	53.5	37.5	43.0	57.4	59.9	64.8	66.0
10	61.3	76.8	78.4	63.5	77.9	79.0	85.0	87.7	90.7
14	66.3	81.2	83.9	69.0	84.5	86.1	88.5	98.8	98.8
17	72.3	83.9	88.4	76.2	87.2	92.8	91.2	100.0	100.0



Detection of non-conventional events on video scenes

Published in:
2007 IEEE International Conference on Systems, Man and Cybernetics

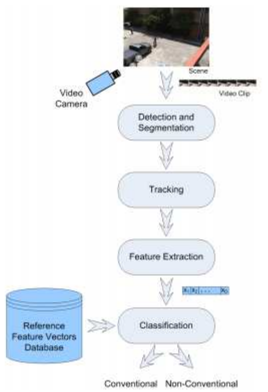
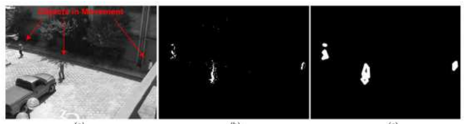


Fig. 1. Overview and main components of the proposed approach to detect non-conventional events in video scenes.



(a) (b) (c)

Fig. 2. An example of movement detection and segmentation on a video clip from Parking Lot Database: (a) original video frame with objects in movement, (b) movement segmentation by Gaussian functions, (c) resulting *blobs* after applying filters, background subtraction and contour detection.

Correct classification around 78%

Visual and acoustic identification of bird species

Published in:
2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)

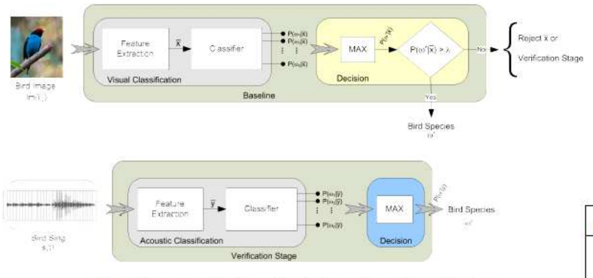


Fig. 1. Visual classification with rejection and acoustic verification.

50 espécies de pássaros

N best hypotheses	Correct Classification Rate (%) Visual	Acoustic
TOP 1	27.03	45.97
TOP 2	36.76	57.58
TOP 3	43.78	64.69
TOP 4	48.92	72.04
TOP 5	54.26	75.83
TOP 6	57.77	79.62
TOP 7	60.88	81.75
TOP 8	64.05	84.36
TOP 9	66.76	86.49
TOP 10	68.72	86.97

Table 1. Correct classification rates for the visual and acoustic classifiers on 1,480 images and 422 audio samples of the testing set at 0% rejection level.

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PATTERN RECOGNITION

Dynamic selection of classifiers—A comprehensive review

Alceu S. Britto Jr.[a,b,*], Robert Sabourin[c], Luiz E.S. Oliveira[d]
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[b] Universidade Estadual de Ponta Grossa (UEPG), Ponta Grossa, PR, Brazil
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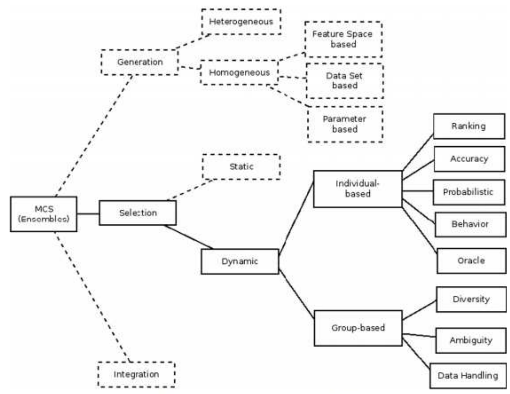
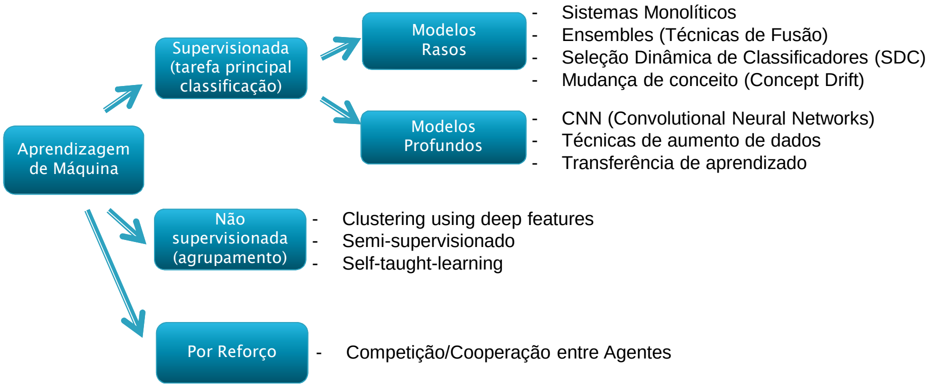


Fig. 2. Proposed DS Taxonomy in the context of MCS.

Pesquisas em Andamento

- Aplicada
  - Análise de sentimentos (áudio e imagem)
  - Indexação/Recuperação de imagens documentos (word/object spotting)
  - Verificação de assinaturas
  - Biometria da face/íris/região periocular
  - Detecção de pornografia em vídeos
- Teórica
  - Escolha da Representação Adequada para um Problema
  - Seleção Dinâmica de Classificadores
  - Geração de Pool de Classificadores

Aprendizagem de Máquina – Temas e tendências



- Quanto à forma de representação
  - Handcrafted .vs. deep features
  - Espaço de características .vs. dissimilaridade
  - Representação esparsa

Desafio

- Criar um classificador dada uma base com 1000 imagens e 10 classes
  - Como representar o problema?
    - Handcrafted .vs. Deep features
  - Que espaço utilizar?
    - Espaço de características ou dissimilaridade?
  - Qual abordagem utilizar?
    - Sistema monolítico
    - Múltiplos classificadores (SMC clássico ou SDC)
    - Modelos profundos