Sample of

Lectures and Resumes

by

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Computer Science

Computational Psychology

Computer Vision

Machine Learning

Deep Learning

Artificial Intelligence

READING #1. “Implementation of Convolutional Neural Network to realize a real time Emotion based Music Player” in the IJRTE Septembre 2019
P.H. Abhirami, Elizabath Saba, Regina Mathew, E. Jacob Sebastian, Cerene Mariam Abraham

Dataset used :

- \- Extended Cohn Kanada (CK+)
- \- Kaggle facial expression dataset
- \- IMM dataset
- \- JAFFE dataset
- \- Toronto Face dataset
- \- Acted Facial Expressions in the Wild database

4 modules:

- \- face detection
- \- feature extraction
- \- emotion detection
- \- song classification

Notes

Reshape images to fit a standard

Convert images to gray scale images

Viola Jones for face detection (low false positive rates and robustness)

For accurate human detection, haar feature cascade and Histogram of gradients features are integrated

CNN for feature extraction and emotion detection

Cascade architecture built on CNN model is used to address the challenges.

In CNN use leakyReLu instead of ReLu to address dying ReLu issue

READING #2. Mohamed Dahmane " Analyse de mouvements faciaux à partir d'images vidéo" PHD thesis UdeM 2011

Chapter 1 Facial action

1.2 facial expression classification

duality between face recognition and expression recognition

holistic approach is suited for face recognition

non-holistique (based on local attributes) best suited for expression recognition.

The approach to recognize facial expression is in 3 steps:

- - Face detection
- - Extraction of facial attributes
- - Classification of facial expression

1.2.1 Detection and representations of the face Most recent work can be divided in 4 groups 1.2.1.1 Component based approach

Viola Jones use AdaBoost and HAAR like features. to detect face.

Heisele uses SVM and Linear Discriminant analysis

A new approach with decision tree and Linear discriminant analysis works really well when dealing with occultings (bad lightning setup, etc)

It is said AdaBoost offers the best results and is much faster than SVM

1.2.1.2 Appearance based approach

Use MLP, Distance from feature space (based on principal component analysis) with training set half of pictures positive half of pictures negative.

1.2.1.3 matching of template

McKenna uses Gabor wavelet to extract features from the face

Bayesian Shape Model (BSM) can be useful to extract features from the face

1.2.1.4 geometric approach

Some geometric approaches use prior knowledge about the face to guide the search for facial features.

The Elastic Bunch Graph (EBG) is a typical model. (the picture in the thesis make this model look really good)

EBG is a labeled graph where nodes are features of the face (points of interest) in the form of a vector representation of the Fourrier transform of Gabor wavelet.
see L.Wiskott et al. "Face Recognition by Elastic Bunch Graph Matching." IEEE Trans. Pattern Analysis and Machine Intelligence 1997

To summarize, in the litterature the 3 most successful face detection systems are :

- - Rowley et al.
- - Roth et al.
- - Viola & Jones

and all 3 are appearance based approaches

1.2.2 Facial mouvement

Most known system for the representation of facial movement is 'Facial Action Coding System' (FACS). It uses the 'Action Unit' (AU) and combinations of AU to represent facial movement. We find that what is important for emotion classification is the representation of the facial features more than the classifier, they seem to all work fine.

So let's say we have 3 approaches to extracting expressions:

- - Based on AU
- - Based on prototypical facial expressions (non-AU)
- - Based on continuous emotion dimensionality (more recent work)

1.2.2.1 Action Unit (AU) based approaches

Assign facial movement to one of the 44 AUs described by Ekman

1.2.2.2 atypical facial expression (non-AU) based approaches

Assign facial movement to a set of possibilities. Doesn't have to respect Ekman's work.

Can use local predicates and a system based on rules

Can use the optic stream associated to movement's Energy.

Can use Tree-Augmented Naive Bayes

Can use Hidden Markov Model

Can use Bayesian Network

Can use SVMs combined with Multiclass Logistic Regression

1.2.2.3 continuous emotion dimensionality based approach

Fontaine and al. highlight that most emotional categories can be represented by 4 dimensions:
- Activation - Expectation - Control
- Incentive

1.2.3 Challenges

Even with all this great work being done, it is good to remind that emotion are a holistic expression of the body and can't be grasped by a look at the face alone.

1.2.3.1 challenges due to appearance and geometric issues

there are many challenges in automatic emotion detection.
aging, ethnicity, physiological disorder, bad resolution of image, bad lightning,

1.2.3.2 contextual challenges

Even if we can identifie genuine emotions, there are still some questions raised towards the meaning of those expressions, let's say in an open interaction between 2 persons.

weak intensity in the expression itself can be a challenge.

head movement, nodding, or hicup are all issues we will have to account for in a near future.

1.2.3.3 Dynamic relative challenges

static classifier vs dynamic classifier (requires a lot more time-dependant data)

1.3 Structure of the thesis

Thesis by journal articles is divided like so:

Chapter 2 will approach different works that relates to a Journal articles written by the author of the thesis that is also presented in chapter 3.

Chapter 3 is related to some Journal Articles written by the author “SIFT-flow registration for facial expression using Prototypic Referential Models”

chapter 4 approach some models of representation of facial features chapter 5 is related to a second Journal Article written by Dahmane chapter 6 is the conclusion and discussion to close the thesis.

READING #3. “Generalization of a Vision-Based Computational Model of Mind-Reading”
Rana el Kaliouby and Peter Robinson
only 15 references

mind-reading is a reference to infering state of mind with states outside emotions.

Infering state of mind by looking at the behavior of the person.

the paper describes the use of a Dynamic Bayesian Network to model the unfolding of the mental state over time

give reference to el Kaliouby phd thesis

READING #4. R. el Kaliouby. “Mind-Reading Machines: Automated Inference of Complex Mental States.” Phd thesis, University of Cambridge, Computer Laboratory, (2005).
Chapter 1 Introduction

1.1 Motivation

Mind reading or theory of the mind is used in psychology to describe people’s ability to attribute mental state of mind to others. To classify people’s mental state of mind is useful in many ways and dictate the way we interact with others. Some people diagnosed with Autism Spectrum Disorder have some issues with it, the intensity of the problem vary from person to person. Such disorder can be a burden, as it is harder to create an accurate representation of others during any
interaction. Mind-reading is essential for human and would mostly benefit Human Computer Interaction if the machine could do it a little better. There are numerous aspects of HCI that would benefit from extensive work on the subject.

1.2 aims and challenges
the aims of the dissertation are twofold:

1. Advance the nascent ability of machines to infer complex mental states from a video stream of facial expressions of people. To Widen the scope of application of automated facial expression analysis.
2. Develop a working prototype of an automated mental state inference system built for intelligent HCI

Challenges are numerous since a state of mind is inferred indirectly through observation of the person’s behavior. There is no cook-book recipe to mapping facial expression and inferring mental state of mind.

1.3 Dissertation overview

Table of Content

5. Extraction of Head and Facial Actions

6. Recognition of Head and Facial Display

7. Inference of Complex Mental States 8. Experimental Evaluation

9. Conclusion

Chapter 2 Background 2.1 Mind-reading
TO DO

READING #5 L.Wiskott et al. “Face Recognition by Elastic Bunch Graph Matching.” IEEE Trans. Pattern Analysis and Machine Intelligence 1997

Dataset : FERET database, Bochum database To get FERET database https://www.nist.gov/itl/products-and-services/color-feret-database

1. Introduction

The goal is to extract the features of the face to identify one person out of a large database with 1 picture per person.

Our basic object representation is the labeled graph with wavelet responses locally bundled in jets. Stored model graphs can be matched to new images to generate image graph. which can then be added to a gallery to become model graphs. Wavelets as we use them are robust to moderate lighting change. Model graphs can easily be translated, scaled, oriented or deformed during matching process.

Unfortunately having 1 picture per person in the galleries does not provide sufficient information to handle rotation in depth analogously. However the present paper presents results on recognition across different poses.
The general structure is useful for handling any kind of coherent objets.

Early work on facial expression recognition [154]
A. Samal et P. A. Iyengar. Automatic recognition and analysis of human faces and facial expression: a survey. Pattern Recognition, 25(1):66–77, 1992.
Google research on Gabor Wavelet
gabor wavelet
Daugman, **1988**; Lades et al., 1993; Liu, 2002; Marcelja, 1980 Gabor 1949
READING ON GABOR WAVELET
https://cvtuts.wordpress.com/2014/04/27/gabor-filters-a-practical-overview/
READING ON NODE SELECTION #7 A systematix way of selecting nodes from a dense set is presented in Kruger,1997 and Kruger et al.,1997

SURVEY READING #1 M. Pantic and L. J. Rothkrantz. "Automatic Analysis of Facial Expressions: The State of the Art." IEEE Trans. on Pattern Analysis and Machine Intelligence (PAMI), 22:1424–1445, 2000.
SURVEY READING #2 B. Fasel and J. Luettin. Automatic Facial Expression Analysis: A Survey. Pattern Recognition, 36:259–275, 2003.
SURVEY READING #3 I. Michael Revina and W.R. Sam Emmanuel "A Survey on Human Face Expression Recognition Techniques
SURVEY READING #4 Shan Li and Weihong Deng "Deep Facial Expression Recognition: A Survey"
SURVEY READING #5 Vaibhavkumar J. Mistry, Mahesh M. Goyami "A Literature Survey on Facial Expression Recognition using Global Features"
SURVEY READING #6 Jyoti Kumari, R. Rajesh, KM. Pooja "Facial Expression Recognition: A Survey"
READING #6 Yooyoung Lee, Ross J. Micheals, P. J. Phillips, James J. Filliben, "VASIR: An Open-Source Research Platform for Advanced Iris Recognition Technologies", Journal of Research of NIST, Volume 118, p218-259, 2013
EKMANREADING: P.EkmanandW.V.Friesen.FacialActionCodingSystem: A Technique for the Measurement of Facial Movement. Consulting Psychologists, 1978. --- Out of distribution? cost 350$ on his web-site.
5. Texts on AU feature decomposition
5.1.1 M.S. Bartlett, J.C. Hager, and T.J. Sejnowski "Measuring facial expressions by computer image analysis" Psychophisiology 36(2):253-263, 1999
5.1.2 J. F. Cohn, A.J. Zlochower, J. Lien et T. Kanade. "Automated face analysis by feature point tracking has high concurrent validity with manual facs coding." Journal of Psychophysiology, 36(1):35-43, 1999
5.1.3 J.Whitehill et C. W. Omlin "Local versus Global Segmentation for Facial Expression Recognition." Proc. of IEEE Conference on Automatic Face and Gesture Recognition, pages 357-362, 2006
5.1.4 F. de la Torre, T. Simon, Z. Ambadar, et J.F. Cohn. "Fast-facs: a computer-assisted system to increase speed and reliability of manual facs coding." Affective Computing and Intelligent Interaction (ACII), 2011.
5.3.0 articles qui regroupent d'autres articles 5.3 see 57
5.4 see 139

8. Castrilln, M., et al. "ENCARA2: Real-time detection of multiple faces at different resolutions in video streams." Journal of visual communication and image representation 18.2 (2007): 130-140.
9. W.L. Liao et I. Cohen “Classifying Facial Gestures in Presence of Head Motion.” Dans IEEE Conference on Computer Vision and Pattern Recognition CVPRW page 77, 2005
10. “https://www.learnopencv.com/histogram-of-oriented-gradients/”
Use computer vision to detect objects.
11.Irina Rish paper on alternative to gradient backpropagation