Adaptive Gesture Recognition System Integrating Multiple Inputs

Master Thesis - Colloquium

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Table of contents

Introduction
Set-Up
Multiple Inputs & Adaptivity
Conclusion

Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
Conclusion

Overview

- Introduction
  - Gesture Recognition in General
  - Motivation
- Set-Up
- Multiple Inputs & Adaptivity
- Conclusion

Gesture Recognition in General

- several applications (more natural interaction with robots, way of communication, sign language, ...)
- Gesture recognition "is the process by which the gestures made by the user are recognized by the receiver." *(Mitra & Acharya, 2007 [3])*
- static vs. dynamic gestures

Overview

- Introduction
  - Gesture Recognition in General
  - Motivation
- Set-Up
- Multiple Inputs & Adaptivity
- Conclusion

Previous Work

- TAMS - Master Project “Intelligent Robotics” (2013-2014)
- vision-based system (Microsoft Kinect) for recognizing static gestures
- depth images and Support Vector Machines (SVMs)
- project paper *(Paetzel & Staron, 2014 [4])*

Problems in Gesture Recognition

- recognition results in general
- context-depended applications
- changed circumstances, e.g. new users / users with different figures, changed environments, changed camera properties (position, calibration, ...), light changes, ...

$\Rightarrow$ exploiting features of Robotics (a robot might have more than one sensor; possible interaction between user and robot)

Hypotheses

- use of multiple inputs ⇒ improved recognition results (& context-independent systems)
- use of multiple inputs ⇒ robustness
- possible interaction between user and robot ⇒ ability of the system to adapt to changed circumstances
- possible interaction between user and robot ⇒ omitting of preliminary training

⇒ development of an adaptive gesture recognition system that makes use of multiple inputs

Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
Conclusion

Overview

Introduction
Set-Up
- Inputs
- Data
- Evaluation Criteria
- k-Nearest Neighbor (k-NN) Classifiers

Multiple Inputs & Adaptivity
Conclusion

Depth Images

- gray value images
- information about distances to the camera
- preprocessing (noise reduction, foreground separation, histogram equalization, grid) *(Biswas & Basu, 2011 [2])*
- gray value binning in grid cells ⇒ 520 features

Exemplary Preprocessing of a Depth Image

RGB image of an exemplary gesture.

Exemplary Preprocessing of a Depth Image

The corresponding depth image prior to preprocessing.

Exemplary Preprocessing of a Depth Image

The depth image but with reduced noise.

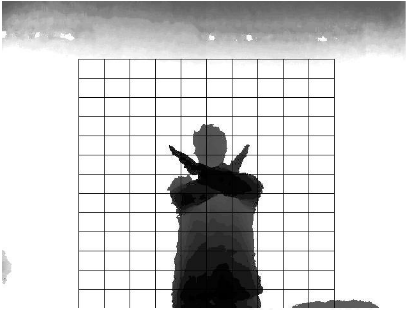
Exemplary Preprocessing of a Depth Image

Only the foreground of the depth image.

Exemplary Preprocessing of a Depth Image

The foreground of the depth image after histogram equalization.

Exemplary Preprocessing of a Depth Image



The equalized foreground of the depth image with a grid put on it.

Skeletal Information

- OpenNI tracker
- position and orientation of several joints of the human skeleton
- a coordinate frame for each joint $\Rightarrow$ transformations into target frame
- 8 joints $\Rightarrow$ 56 features

Overview

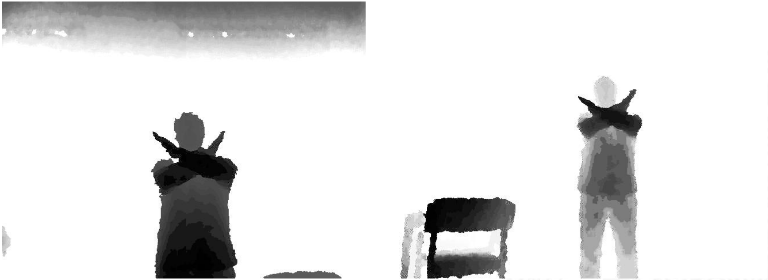
Introduction
Set-Up
- Inputs
- Data
- Evaluation Criteria
- k-Nearest Neighbor (k-NN) Classifiers

Multiple Inputs & Adaptivity
Conclusion

Collecting Training and Test Data

- 12 gestures
- 10 test users $\Rightarrow$ different groups (users with similar/differing figures)
- different poses and positions (to the left or right)
- but no different distances to the camera
- different environments
- camera calibration and illumination remained unchanged

Different Environments



Overview

Introduction
Set-Up
- Inputs
- Data
- Evaluation Criteria
- k-Nearest Neighbor (k-NN) Classifiers

Multiple Inputs & Adaptivity
Conclusion

Evaluation Criteria

- precision: proportion of test instances classified correctly
- recall: proportion of instances that should have been classified as a certain gesture that have actually got the respective label
- F_1-score $= (2 \cdot \textit{precision} \cdot \textit{recall})/(\textit{precision} + \textit{recall})$
- average classification and (initial) training time
- nr. of training instances

Overview

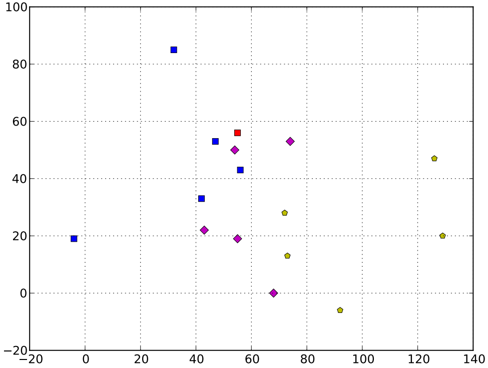
Introduction
Set-Up
- Inputs
- Data
- Evaluation Criteria
- k-Nearest Neighbor (k-NN) Classifiers

Multiple Inputs & Adaptivity
Conclusion

k-Nearest Neighbor (k-NN) Classifier

- supervised learning method
- arbitrary number of dimensions
- no explicit training (computations during classification)
- label that occurred most among the k-nearest neighbors of a query instances is chosen
- distance measure (e.g. Euclidean distance)

Exemplary Dataset in the 2-Dimensional Space



Three classes, represented by blue squares, magenta diamonds and yellow

Weighted k-NN Classifier

- if a training example matches the query instance, its label will be chosen $\Rightarrow$ Generalization
- the nearer one of its k-nearest neighbors lies by the query instance, the higher the probability that its label is the result

Training of Classifiers

- classifiers for each kind of input, for each group of users and for each environment
- the same amount of training (and test) data for each classifier

Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
Conclusion

Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
- Combining Multiple Inputs
- Adaptivity
- Integrated System

Conclusion

Sensor Fusion

- low-level sensor fusion: fusion at signal level, one classifier
- high-level sensor fusion: fusion at a more symbolic level, one classifier per input, classification results are fused
- low-level sensor fusion does not allow for variations regarding the chosen inputs (e.g. adding or removing of sensors) without omitting previous data / retraining everything
- $\Rightarrow$ high-level sensor fusion was chosen

Hypotheses Verification

- inspired by Aldoma et al. *(Aldoma et al., 2013 [1])*
- high-level sensor fusion approach
- one classifier per kind of input
- each classifier can generate an unspecified number of hypotheses
- each hypothesis is weighted
- hypothesis with the highest weight is chosen as recognition result

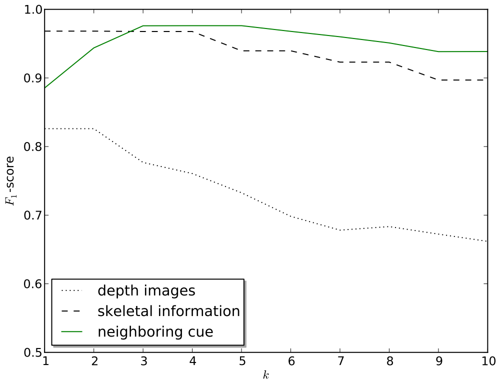
Weighting Cues

- each hypothesis is weighted by an unspecified number of weighting cues
- neighboring cue (in case of k-NN classifiers): all labels occurring among k-nearest neighbors as hypotheses; weights depend on nr. of examples with respective labels / on their distance to the query instance
- meta-features: e.g. reliability of classifiers
- summation of weights of a hypothesis

Evaluation (1)

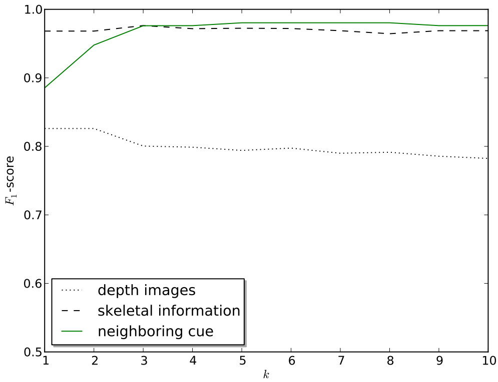
- the same data were used as for testing the classifiers with depth respectively skeletal information individually
- k-NN classifier: best performance for the neighboring cue
- weighted k-NN classifier outperformed the standard one
- improved robustness

Evaluation (1)



Comparison of the individual inputs and their combination via

Evaluation (1)



Comparison of the individual inputs and their combination via

Evaluation (1)

-	depth images	skeletal data	combined inputs
F_1-score	0.027499	0.837523	0.805485

Table: Comparison of the individual inputs and their combination via neighboring cues for the weighted 5-NN classifier, trained on data from users with similar figures and tested on data from the same users, but in a different environment.

Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
- Combining Multiple Inputs
- Adaptivity
- Integrated System

Conclusion

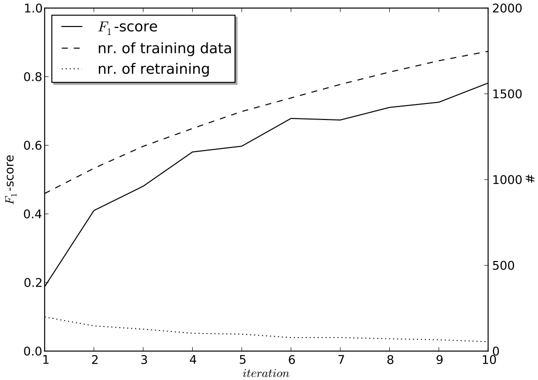
Online Learning

- goal: recognition of gestures under changed circumstances
- classifiers try to recognize query instances and are told the correct label afterwards to update their model
- no online version for SVMs (they need to be retrained every time new training are added) $\Rightarrow$ k-NN classifiers
- different points when to learn showed no apparent effects

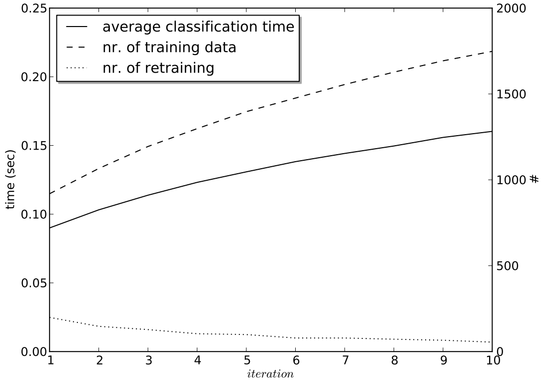
Evaluation (2)

- 5-NN classifier
- trained on depth images from users with similar figures and tested on depth images from the same users, but in a different environment
- online learning after each misclassification
- training data and the test data of iteration 1 the same as for previous tests
- similar tests in the remaining iterations, but with newly sampled test data

Evaluation (2)



Evaluation (2)



Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
- Combining Multiple Inputs
- Adaptivity
- Integrated System

Conclusion

Multiple Inputs

- Hypotheses Verification
- additional weighting cues are enabled by online learning: the experience of a classifier (the number of examples it has been trained with)

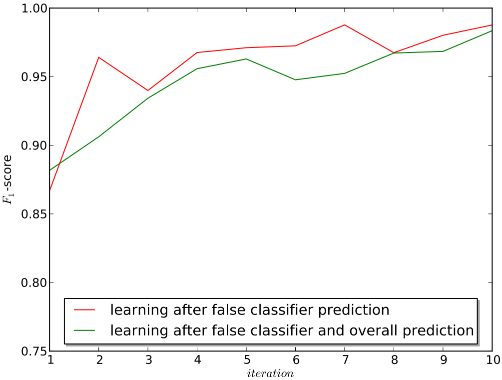
Adaptivity

- online Learning
- what examples to learn
- previously: all misclassified ones
- alternative: misclassified examples as soon as the fusion result is wrong, too

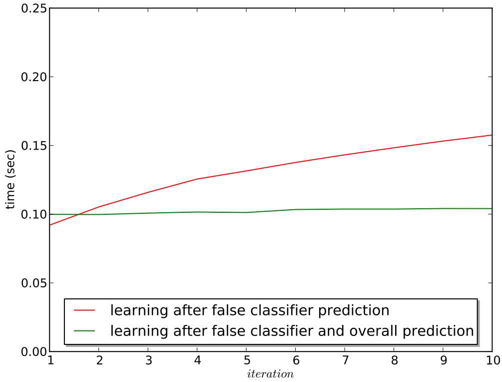
Evaluation (3)

- 5-NN classifier
- trained on data from users with similar figures and tested on data from the same users, but in a different environment
- depth images and skeletal data combined via neighboring cue
- online learning after each misclassification
- training data and the test data of iteration 1 the same as for previous tests
- similar tests in the remaining iterations, but with newly sampled test data

Evaluation (3)



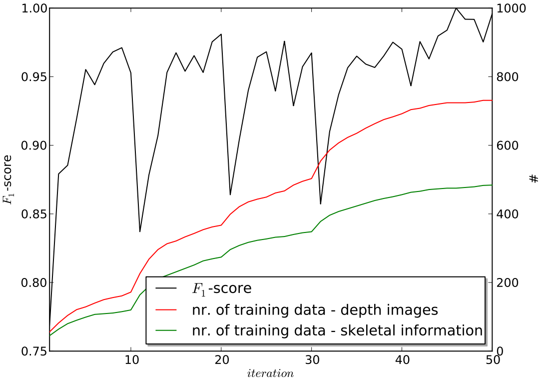
Evaluation (3)



Evaluation (4) - Final Test

- weighted 5-NN classifier
- depth images and skeletal data combined via neighboring cue
- online learning after each misclassification when fusion result false, too
- no preliminary training
- test data from users with similar figures (first ten and last ten iterations), data from users with varying figures (iteration 11 - 20), original users, but in a different environment (iteration 21 - 30) and the users with the varying figures in that environment (iteration 31 - 40)

Evaluation (4) - Final Test



Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
Conclusion

Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
Conclusion
  Summary
  References

Hypotheses

- use of multiple inputs lead to improved recognition results as well as a more robust system
- system is able to adapt to changed circumstances due to online learning
- preliminary training can be omitted because of online learning

$\Rightarrow$ adaptive gesture recognition system that makes use of multiple inputs

Overview

Introduction
Set-Up
Multiple Inputs & Adaptivity
Conclusion
    Summary
    References

References I

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3. Sushmita Mitra and Tinku Acharya. Gesture Recognition: A Survey. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, 37(3):311–324, 2007.
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The End

Thanks for Your Attention!