<u>Using a Context Quality Measure</u> <u>for Improving Smart Appliances</u>

Presentation of Martin Berchtold Telecooperation Office (TecO) www.teco.edu University of Karlsruhe

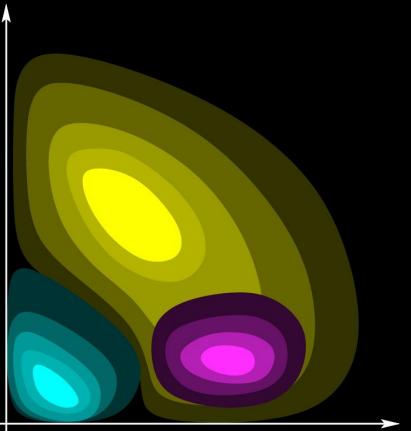


Christian Decker Till Riedel ECHNISCHE UNIVERSITÄT Michael Beigl CAROLO-WILHELMINA zu Braunschweig

Particle Computer Tobias Zimmer

Problem of Context Recognition

- Context recognition is not reliable
 - → context classification is faulty
 - → error lies in used sensors and/or algorithm
 - → dependability on faulty systems
 - → improvement only to a certain degree



Abstraction of Context Space for three Fuzzy Context States

Reasoning in Large Scale Ubiquitous Environments

- Reasoning is depending on faulty knowledge
 → Reasoning increases error exponentially
 → Error is known only in absolute manner
 - \rightarrow Single data error is mostly not known at runtime
- Combination of reliable with unreliable data should be avoided

Possible errors should not be included in further reasoning

→ Filtering out faulty data can save communication and calculation resources

Existing Systems for Context Recognition

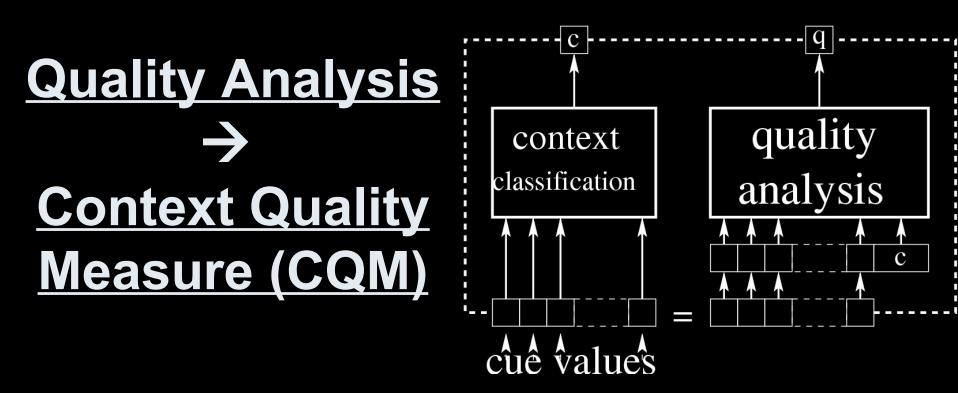
- Existing systems for recognizing context want to be reused
 - → Obtaining a Context Quality Measure (CQM) should not interfere with existing algorithms
 - → User of Quality Analyzing System should need no knowledge of existing recognition system
 - → Each piece of context data should be equipped with a CQM

Our system for quality analyzing can meet these demands and provides a CQM to filter out faulty data!

Fuzzy Inference System (FIS) → Non-Linear Error Approximation

- Adaptation on system error
 - \rightarrow Systems mostly non-linear
 - \rightarrow System error is non-linear
- Fuzzy Inference Systems (FIS)
 - \rightarrow FIS is universal approximation function
 - \rightarrow Infinite set of rules \rightarrow infinite precise approximation [1]
- TSK-FIS [2] can deal with non-complete data
 - → Lack of data for one state yields to zero mapping of the data → zero mapping concludes highest error in our model

[1] L X Wang. Adaptive Fuzzy Systems and Control. Prentice-Hall, Englewood Cliffs, 1998.
[2] T Tagaki and M Sugeno. Fuzzy identification of systems and its application to modelling and control. IEEE Trans. Syst. Man and Cybernetics, 1985, vol SMC-15, no. 1, pp 116-132, 1985.



- Context classification is considered as a 'Black-Box'
- Quality analysis input = input of context classification + classification output → quality analysis does not interfere with existing contextual algorithms
- Knowledge of classification error is stored in FIS due to automated construction and training
 - \rightarrow CQM is representing the error due to elements of the interval [0,1] ⁶

<u>Automated Construction and</u> <u>Training of Qualitative FIS</u>

V. O

 $F_{11}(v_1)$

 $F_{21}(v_2)$

 $F_{(n+1)1}(v_{n+1})$

 $F_{12}(v_1)$

 $F_{22}(v_2)$

 $F_{(n+1)2}(v_{n+1})$

 $F_{1m}(v_1)$

 $F_{2m}(v_2)$

 $f_1(\vec{v_0})$

 \vec{v}_Q $f_2(\vec{v}_Q)$

 $f_{m}(\vec{v}_{Q})$

Q

(+)

 $S_{\hat{Q}}(\vec{v}_{Q})$

 $\bigotimes^{\mathbf{W}_1(\vec{\mathbf{v}_Q})}$

 $\times \frac{W_2(\vec{v_0})}{2}$

- Designated output:
 - 1 \rightarrow right classification
 - $0 \rightarrow$ false classification
- Clustering determines rules [1]
- Linear regression fits output
 functions onto designated output
- ANFIS [2] enables training →
- Hybrid training for fine grain tuning _{F(n+1)n}(v_{n+1}
 backward-pass: gradient descent

→ Back-Propagation

forward-pass: linear regression on bases of Back-Propagation changes

[1] Stephen Chiu. *Method and software for extracting fuzzy classification rules by subtractive clustering*. *IEEE Control Systems Magazine*, 1996, vol. pp. 461-465, 1996.

[2] Jyh-Shing Roger Jang. ANFIS: Adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man and Cybernetics, 1993, vol. 23 pp. 665-685, 1993.

The AwarePen with CQM

sensors

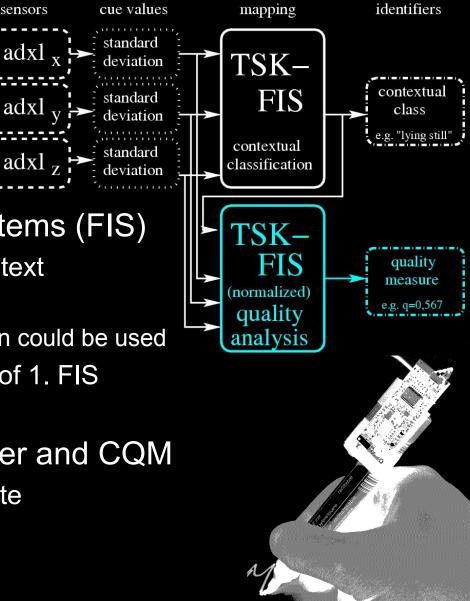
- **Input:** ADXL-sensors \rightarrow x-, y- and z- acceleration
- Cueing: standard deviation \rightarrow sliding window over 24 values

Mapping: Fuzzy Inference Systems (FIS)

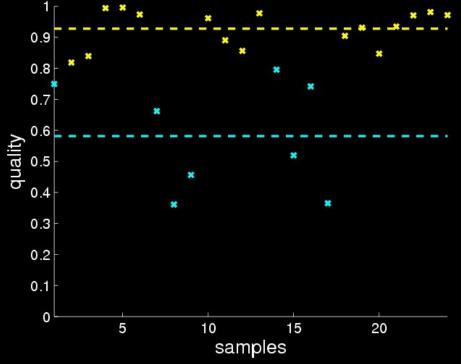
- 1. FIS: mapping cue values onto context
 - \rightarrow classification of result
 - \rightarrow instead of FIS any other projection could be used
- 2. FIS: holds knowledge about error of 1. FIS
 - \rightarrow normalization of result

Output: tuple of context identifier and CQM

- \rightarrow Identifier of current contextual state
 - \rightarrow 'lying', 'writing' and 'playing'
- CQM is element of interval [0,1]

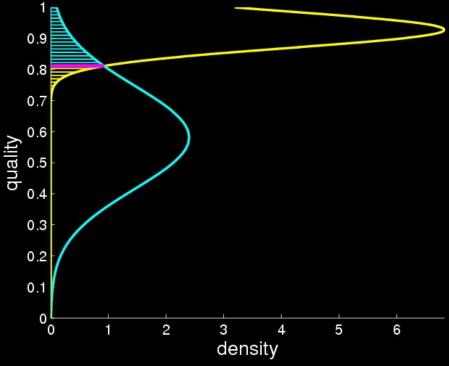


Using CQM to Filter Contexts



Context Quality Measure (CQM)

- Right Classified Contexts
 → Yellow with mean (dashed line)
- False Classified Contexts
 - \rightarrow Turquoise with mean (dashed line)

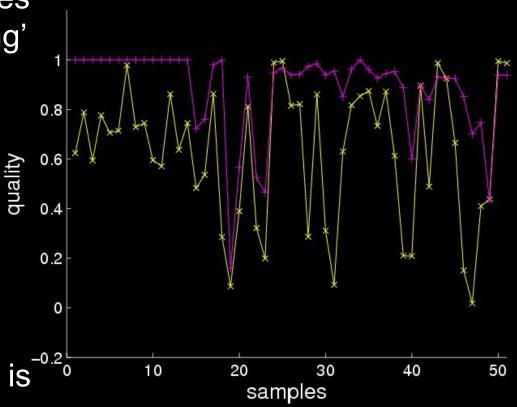


Probabilistic Analysis of CQM

- Density of Right Classified
 → Yellow curve
- Density of Wrong Classified
 → Turquoise curve
- Possible Filter Threshold 9
 → Purple line

Argument for Separate CQM-System

- CQM for consecutive states 'lying', 'writing' and 'playing'
 → Purple line
- Normalized distance of contextual FIS output to class-centre
 - \rightarrow Yellow line
- \rightarrow QCM contains less noise
- → Reliability of classification is state dependent
- → High correlation proofs comparability



Conclusion and Future Work

- Introduction of a system that can provide a Context Quality Measure (CQM)
 - Quality analyzing system is independent of contextual algorithm
 - Quality analyzing system can be used for error representation of any contextual algorithm
 - Filtering contextual knowledge upon CQM is possible with high odds

Future Work

- Suitability of quality analysis for other contextual algorithms and systems other than context recognition
- Combination of quality analysis with context recognition and preservation of state dependability
- Reasoning with CQM according to reasoning with contextual knowledge