A Modular Sensor Fusion Approach for Agricultural Machines

Sebastian Blank[1], Georg Kormann[2], Karsten Berns[1]

[1] Robotics Research Lab
University of Kaiserslautern, Germany

[2] John Deere European Technology Innovation Center
Kaiserslautern, Germany

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Overview

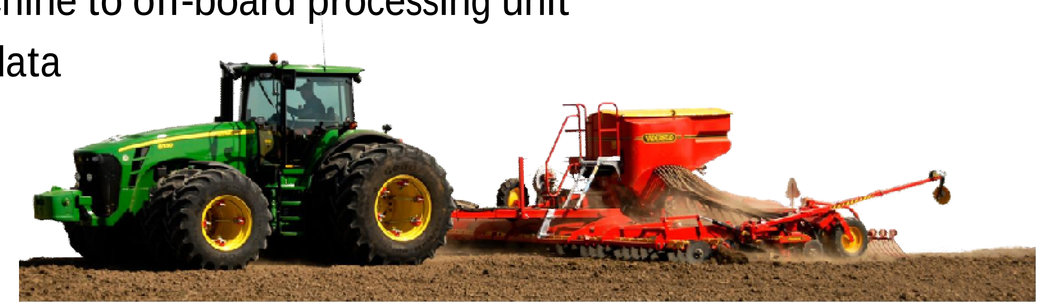
- State-of-the-art: data handling
- Challenges
- Derived Requirements
- A modular approach to data handling
- Conclusions/Outlook

State-of-the-art: Data Handling

- Primary applications (today)
  - telematics solutions
  - documentation

- Assumptions:
  - single vehicle centric → does not reflect actual usage pattern
  - static configuration → unable to process data from implement/other machines

- Data acquisition:
  - hard coded: snapshot reflects only limited number of data sources
  - averaging interval (typically 30s to few minutes) → potential is wasted
  - bottleneck: data transfer from machine to off-board processing unit
  - no/little data fusion → conflicting data



Motivation - Challenges

- Heterogeneous machines
  - large number of equipment OEMs → no common standard
  - isolated subsystems → limited machine-wide communication

- Future increase in:
  - number of data sources (sensors)
  - need for documentation
  - degree of automation → (semi-)autonomous machines

- Further challenges
  - complexity challenge: current SW paradigm cannot keep up with HW development
  - multiple sensor readings of same physical properties (→ inconsistent data)
  - architecture gap: no mechanism for resolving data conflicts
  - no system-wide data visibility & accessibility
  - challenge will become even harder in the future

Derived Requirements

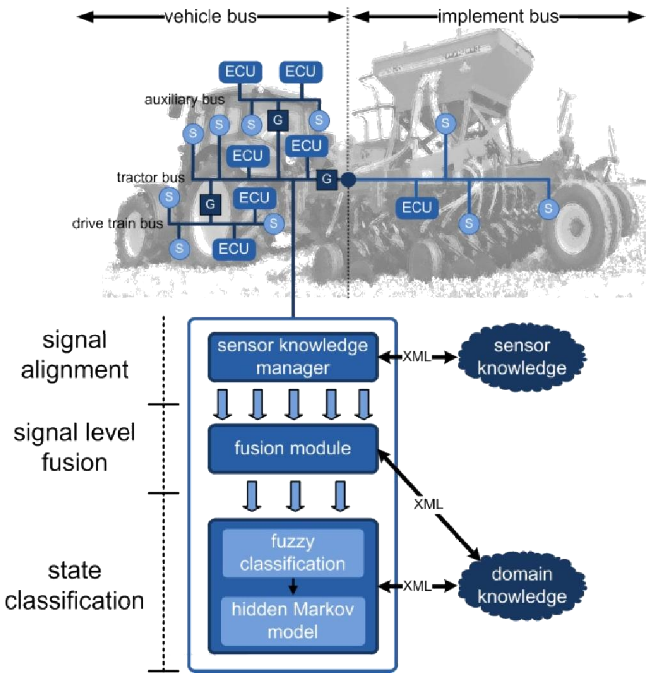
- Uniform data handling / aggregation needed
  - scalable with host machine (low spec. vs. high spec.)
  - machine wide
  - high flexibility: modular design
  - automatic reconfiguration: no operator interaction
  - lean architecture & algorithms (limited comp. power)
  - paradigm shift: vehicle centric → data centric (open interfaces)

- Potential benefits
  - robustness: reliable sensor data (utilize redundancy)
  - task specific machine data processing (e.g. vehicle state ↔ implement)
  - fully automatic: no need for manual configuration
  - ease future system design: abstraction & holistic concepts

> "We are drowning in information but starved for knowledge" (John Naisbitt)

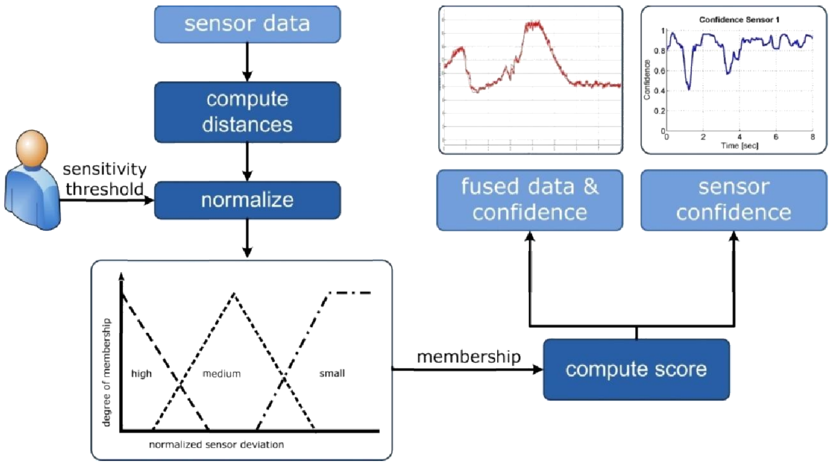
Modular Approach To Data Handling

- Tasks
  - system-wide & uniform approach for data management
  - ensure data consistency (low level fusion)
  - Integrated data processing/aggregation
- Data scopes
  - hardware information
  - domain/process knowledge
  - little component knowledge inhibits usage of standard fusion approaches (e.g. Kalman filters)



- Architecture
  - inspired by: biological fusion (human) & swarm intelligence
  - 3 levels: alignment, low-level fusion, high-level data aggregation/interpretation
  - data centric: machine border dissolve
  - lean algorithms

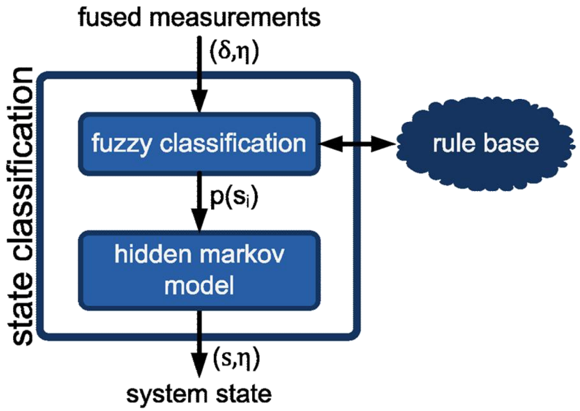
Low-Level Fusion



- Demand imposed by application:
  - robustness (failure & adaptation to changing environment conditions)
  - low computational demand
  - reliable & accurate results
- Fuzzy voter approach
  - no assumptions/models required
  - utilizes relative sensor distance
  - computational efficient: $O(n^2)$
  - excellent robustness & accuracy
  - result + confidence metric (sensor monitoring)
- Error detection/correction
  - plausibility limits (domain knowledge)
  - dynamic thresholding (rejection mechanism)
  - adaptive weights assignment

Feature-Level Data Aggregation

- 2-stage approach
  - fuzzy classifier (deterministic) → state probabilities
  - Hidden Markov Model (probabilistic) → optimize w.r.t. transition sequences
  - domain knowledge used to extract rule base
  - scales well with machine complexity
  - real-time capable with modest comp. power

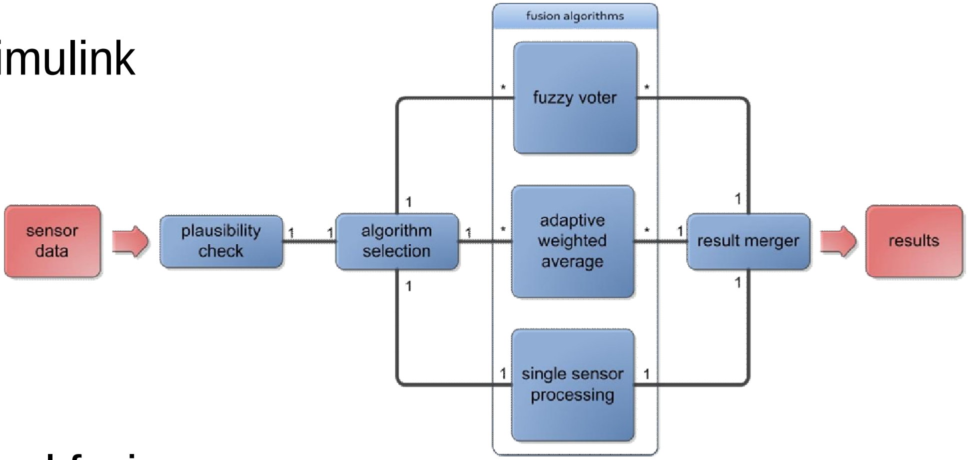


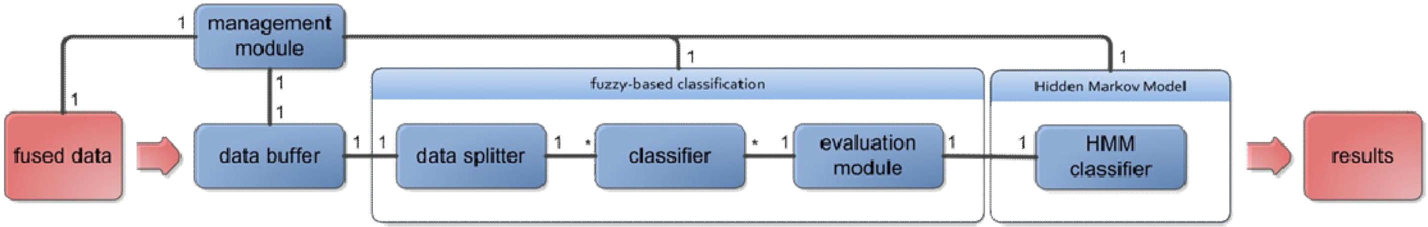
- Fuzzy classification
  - intuitive & computational inexpensive
  - interface to fusion: result confidence is considered
  - easily expandable (new/different states)

- Hidden Markov Model (HMM)
  - input: output of fuzzy classification
  - offers more expressiveness (notion of time → sequences)
  - computational inexpensive (pre-classified vs. raw sensor data)

Implementation

- Components implemented in Matlab/Simulink
- Modular SW design
- Interaction via lean interfaces
- Independent loop times for low/high level fusion
  - low level: loop time set dynamically per sensor group (sensor update rate) [approx. 1 -1000 ms]
  - high level: fixed loop time at startup (buffer mechanism) [approx. 5 ms - 100 sec]

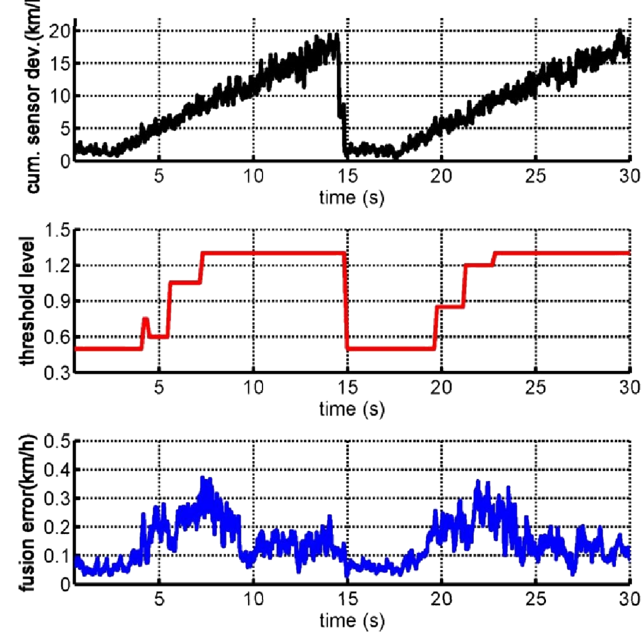




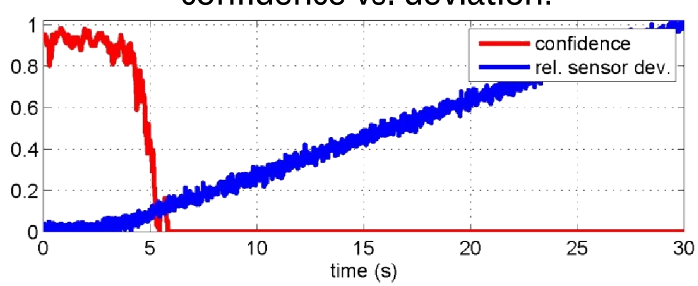
Preliminary Test

- Simulated tests
  - focus: low level fusion algorithms (accuracy/precision & robustness)
  - full system feasibility test: component integration
- Rapid Prototyping Tests
  - so far: single component tests
  - modified utility vehicle + implement (reconf.)
  - HW platform: dSpace Autobox (loop time: 1ms)

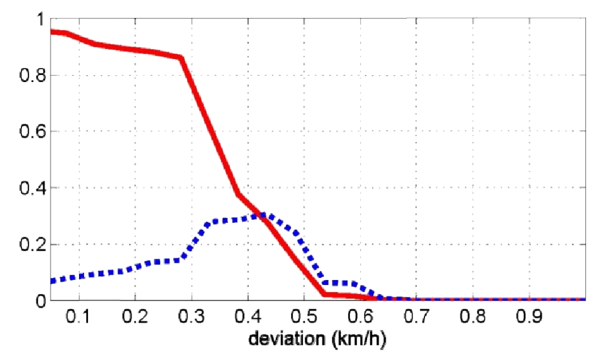
self-adaption & resulting error:



confidence vs. deviation:



confidence variance:



Conclusions

- Advantages
  - self-adjusting sensor fusion architecture
  - global (consistent) information scope
  - platform independent (generic) approach → reuse
  - machine complexity hidden from user (components supply meta information)
  - matches requirements of Ag applications
  - mapping of HW dynamics into data handling approach
  - embedded in iGreen Infrastructure (meta data/result exchange)
  - integrated management solution for multicolored fleets

- Outlook
  - full system test on real machine by end of 2011
  - potential as supplement to ISOBUS standard

Thank you for your attention !

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