Run-time Reasoning from Uncertain Observations with Subjective Logic in Multi-Agent Self-Adaptive Cyber-Physical Systems

Huawei presentation
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About me

Born in North Macedonia

[2011-2014] **B.Sc. in Computer Science**
Faculty of Computer and Information Science, University of Ljubljana

[2014-2016] **M.Sc. in Informatics**
Department of Informatics, Technical University of Munich

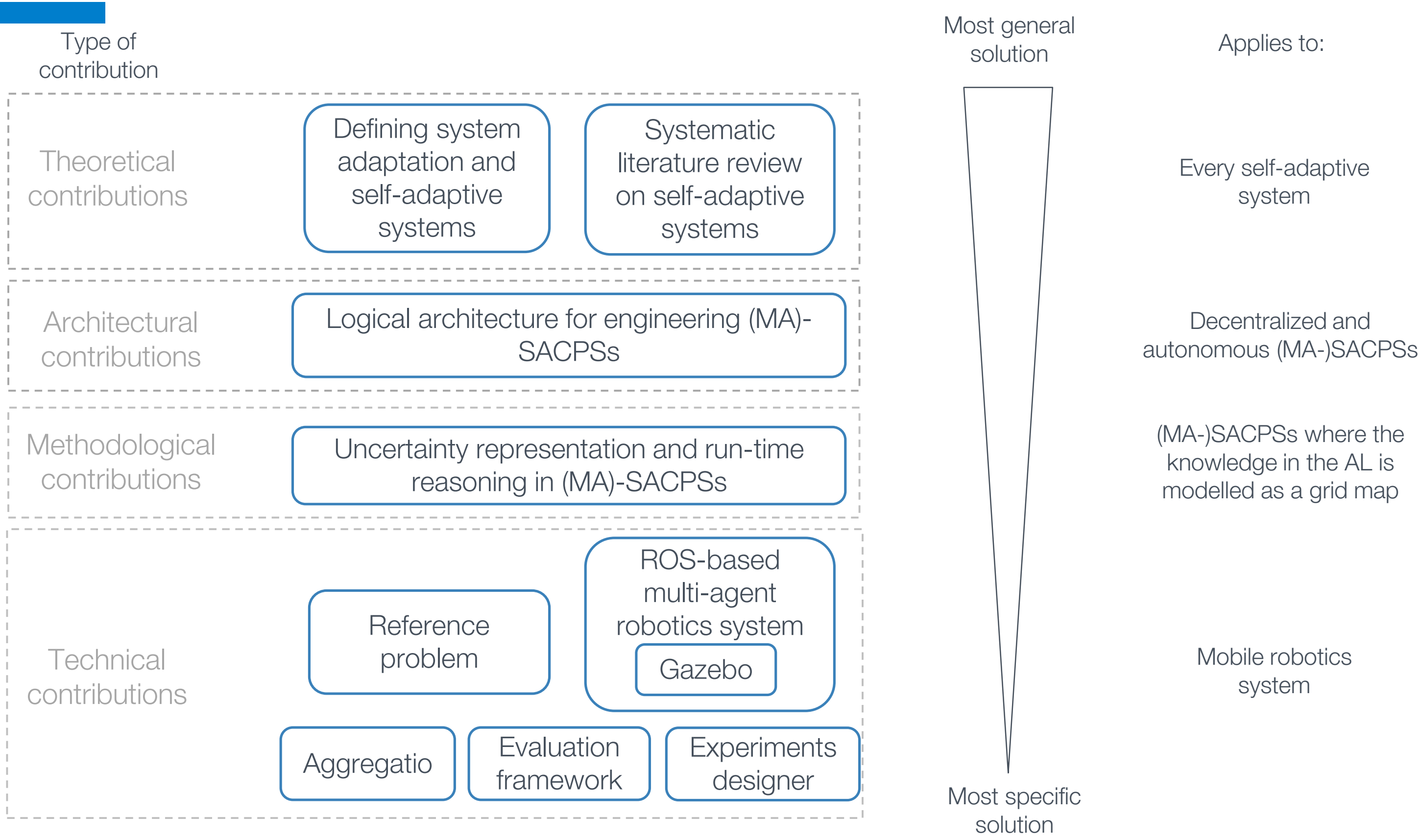
[2017 – end of 2022 (expected)] **Research Assistant and a Ph.D. candidate**
Department of Informatics, Technical University of Munich, Chair of Software and Systems Engineering

- Worked on BMBF project: Collaborative Embedded Systems [funded full time for 3 years]
- Research on the foundations of self-adaptive systems and engineering self-adaptive CPSs
- Lecturer and TA in multiple courses in the bachelor and master degree
- Organized and led a master practical course (a lab) in SS19, supervising 14 students
- Supervised 17 theses
- Wrote more than 20 peer-reviewed papers [10 first author, 10 co-authored]

[2017 – present] IN.TUM Gender Equality Officer

[2019 – present] General Team Lead at Women in CS @ TUM (Informatik Forum Frauen IFF)

On engineering self-adaptive cyber-physical systems



Additional contributions

Theoretical contributions

- Defining system adaptation and self-adaptive systems — IST, TAAS
- Systematic literature review on self-adaptive systems — ACSOS 22
- Formally defining levels of autonomous systems — ECSA 21
- Self-awareness and self-adaptation in computing systems — SeAC 21
- Context modelling for collaborative CPSs in dynamic context, Context taxonomy — MRC 2018
- Uncertainty classification for collaborative CPSs — SICS
- Meta-model for modelling functions of CPSs and collaborative CPSs' groups — MEKES 2018

Architectural contributions

- Logical architecture for engineering (MA)-SACPSs — IST

Methodological contributions

- Uncertainty representation and run-time reasoning in (MA)-SACPSs — SEAMS 20, SEAMS 21
- Bayesian optimization-based analysis and planning approach for (MA)-SACPSs — ACSOS 21, SAC 22
- Anomaly detection for MA-CPSs
- POMDPs (MA-POMDPs and BA MA-POMDPs) for planning and learning in (MA)-SACPSs

Technical contributions

- Reference problem
- ROS-based multi-agent robotics system
  - Gazebo
  - Custom simulator
  - Deployment on real robots
- Experiments designer
- Evaluation framework
- Aggregatio
- BO tooling

Problem

MA-SACPSs are exposed to a variety of run-time uncertainties resulting in inaccurate and partial observations, which potentially lead to conflicting observations made by different CPSs.

Gap

Although knowledge representation, aggregation and reasoning are essential for building MA-SACPSs [8], there is a scarcity of approaches for modeling K that allow capturing uncertain and conflicting observations from multiple, decentralized CPSs.

Solution

We present a Subjective Logic-based methodological approach for knowledge aggregation and reasoning in MA-SACPSs that is domain-independent and can deal with reasoning on uncertain, partial, and conflicting observations.

Contributions

(i) SL-based approach for knowledge aggregation and reasoning in MA-SACPSs

(ii) Open-source implementation of a in-house ROS-based multi-robot system

(iii) Evaluation through extensive controlled experiments

Disclaimer: the talk is based on [1] and [2], published at SEAMS2020 and SEAMS 2021, respectively.

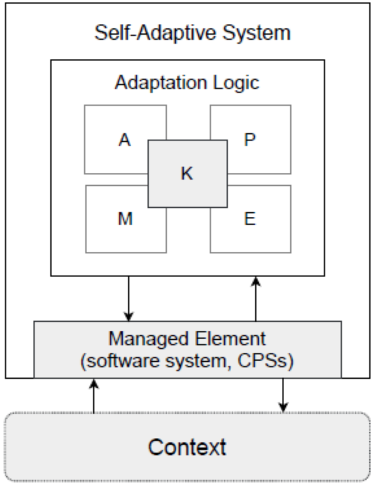
[1] **Ana Petrovska**, Sergio Quijano, Ilias Gerostathopoulos, Alexander Pretschner: *Knowledge Aggregation with Subjective Logic in Multi-Agent Self-Adaptive Cyber-Physical Systems.* 2020 IEEE/ACM 15th International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS), 2020.
[2] **Ana Petrovska**, Malte Neuss, Ilias Gerostathopoulos, Alexander Pretschner: *Run-time Reasoning from Uncertain Observations with Subjective Logic in Multi-Agent Self-Adaptive Cyber-Physical Systems.* 16th Symposium on Software Engineering for Adaptive and Self-Managing Systems, SEAMS, 2021.

Use case

Class of use cases

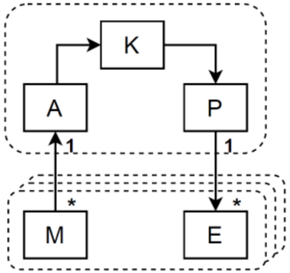
In this work, we focus on MA-SACPSs in which MAPE-K loops are structured according to the Master-Slave pattern [3]:

- decentralized monitoring (M) and execution (E) of the adaptation actions, and
- controlled by a single, centralized instance of planning (P), analysis (A) and knowledge (K).



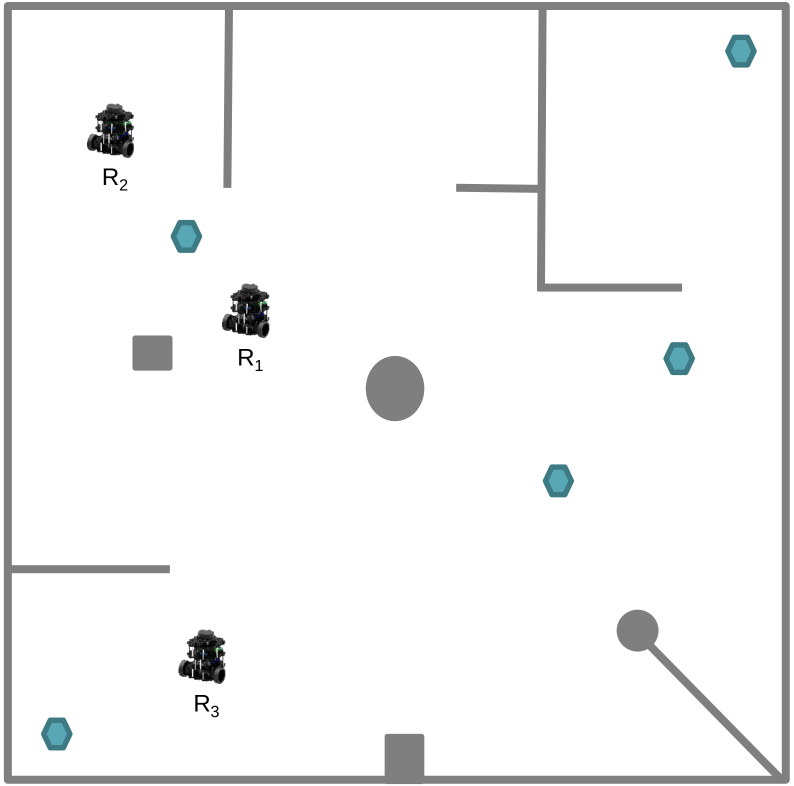
The *analysis* phase reasons on the uncertain, partial and potentially conflicting observations from the *decentralized monitors*.

- once the observations are aggregated, they become *knowledge*.



Modified Master-Slave pattern [3]

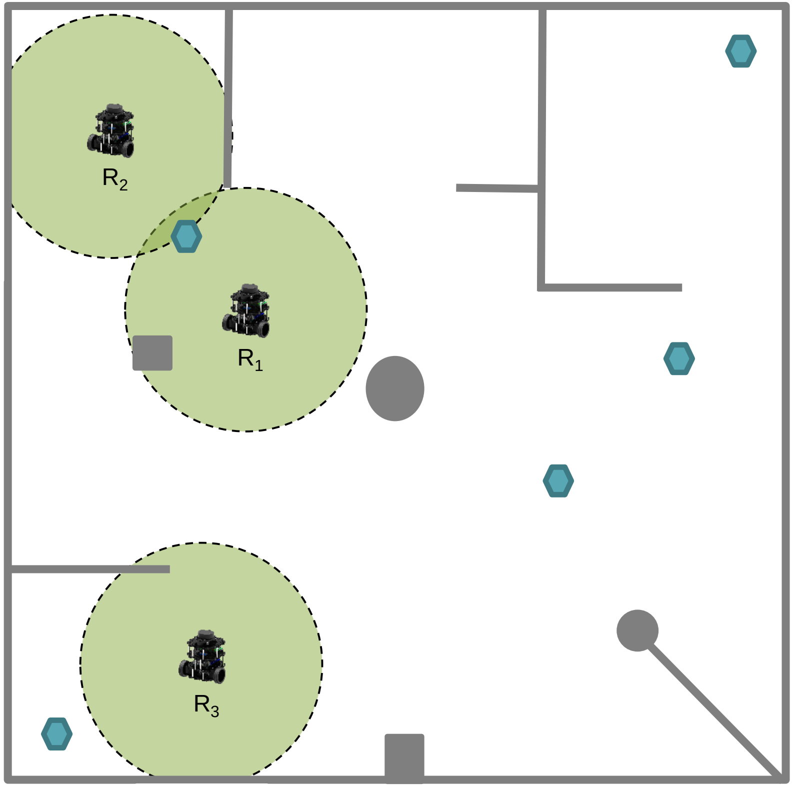
Running example



Mission goal: Discover and attain tasks.

Adaptation goals: Improve the quality of the cleaning process, e.g., attain the tasks in the shortest possible time.

Running example



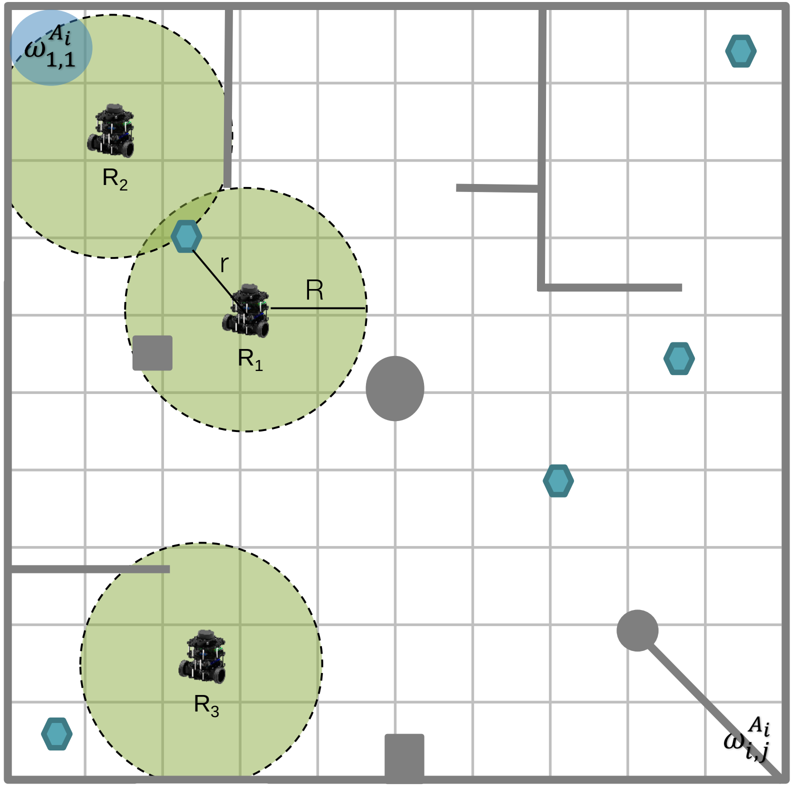
External uncertainties: manifested via the continuous appearance of tasks in the room—with unknown location patterns and frequencies.

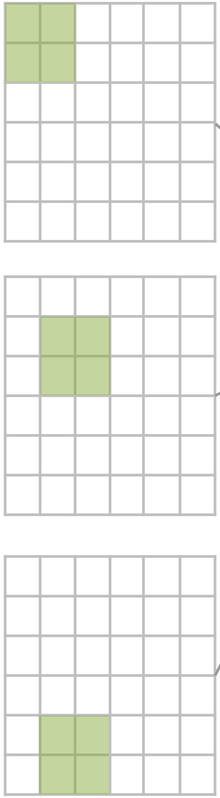
Internal uncertainties: different sensor uncertainties that cannot be anticipated during the design of the system including sensor imprecision and failure, and partiality in the observations.

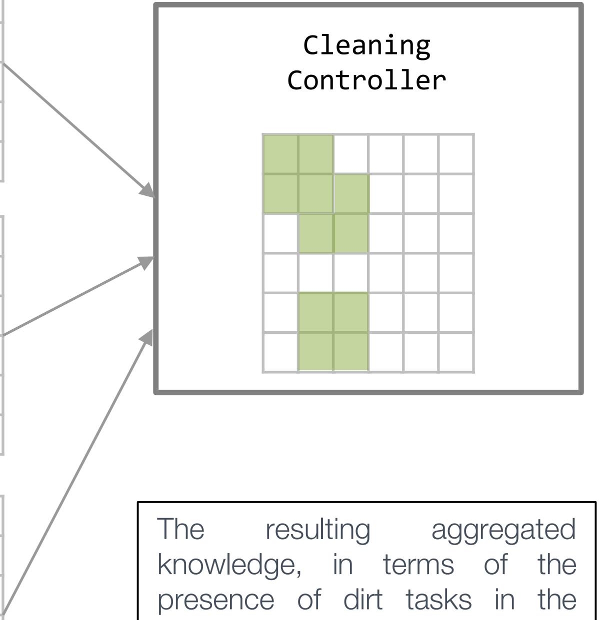
Results in different robots holding different opinions regarding the space they observe:

- Introduces inefficiency in the overall system performance
- Requires appropriate conflict resolution and aggregation process

Running example







The resulting aggregated knowledge, in terms of the presence of dirt tasks in the room, is the “best”, most complete representation of the dynamic and uncertain context (i.e., the room) at a specific time.

Background on Subjective Logic

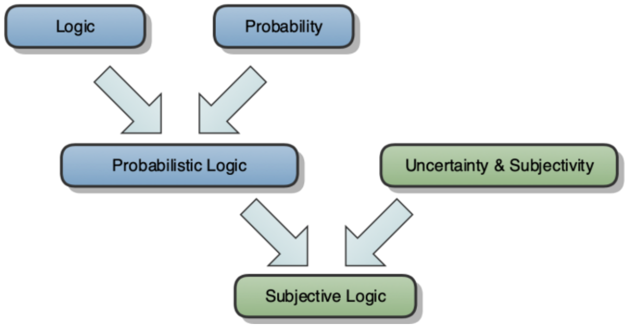
Subjective Logic (SL)

Subjective Logic (SL) [4, 5]

- is a framework for artificial reasoning, based on probabilistic logic and Dempster-Shafer theory [6, 7] of evidence
- capability to deal with the degree of (un)certainty of propositions, inherently allowing:

1) uncertainties representation as part of the fundamental building block of SL, called *Subjective Opinions*

2) reasoning about the uncertainties through a process of *Belief Fusion* in which multiple Subjective Opinions are aggregated based on the selected fusion operator.



Subjective Opinions

Domains

- Domains can be binary or n-ary
- A binary domain is denoted by $\mathbb{X} = \{x, \bar{x}\}$, where $\bar{x}$ is the complement of x
  - $\mathbb{X} = \{occupied, unoccupied\}$.

Binomial Opinion Representation [4]

- A binomial subjective opinion is a function $\omega_X^A = (b_X, d_X, u_X, a_X)$, where:
  - b_X: belief mass in support of x being TRUE $(\mathrm{X} = x)$
  - d_X: disbelief mass in support of x being FALSE $(\mathrm{X} = \bar{x})$
  - u_X: uncertainty mass, i.e. lack of confidence
  - a_X: base rate, i.e. prior probability of x without any evidence
- $b_X + d_X + u_X = 1$
- Projected probability: $P(x) = b_x + a_x u_x$.

Belief Fusion

Multiple opinions regarding the same proposition (i.e. context variable) are merged or aggregated into a single, collective opinion

Advantage: we can model and analyze situations involving an arbitrary number of sources.

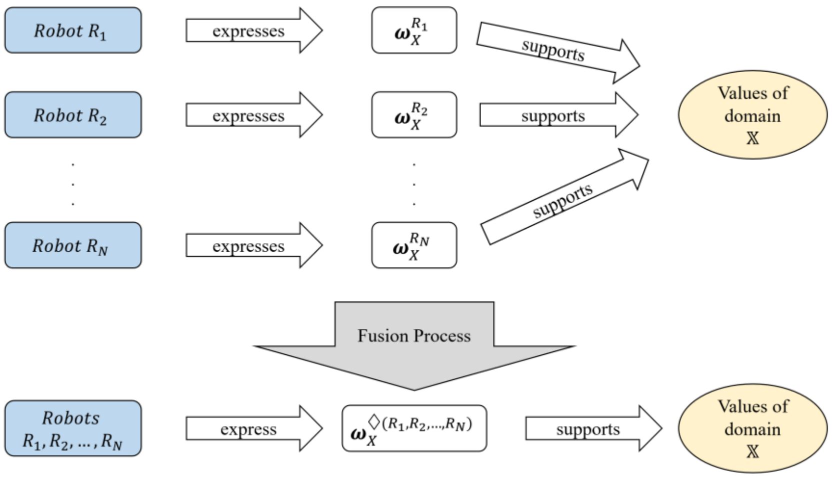
SL operator

Sources

Derived opinion

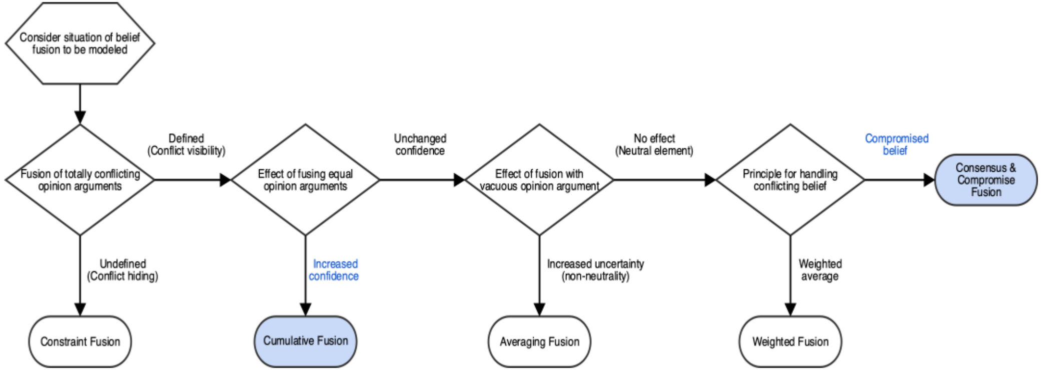
$$\omega_X = \omega_X^A \otimes \omega_X^B$$

Propositions/Variables



Selection of Belief Fusion operators

Belief fusion can be realized using different operators, each of them emphasizing different aspects when fusing multiple opinions.



Updated from [5], pp 214

In our running example:

1. the observations are made independently by multiple agents; thus, their opinions can be treated as independent pieces of evidence → **Cumulative Belief Fusion (CBF)**
2. compromises between said opinions are desired, such that the aggregated opinion is as accurate as possible. → **Consensus & Compromise Fusion (CCF)**

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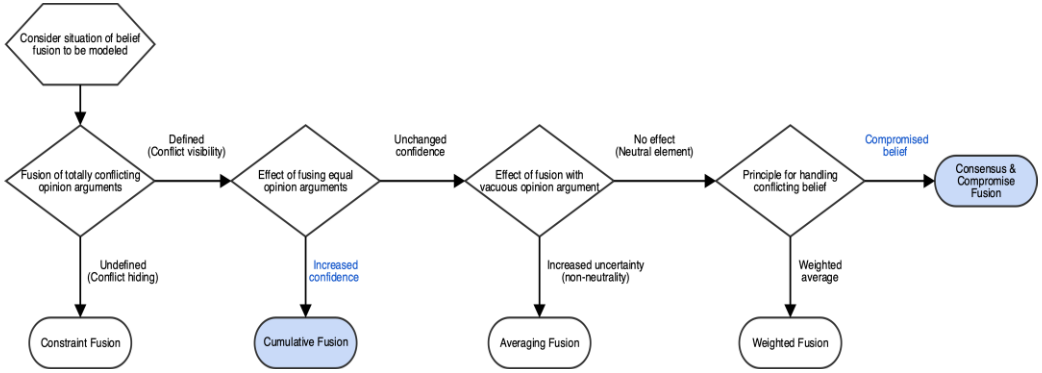

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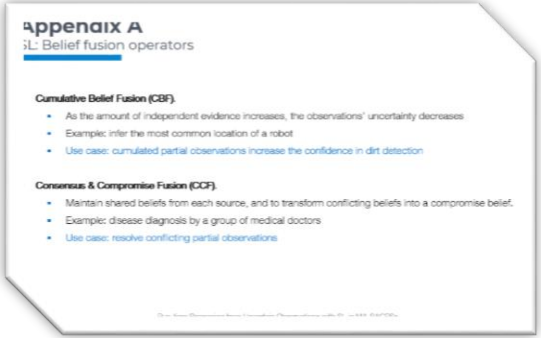

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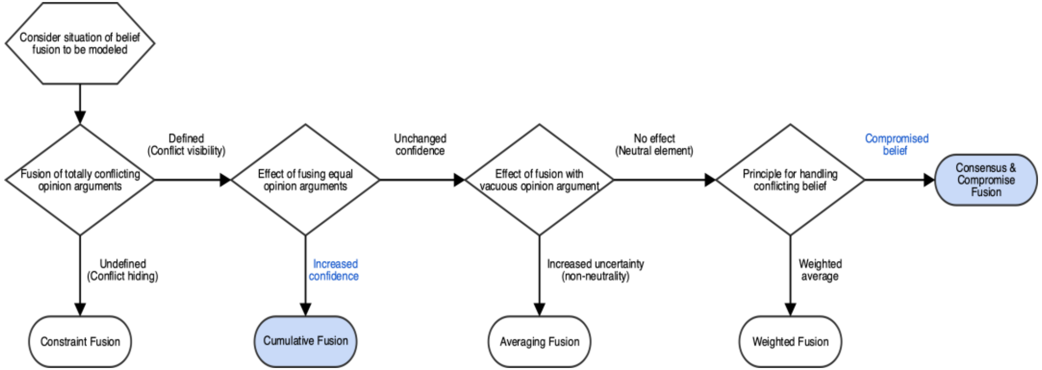

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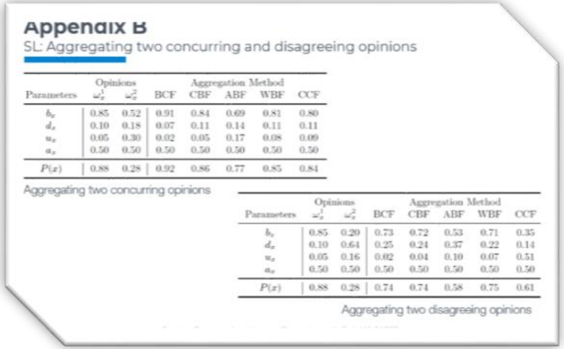


Appendix B

SL: Aggregating two concurring and disagreeing opinions

Parameters	Opinions ω_x^1	ω_x^2	Aggregation Method BCF	CBF	ABF	WBF	CCF
b_x	0.85	0.52	0.91	0.84	0.69	0.81	0.80
d_x	0.10	0.18	0.07	0.11	0.14	0.11	0.11
u_x	0.05	0.30	0.02	0.05	0.17	0.08	0.09
a_x	0.50	0.50	0.50	0.50	0.50	0.50	0.50
$P(x)$	0.88	0.28	0.92	0.86	0.77	0.85	0.84

Aggregating two concurring opinions

Parameters	Opinions ω_x^1	ω_x^2	Aggregation Method BCF	CBF	ABF	WBF	CCF
b_x	0.85	0.20	0.73	0.72	0.53	0.71	0.35
d_x	0.10	0.64	0.25	0.24	0.37	0.22	0.14
u_x	0.05	0.16	0.02	0.04	0.10	0.07	0.51
a_x	0.50	0.50	0.50	0.50	0.50	0.50	0.50
$P(x)$	0.88	0.28	0.74	0.74	0.58	0.75	0.61

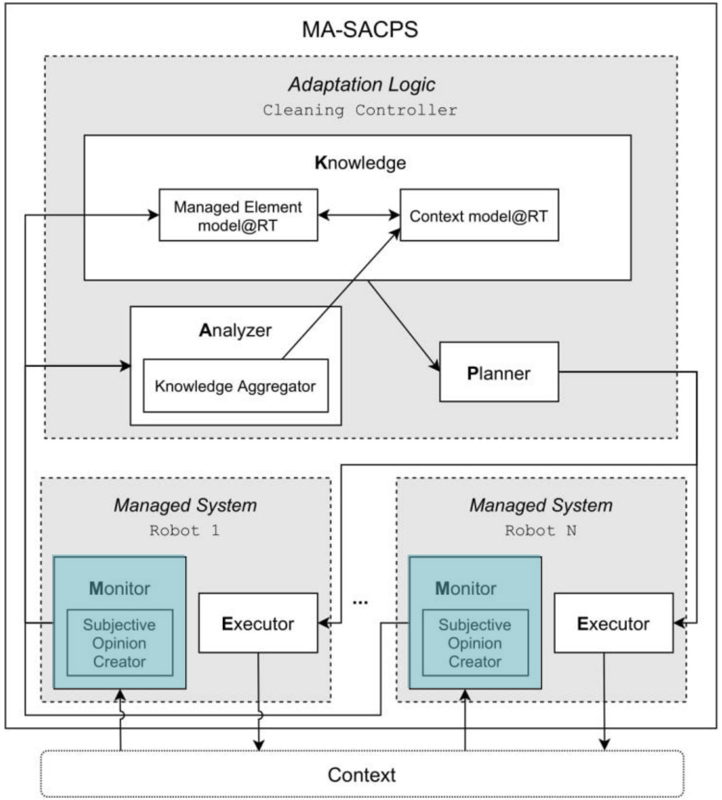
Aggregating two disagreeing opinions

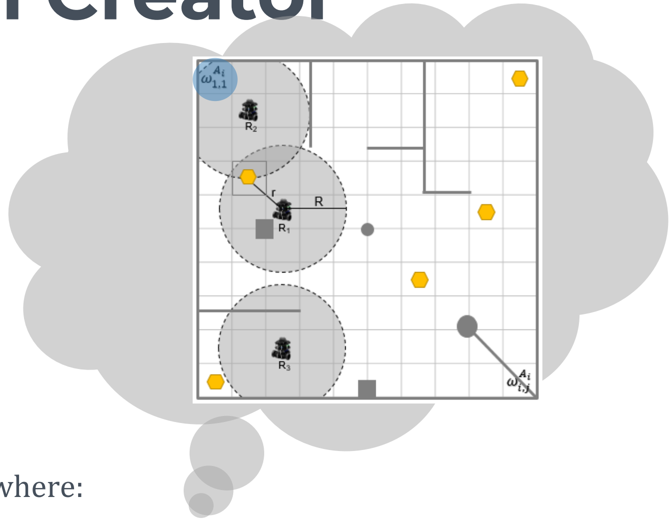
<u>In our running example:</u>

1. the observations are made independently by multiple agents; thus, their opinions can be treated as independent pieces of evidence → **Cumulative Belief Fusion (CBF)**
2. compromises between said opinions are desired to increase the accuracy of the aggregated opinion. → **Consensus & Compromise Fusion (CCF)**

Methodological approach

Monitor, Subjective Opinion Creator





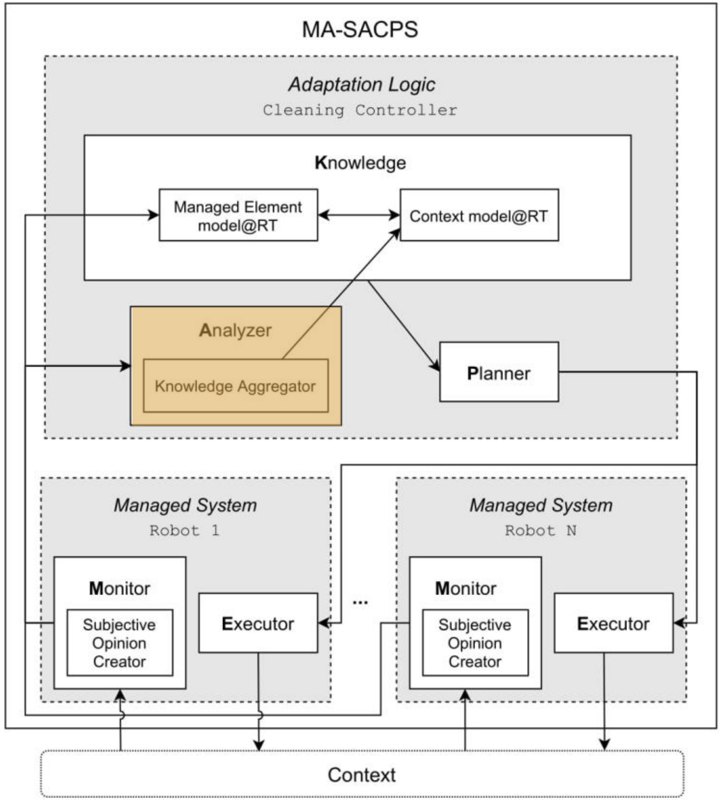
$$w_X^{Ai} = (b_X, d_X, u_X, a_X) \text{ where:}$$

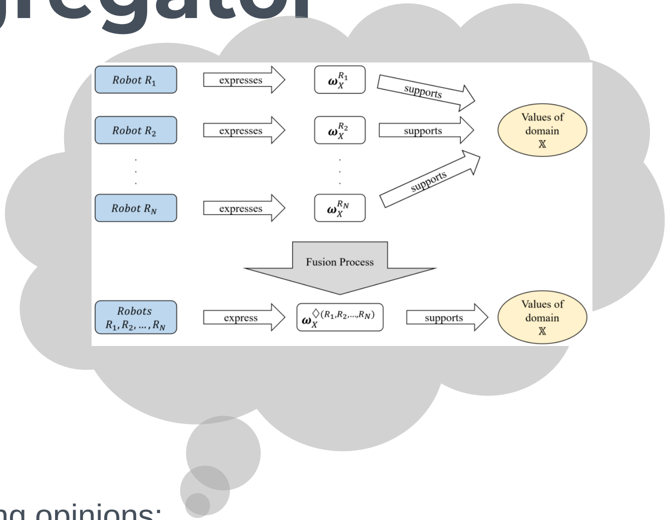
$$b_X = \begin{cases} 1 - u_X, for\ X = occupied \\ 0.0, \text{otherwise} \end{cases} \qquad d_X = \begin{cases} 1 - u_X, for\ X = unoccupied \\ 0.0, \text{otherwise} \end{cases}$$

$$u_X = \min(0.99, \frac{r}{R}) \qquad a_X = 1/2$$

r = distance between the agent and the cell
R = agent's sensor range

Analyzer, Knowledge Aggregator





Updated by aggregating opinions:

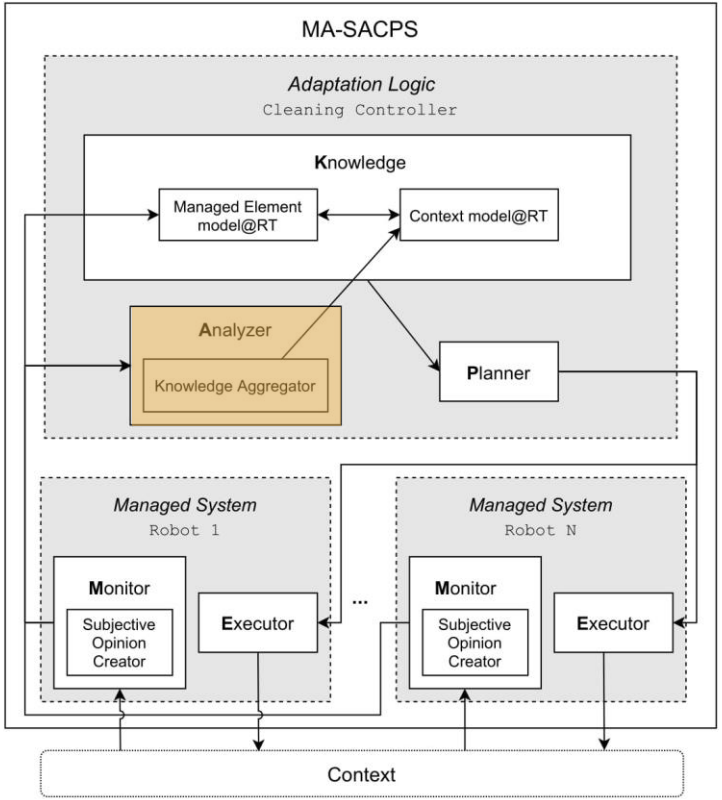
$$\omega_x^{agg} = F\left(\omega_x^{g}, \omega_x^{A_i}\right),$$

where SL is the fusion operator.

If $\mathrm{P}\left(\omega_x^{agg}\right) \geq Threshold$:

Task is propagated as a goal.

Analyzer, Knowledge Aggregator



CBF Scheme: $\omega_x^{agg} = CCF\left(\omega_x^g, \omega_x^{A_i}\right)$

CCF Scheme: $\omega_x^{agg} = CCF\left(\omega_x^g, \omega_x^{A_i}\right)$

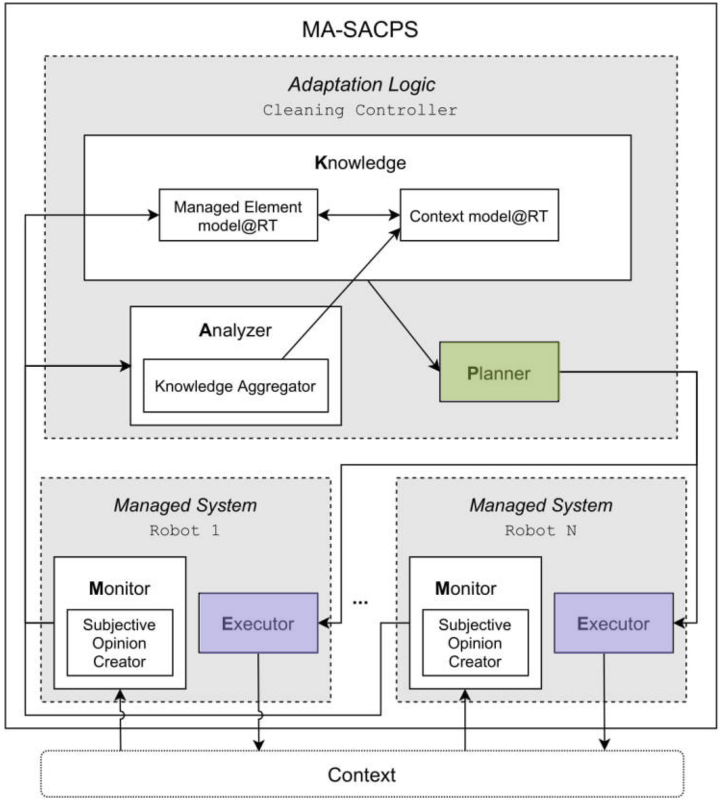
Comb. Scheme:

$$\omega_x^{agg} = \begin{cases} CCF\left(\omega_x^g, \omega_x^{A_i}\right), if\ u(\omega_x^g) < k \cap OT(\omega_x^g) \neq OT(\omega_x^{A_i}) \\ CBF\left(\omega_x^g, \omega_x^{A_i}\right)\ , otherwise \end{cases}$$

where $u(\omega_x^g)$ is the uncertainty of the context variable, k is the constant and $OT(\omega_x^{A_i})$ is the opinion type of the new opinion, defined as:

$$OT\left(\omega_x^{A_i}\right) = \begin{cases} occupied, & b\left(\omega_x^{A_i}\right) \geq d\left(\omega_x^{A_i}\right) \\ unoccupied, & b\left(\omega_x^{A_i}\right) < d\left(\omega_x^{A_i}\right) \end{cases}$$

Planner and Executor



The *Planner* is a centralized component responsible for selection of the adaptation actions or plans, which are later executed by the *Executor* components housed in every agent.

The Planner relies on the aggregated knowledge to determine the actions for all the agents, in order for the MA-SACPS to adapt and accomplish the adaptation goals in the most efficient way.

Implementation

Implementation

ROS-based communication, simulated in Gazebo [6, 7]

- TurtleBot3 Burgers[1]
- high-fidelity simulations
- AMCL for localization and navigation
- Lidar sensor, with limited sensor range

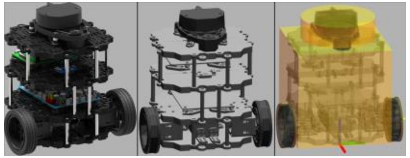
Simulate many robots, and different room maps can be used

Realistic sensing through more sophisticated sensing model, which includes:

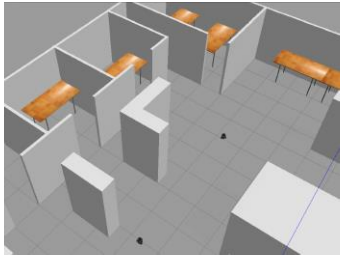
1) sensor failure
2) sensor inconsistency and noise

Implementation is open-source[2]

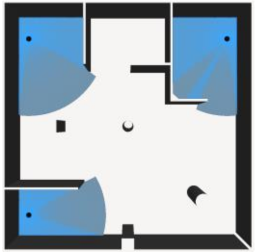
- For the subjective logic we used an open-source Java library[3]



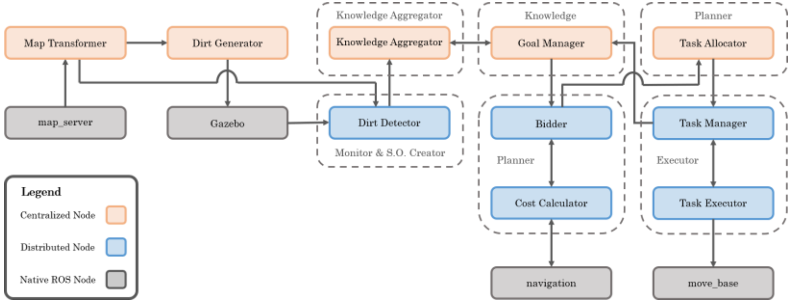
TurtleBot3 Burger



Robots in MI library



Map of the room



ROS implementation architecture

1 https://www.turtlebot.com/
2 https://github.com/tum-i4/Aggregatio
3 https://github.com/vs-uulm/subjective-logic-java

Evaluation

Research Questions

RQ1. How do the different SL aggregation schemes influence the KA in MA-SACPSs?

We investigate the feasibility of different SL aggregation schemes for KA.

RQ2. Can SL-based KA in MA-SACPSs correct faulty measurements?

We evaluate the effectiveness of the best aggregation scheme of our approach.

RQ3. How does the value of the threshold impact the SL-based KA in MA-SACPSs?

We investigate the sensitivity of our approach in respect to the threshold, i.e., the expected probability P(x).

Experimental setup

Parameter	RQ1	RQ2	RQ3
	Topic of Investigation		
Experiment	1	2	3
KA	CBF, CCF, Comb.	[No, Comb., Comb.]	Comb.
Threshold	0.8	0.8	0.2, 0.4, 0.6, 0.8
No. of Robots	2	[1, 2, 5]	2
FP Prob. R_1	0	0.1, 0.2, ... 0.9	[0.2, 0.5, 0.8]
FP Prob. R_2	0	0.1	[0.2, 0.5, 0.8]
Rate of TP (s)	15, 60	60	60
Location (seed)	71, 72, ... 75	71, 72, ... 75	71, 72 ... 75

Part of the adaptation logic: KA, Threshold

Part of the managed elements (the robots): No. of Robots, FP Prob.

Part of the context: Rate of TP (s), Location (seed)

Exp. 1: Feasibility of different SL aggregation schemes

Initial idea: evaluation using either Cumulative Belief Fusion (CBF) or Consensus & Compromise Fusion (CCF) operator; however:

- CCF is suitable when opinions are conflicting → hard to achieve extreme belief or disbelief when the opinions are agreeing
    - Discovered issues: hard to pass the required threshold P(x)

- CBF is ideal when opinions agree
    - Discovered issues: task completion rate using CBF slowly deteriorates and eventually stops for longer aggregations

Twofold evaluation:
- Analytically
- Empirically using the implemented robotics use case

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Aggregating two concurring opinions

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Aggregating two disagreeing opinions

Exp. 1: Feasibility of different SL aggregation schemes

Analytical Discussion:

1. Let $\omega_X^{agg} = \omega_X^{vac}$

2. Aggregate ω_X^{occ} with ω_X^{agg} 30 times

$$\omega_X^{agg} = CBF\left(\omega_X^{occ}, \omega_X^{agg}\right)$$

3. Aggregate ω_X^{unoc} with ω_X^{agg} 30 times

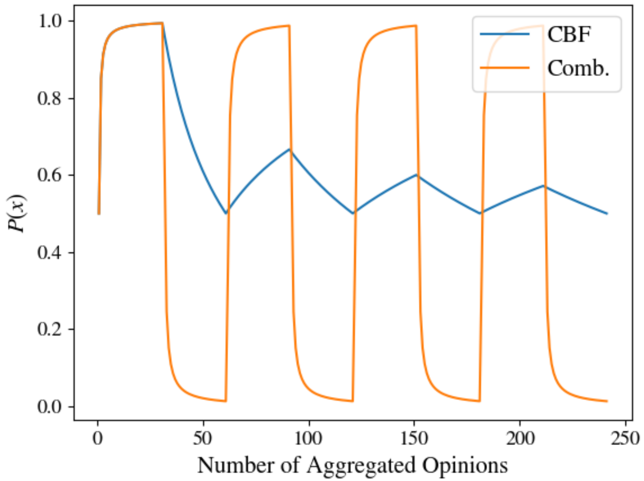
$$\omega_X^{agg} = CBF\left(\omega_X^{unoc}, \omega_X^{agg}\right)$$

4. Repeat steps 2 & 3 four times

$$\omega_X^{vac} = (b_X = 0, d_X = 0, u_X = 1, a_X = 0.5)$$

$$\omega_X^{occ} = (b_X = 0.7, d_X = 0, u_X = 0.3, a_X = 0.5)$$

$$\omega_X^{unoc} = (b_X = 0, d_X = 0.7, u_X = 0.3, a_X = 0.5)$$



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3. Aggregate ω_X^{unoc} with ω_X^{agg} 30 times
$$\omega_X^{agg} = CBF(\omega_X^{unoc}, \omega_X^{agg})$$
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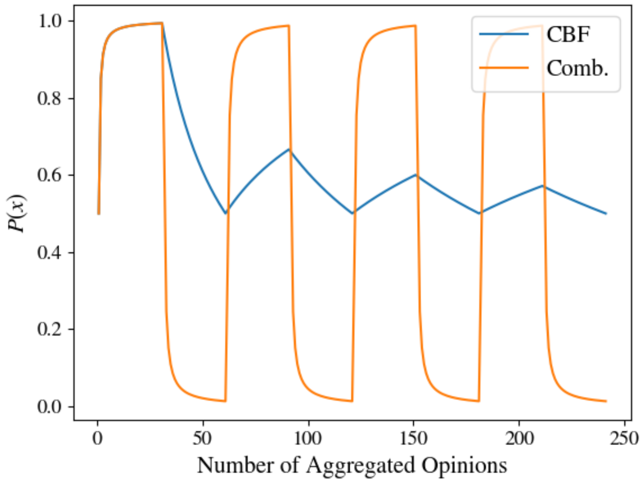
$$\omega_X^{unoc} = (b_X = 0, d_X = 0.7, u_X = 0.3, a_X = 0.5)$$



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3. Aggregate ω_X^{unoc} with ω_X^{agg} 30 times

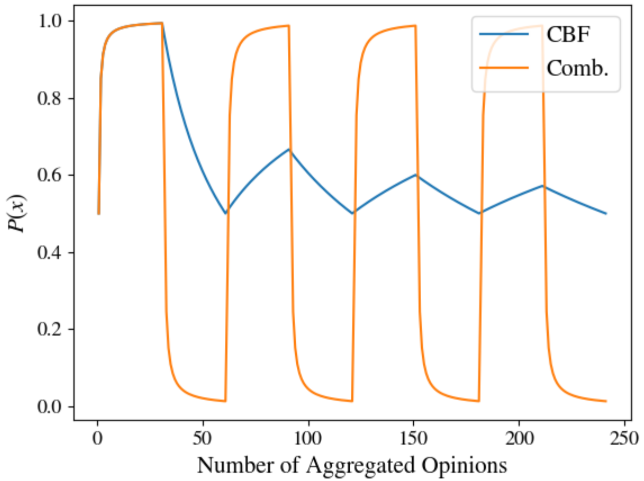
$$\omega_X^{agg} = CBF\left(\omega_X^{unoc}, \omega_X^{agg}\right)$$

4. Repeat steps 2 & 3 four times

$$\omega_X^{vac} = (b_X = 0, d_X = 0, u_X = 1, a_X = 0.5)$$

$$\omega_X^{occ} = (b_X = 0.7, d_X = 0, u_X = 0.3, a_X = 0.5)$$

$$\omega_X^{unoc} = (b_X = 0, d_X = 0.7, u_X = 0.3, a_X = 0.5)$$



Exp. 1: Feasibility of different SL aggregation schemes

Analytical Discussion:

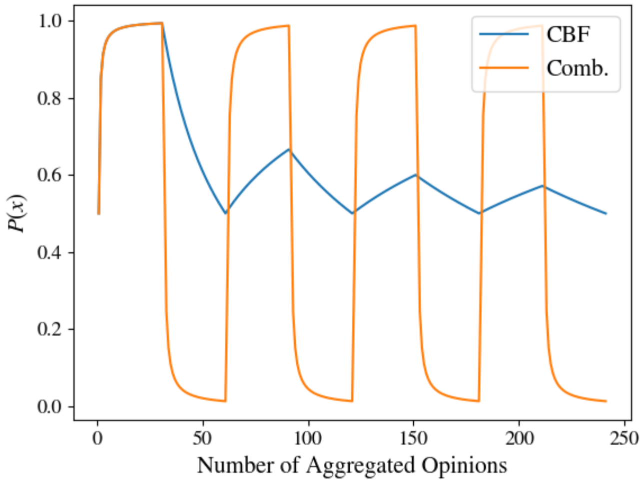
1. Let $\omega_X^{agg} = \omega_X^{vac}$
2. Aggregate ω_X^{occ} with ω_X^{agg} 30 times

$$\omega_X^{agg} = CBF\left(\omega_X^{occ}, \omega_X^{agg}\right)$$

3. Aggregate ω_X^{unoc} with ω_X^{agg} 30 times

$$\omega_X^{agg} = CBF\left(\omega_X^{unoc}, \omega_X^{agg}\right)$$

4. Repeat steps 2 & 3 four times



$$\omega_X^{vac} = (b_X = 0, d_X = 0, u_X = 1, a_X = 0.5)$$

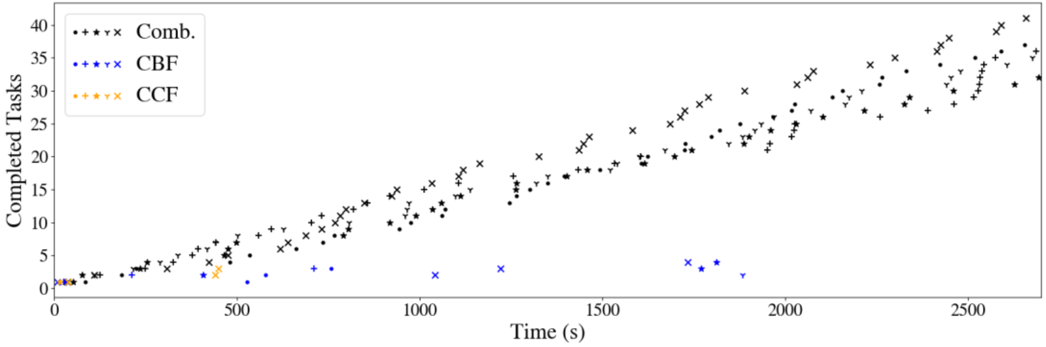
$$\omega_X^{occ} = (b_X = 0.7, d_X = 0, u_X = 0.3, a_X = 0.5)$$

$$\omega_X^{unoc} = (b_X = 0, d_X = 0.7, u_X = 0.3, a_X = 0.5)$$

Exp. 1: Feasibility of different SL aggregation schemes

RQ1. How do the different SL aggregation schemes influence the KA in MA-SACPSs?

Findings: Long-term KA is not feasible by using the original SL operators in isolation, and this limitation is addressed by our newly proposed aggregation scheme.



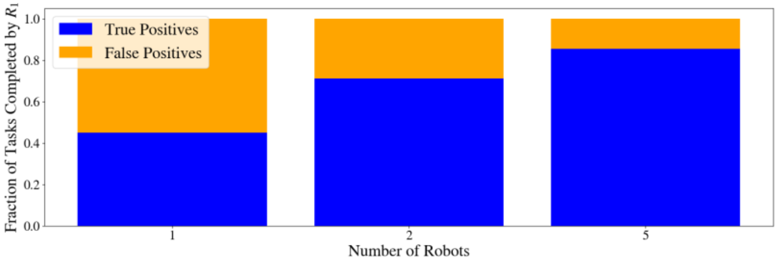
Number of tasks completed using CBF, CCF and Comb. Schemes.

Parameter		Topic of Investigation RQ1	RQ2	RQ3
Experiment		1	2	3
KA		CBF, CCF, Comb.	[No, Comb., Comb.]	Comb.
Threshold		0.8	0.8	0.2, 0.4, 0.6, 0.8
No. of Robots		2	[1, 2, 5]	2
FP Prob.	R_1	0	0.1, 0.2, ... 0.9	[0.2, 0.5, 0.8]
	R_2	0	0.1	[0.2, 0.5, 0.8]
Rate of TP (s)		15, 60	60	60
Location (seed)		71, 72, ... 75	71, 72, ... 75	71, 72 ... 75

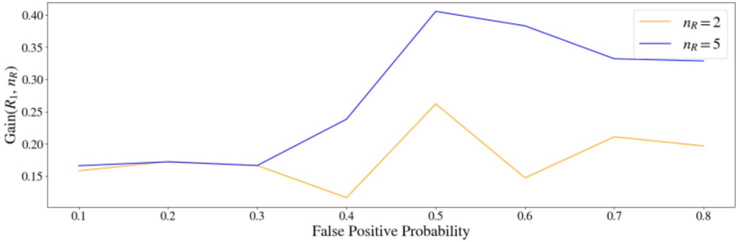
Exp. 2: Effectiveness of the KA

RQ2. Can SL-based KA in MA-SACPSs correct faulty measurements?

FP Probability = 0.5



$$\mathrm{Gain}(R_i, n_R) = \left.\frac{n_{TP}(R_i)}{n_{FP}(R_i)+n_{TP}(R_i)}\right|_{n_R} - \left.\frac{n_{TP}(R_i)}{n_{FP}(R_i)+n_{TP}(R_i)}\right|_{1R}$$



Findings: SL-based KA enables the correction of faulty measurements made by a robot.

Parameter		RQ1	RQ2	RQ3
		Topic of Investigation		
Experiment		1	2	3
KA		CBF, CCF, Comb.	[No, Comb., Comb.]	Comb.
Threshold		0.8	0.8	0.2, 0.4, 0.6, 0.8
No. of Robots		2	[1, 2, 5]	2
FP Prob.	R_1	0	0.1, 0.2, ... 0.9	[0.2, 0.5, 0.8]
	R_2	0	0.1	[0.2, 0.5, 0.8]
Rate of TP (s)		15, 60	60	60
Location (seed)		71, 72, ... 75	71, 72, ... 75	71, 72 ... 75

Exp. 3: Sensitivity analysis of the impact of the threshold value

RQ3. How does the value of the threshold impact the SL-based KA in MA-SACPSs?

Findings: The value of the threshold has an impact to SL-based KA. There is a clear trade-off between the accuracy of KA and the number of completed tasks.

FP Prob.	Threshold	$\overline{TPF}$	$\overline{FPF}$	$\overline{N}$	$N_{max} - N_{min}$
0.2	0.2	0.769	0.231	53.6	7
	0.4	0.773	0.226	49.4	6
	0.6	0.794	0.206	45.6	5
	0.8	0.803	0.197	40.6	11
0.5	0.2	0.455	0.545	79.6	31
	0.4	0.485	0.515	41.8	64
	0.6	0.532	0.468	50.0	41
	0.8	0.578	0.422	25.6	57
0.8	0.2	0.205	0.795	93.6	68
	0.4	0.200	0.800	43.5	36
	0.6	0.219	0.781	47.4	86
	0.8	0.243	0.757	29.6	67

$$TPF = \frac{n_{TP}}{N}$$

$$FPF = \frac{n_{FP}}{N}$$

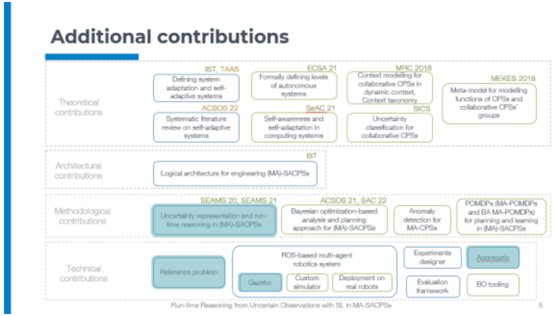
$$N = n_{TP} + n_{FP}$$

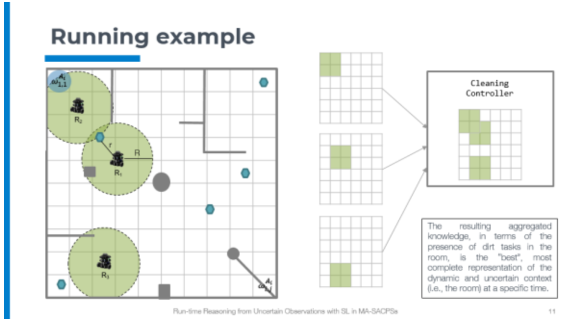
$$N_{max} = \max(N_{seed1}, \dots, N_{seed5})$$

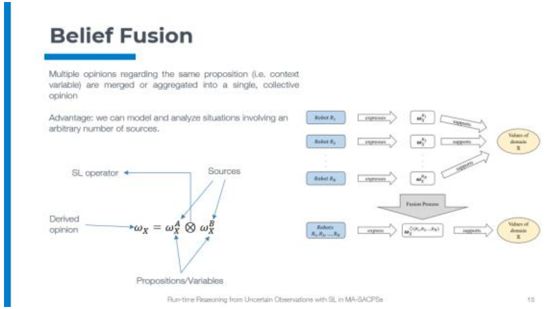
Parameter		Topic of Investigation RQ1	RQ2	RQ3
Experiment		1	2	3
KA		CBF, CCF, Comb.	[No, Comb., Comb.]	Comb.
Threshold		0.8	0.8	0.2, 0.4, 0.6, 0.8
No. of Robots		2	[1, 2, 5]	2
FP Prob.	R_1	0	0.1, 0.2, ... 0.9	[0.2, 0.5, 0.8]
	R_2	0	0.1	[0.2, 0.5, 0.8]
Rate of TP (s)		15, 60	60	60
Location (seed)		71, 72, ... 75	71, 72, ... 75	71, 72 ... 75

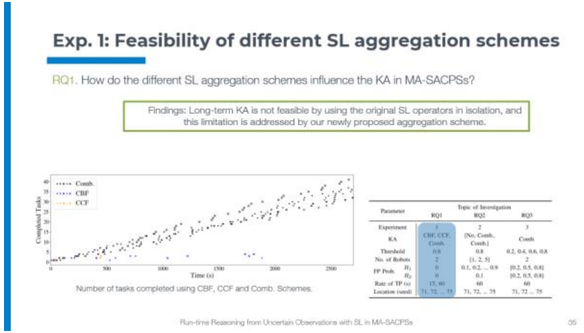
Conclusions

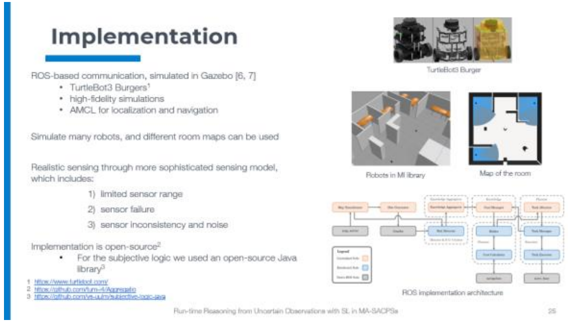
Wrap up

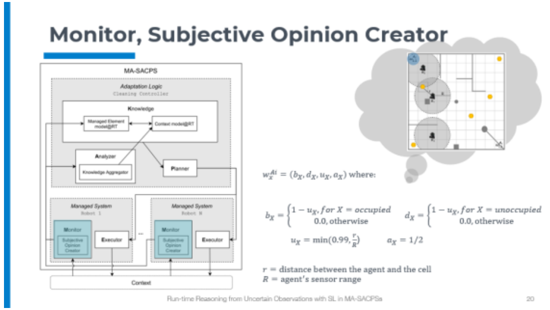

Additional contributions
Theoretical contributions
Architectural contributions
Methodological contributions
Technical contributions
Defining system adaptation and self-adaptive systems
Formally defining levels of autonomous systems
Context modelling for collaborative CPSs in dynamic context, Context taxonomy
Meta-model for modelling functions of CPSs and collaborative CPSs' groups
Systematic literature review on self-adaptive systems
Self-awareness and self-adaptation in computing systems
Uncertainty classification for collaborative CPSs
Logical architecture for engineering (MA)-SACPSs
Uncertainty representation and run-time reasoning in (MA)-SACPSs
Bayesian optimization-based analysis and planning approach for (MA)-SACPSs
Anomaly detection for MA-CPSs
Reference problem
ROS-based multi-agent robotics system
Gazebo
Custom simulator
Deployment on real robots
Experiments designer
Evaluation framework
Aggregate
BO tooling
Run-time Reasoning from Uncertain Observations with SL in MA-SACPSs


Running example
Cleaning Controller
The resulting aggregated knowledge, in terms of the presence of dirt tasks in the room, is the "best", most complete representation of the dynamic and uncertain context (i.e., the room) at a specific time.
Run-time Reasoning from Uncertain Observations with SL in MA-SACPSs


Belief Fusion
Multiple opinions regarding the same proposition (i.e. context variable) are merged or aggregated into a single, collective opinion
Advantage: we can model and analyze situations involving an arbitrary number of sources.
SL operator
Sources
Derived opinion
Propositions/Variables
Run-time Reasoning from Uncertain Observations with SL in MA-SACPSs


Exp. 1: Feasibility of different SL aggregation schemes
RQ1. How do the different SL aggregation schemes influence the KA in MA-SACPSs?
Findings: Long-term KA is not feasible by using the original SL operators in isolation, and this limitation is addressed by our newly proposed aggregation scheme.
Comb.
CBF
CCF
Time (s)
Number of tasks completed using CBF, CCF and Comb. Schemes.
Run-time Reasoning from Uncertain Observations with SL in MA-SACPSs


Implementation
ROS-based communication, simulated in Gazebo [6, 7]
TurtleBot3 Burgers
high-fidelity simulations
AMCL for localization and navigation
Simulate many robots, and different room maps can be used
Realistic sensing through more sophisticated sensing model, which includes:
1) limited sensor range
2) sensor failure
3) sensor inconsistency and noise
Implementation is open-source
For the subjective logic we used an open-source Java library
TurtleBot3 Burger
Robots in MI library
Map of the room
ROS implementation architecture
Run-time Reasoning from Uncertain Observations with SL in MA-SACPSs


Monitor, Subjective Opinion Creator
MA-SACPS
Adaptation Logic
Knowledge
Analyzer
Planner
Managed System
Monitor
Executor
Context
r = distance between the agent and the cell
R = agent's sensor range
Run-time Reasoning from Uncertain Observations with SL in MA-SACPSs

Key takeaways

- Construct the subjective opinions for the concrete use case
    - What is exactly expressed by the SO?
    - Binary or n-ary domain (the theory and the implementation of the n-ary domains might be more challenging), including how the knowledge is modelled
    - Are all the opinions from the same state space?
    - The concrete system at hand
    - Depending if the problem is approached from a safety or a security aspect

- SL works! However, …
    - It is important to choose the right SL operator(s) for the concrete use case
    - Keep in mind the limitations of the original SL operators
    - Be ready that there might be the need for proposing a new, merger operator for your needs

- Available libraries for SL; however, …
    - Written in Java

- Everything SL logic related is good for publishing

Thank you!

Contact

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https://www.cs.cit.tum.de/sse/petrovska/	URL
https://www.linkedin.com/in/anapetrovska92/	LinkedIn
https://github.com/anapetrovska/Huawei-SL/	Slides

References

[1] Ana Petrovska, Sergio Quijano, Ilias Gerostathopoulos, Alexander Pretschner: *Knowledge Aggregation with Subjective Logic in Multi-Agent Self-Adaptive Cyber-Physical Systems.* 2020 IEEE/ACM 15th International Symposium on Software Engineering for Adaptive and Self-Managing Systems (SEAMS), 2020.

[2] Ana Petrovska, Malte Neuss, Ilias Gerostathopoulos, Alexander Pretschner: *Run-time Reasoning from Uncertain Observations with Subjective Logic in Multi-Agent Self-Adaptive Cyber-Physical Systems.* 16th Symposium on Software Engineering for Adaptive and Self-Managing Systems, SEAMS, 2021.

[3] Weyns, Danny, et al. "On patterns for decentralized control in self-adaptive systems." *Software Engineering for Self-Adaptive Systems II*. Springer, Berlin, Heidelberg, 2013. 76-107.

[4] A. Jøsang, "A Logic for Uncertain Probabilities," *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, vol. 9, no. 3, pp. 271–311, 2001.

[5] A. Jøsang, *Subjective Logic*. Springer International Publishing Switzerland, 2016.

[6] Nathan Koenig and Andrew Howard. 2004. Design and Use Paradigms for Gazebo, An Open-Source Multi-Robot Simulator. In 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566). IEEE, 2149–2154. https://doi.org/10.1109/IROS.2004.1389727

[7] Carlos E. Aguero, Nate Koenig, Ian Chen, Hugo Boyer, Steven Peters, John Hsu, Brian Gerkey, Steffi Paepcke, Jose L. Rivero, Justin Manzo, Eric Krotkov, and Gill Pratt. 2015. Inside the Virtual Robotics Challenge. 12 (2015), 494–506. Issue 2. https://doi.org/10.1109/TASE.2014.2368997

[8] Danny Weyns, Bradley Schmerl, Vincenzo Grassi, Sam Malek, Raffaela Mirandola, Christian Prehofer, Jochen Wuttke, Jesper Andersson, Holger Giese, and Karl M Göschka. On patterns for decentralized control in self-adaptive systems. In Software Engineering for Self- Adaptive Systems II, pages 76–107. Springer, 2013.

Appendix A

SL: Belief fusion operators

- **Cumulative Belief Fusion (CBF).**
  - As the amount of independent evidence increases, the observations' uncertainty decreases
  - Example: infer the most common location of a robot
  - Use case: cumulated partial observations increase the confidence in dirt detection

- **Consensus & Compromise Fusion (CCF).**
  - Maintain shared beliefs from each source, and to transform conflicting beliefs into a compromise belief.
  - Example: disease diagnosis by a group of medical doctors
  - Use case: resolve conflicting partial observations

Appendix B

SL: Aggregating two concurring and disagreeing opinions

Parameters	Opinions ω_x^1	ω_x^2	BCF	Aggregation Method CBF	ABF	WBF	CCF
b_x	0.85	0.52	0.91	0.84	0.69	0.81	0.80
d_x	0.10	0.18	0.07	0.11	0.14	0.11	0.11
u_x	0.05	0.30	0.02	0.05	0.17	0.08	0.09
a_x	0.50	0.50	0.50	0.50	0.50	0.50	0.50
$P(x)$	0.88	0.28	0.92	0.86	0.77	0.85	0.84

Aggregating two concurring opinions

Parameters	Opinions ω_x^1	ω_x^2	BCF	Aggregation Method CBF	ABF	WBF	CCF
b_x	0.85	0.20	0.73	0.72	0.53	0.71	0.35
d_x	0.10	0.64	0.25	0.24	0.37	0.22	0.14
u_x	0.05	0.16	0.02	0.04	0.10	0.07	0.51
a_x	0.50	0.50	0.50	0.50	0.50	0.50	0.50
$P(x)$	0.88	0.28	0.74	0.74	0.58	0.75	0.61

Aggregating two disagreeing opinions