Semantic enrichment of spatio-temporal production data to determine lead times for manufacturing simulation - 2019 Winter Simulation Conference

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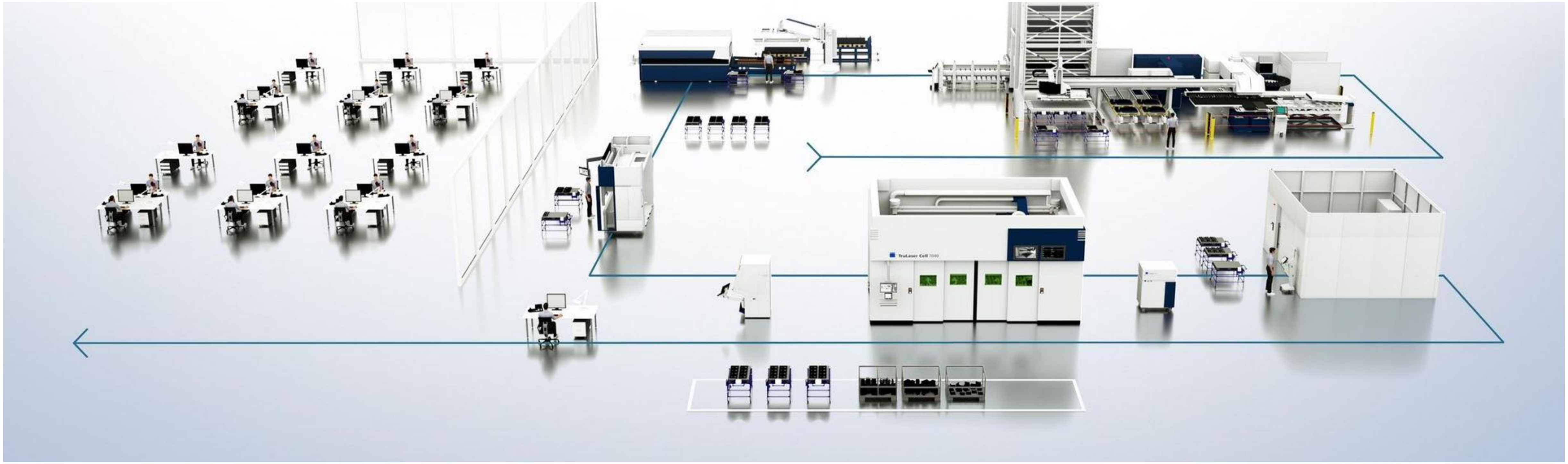

2019 Winter Simulation Conference

Semantic enrichment of spatio-temporal production data to determine lead times for manufacturing simulation

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Agenda

1.Motivation

- introduction
- objective of this contribution

2.Fundamentals

- real-time indoor localization systems (RTILS)
- semantic enrichment
- related work

3.Contribution

- proposed approaches
- comparison of the algorithms
- sensor fusion concept

4.Conclusion

- summary
- future work
- references

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Introduction

Challenges with simulation‘s input data:

- simulation success relies on high-quality data (Wenzel et al. 2007)
- data gathering and processing is time-consuming
- poor data quality causes problems with credibility (Onggo et al. 2013)

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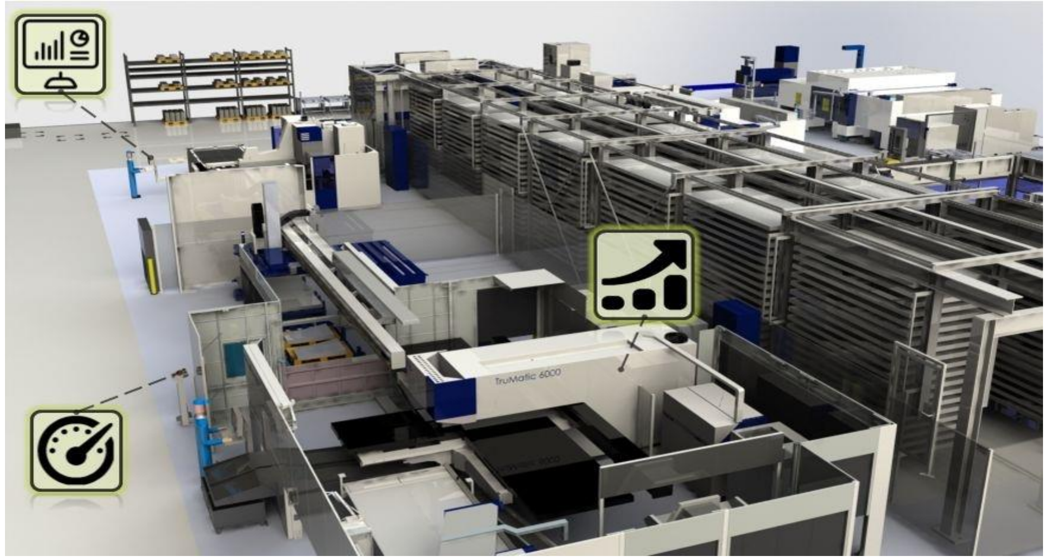
Introduction

Increasing dissemination of cyber-physical systems:

- valuable proposition of new data sources
- considered essential for digital twins
(Yang et al. 2017; Shao and Kibira 2018; Srewil and Scherer 2017)
- the analysis of spatio-temporal data has the potential to discover hidden patterns that result in non-trivial insights
(Nikitopoulos et al. 2018)



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Flashback to:

52nd CIRP Conference on Manufacturing Systems

Framework for the usage of data from real-time indoor localization systems to derive inputs for manufacturing simulation

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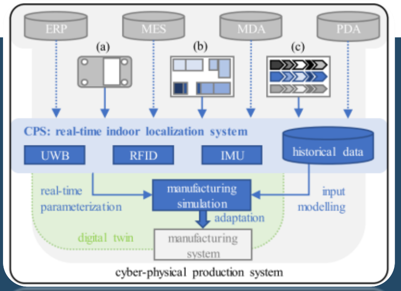
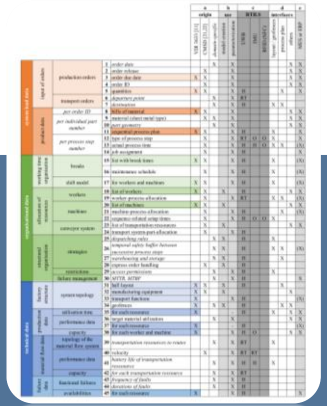
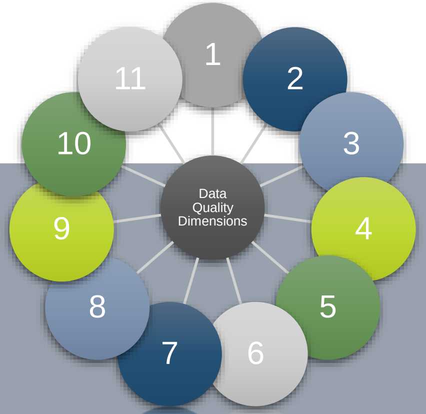


RTILS framework



data model for sheet metal production



improvements of data quality

Motivation

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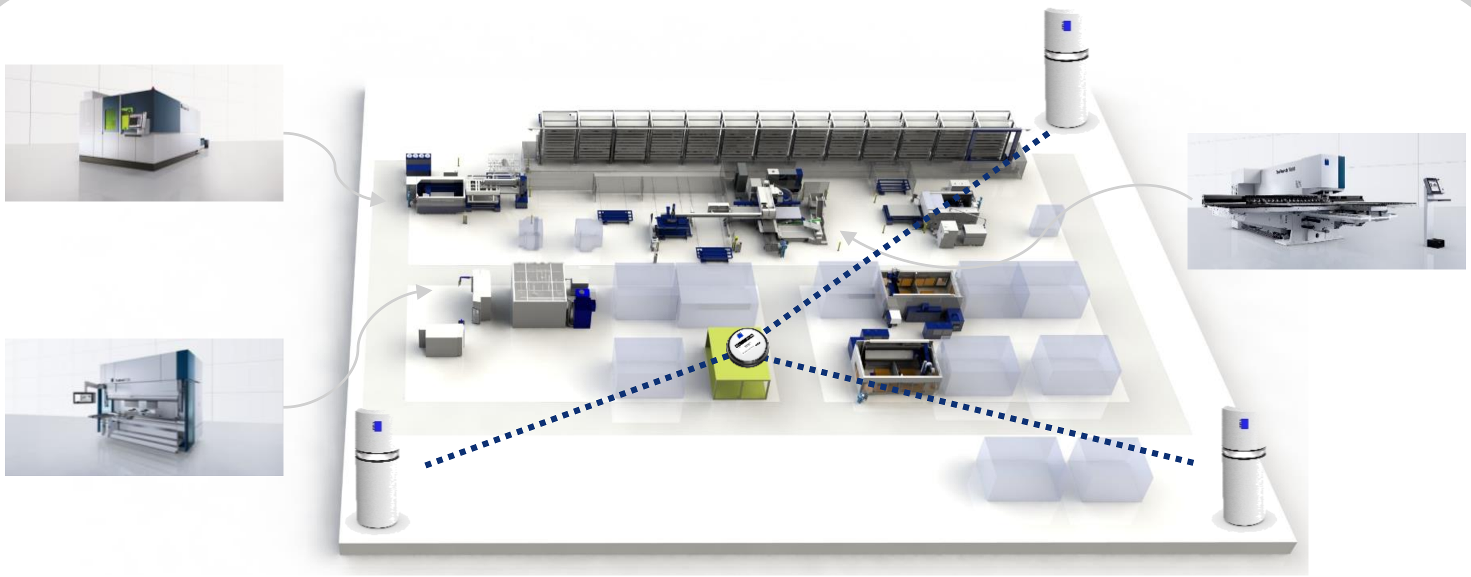
Objective of this contribution

each production order is tracked with the RTILS

+

process sequence and layout are known



three algorithms are presented for the semantic enrichment

→ semantic trajectories can be used for the calculation of lead time distributions

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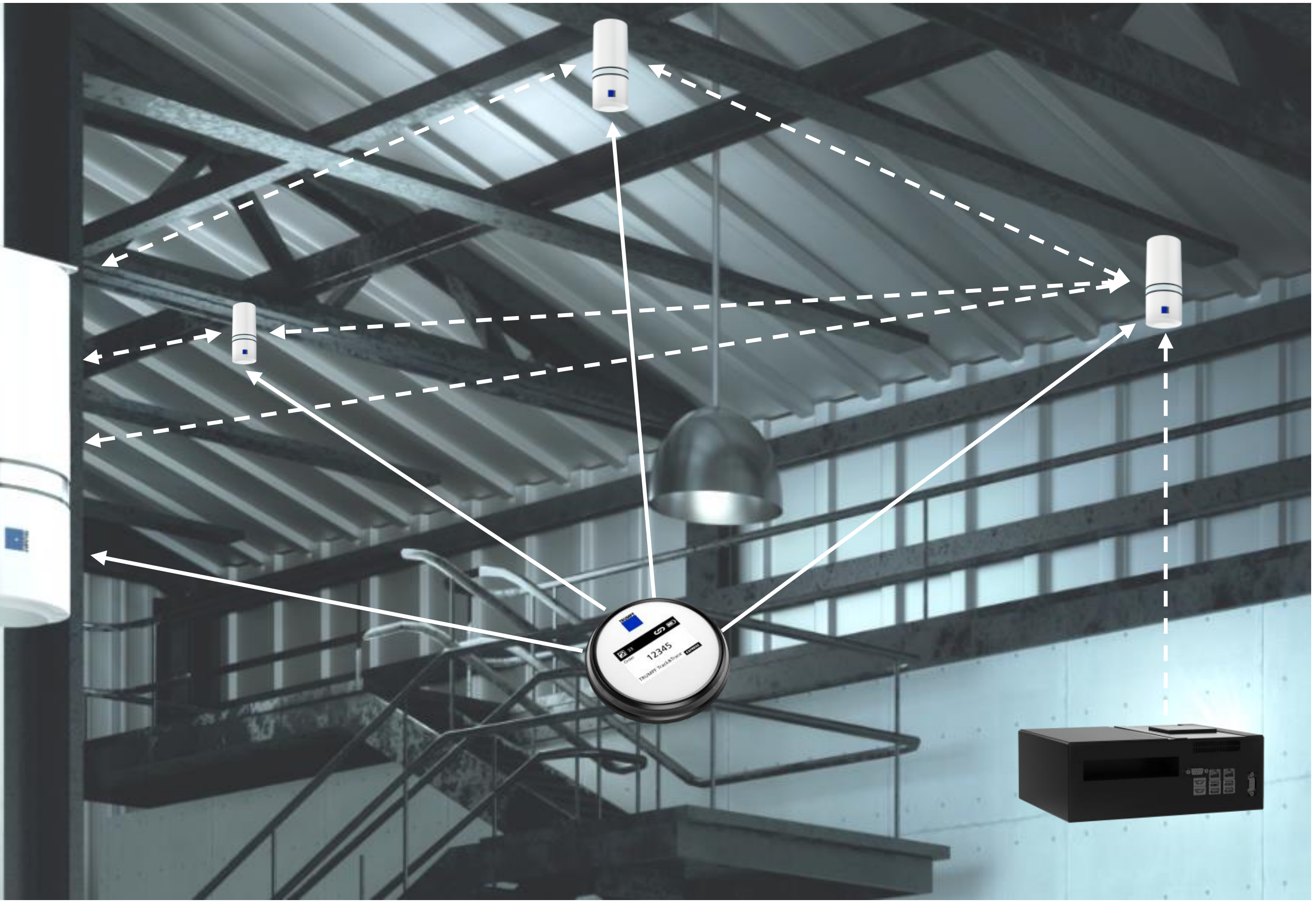
Real-time Indoor Localization Systems

- here: based on ultra-wide band technology
  - bandwith > 500 MHz
  - frequencies 3,1-10,6 GHz
  - TDOA / RTOF
- stationary devices:
  - satellites
  - industrial computer
- mobile devices:
  - markers



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Semantic Enrichment

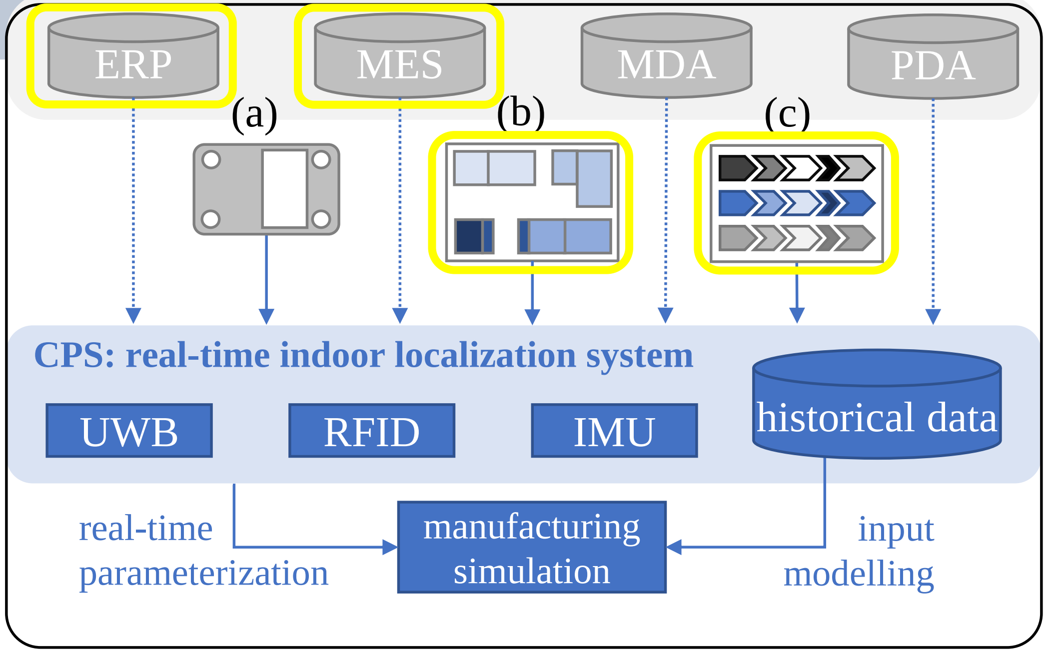
Fundamentals

is the process of annotating spatio-temporal trajectories with meaningful context information (Arslan et al. 2018)

context information from…

semantic spatio-temporal trajectories

$$(x, y, t, \mathrm{ID}_{marker}, \mathrm{ID}_{order}, \mathbf{C})$$



Own illustration taken from Mieth et al. 2019

Related Work

Fundamentals

Previous approaches consider radio-frequency identification (indoor) or GPS data (outdoor):

- **Zhong et al. (2014):** mined operating times from RFID-enabled worker data
- **Srewil and Scherer 2017:** enriched RFID-data with location context of construction sites
- **Rashid et al. 2017:** worker tracking at construction sites for training a hidden markov model for trajectory prediction which is used to calculate risk index for workers (location-based safety alerts)

Open Challenges

- **UWB-based RTILS production data ≠ RFID data**
  - **Yan et al. 2013:** techniques for semantic events inferred from raw GPS-like data should be developed
- **Zheng 2015:** trajectory data mining applications: movements of people, transportation vehicles, animals and natural phenomena → manufacturing not mentioned!

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Related Work

approaches to determine stay points in GPS-data

- Li et al. 2008: stay point detection algorithm→ no semantics ☹
- Palma et al. 2008: a clustering-based approach with adaptive tresholds, clusters are mapped on polygons
- Rocha et al. 2010: a direction-based spatio-temporal clustering method (frequent changes = POI)
- Alvares et al. 2010: trajectory are split whenever borders of areas are crossed → not robust ☹

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(illustrations taken from Graaff et al. 2016)

(a) Alvares's IB-SMoT (b) Palma's CB-SMoT (c) Rocha's DB-SMoT

- Graaff et al. 2016: use accuracy of the location samples, reductions in speed, changes in direction and projection of signals onto parcel polygons

- **there are no approaches for production environments**
- **difficulties:** **outdoor < indoor →** proximity, adjacency, overlap
  signal interferences → inherent inaccuracy of the data (Richly 2018)

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Proposed approaches

Contribution

Online Semantic Annotation (real-time)

- based on the distance to points of interest (POI)
- based on areas of interest (AOI)

Offline Semantic Annotation (when the whole trajectory is known)

- trajectory segmentation as a classification problem (CP)

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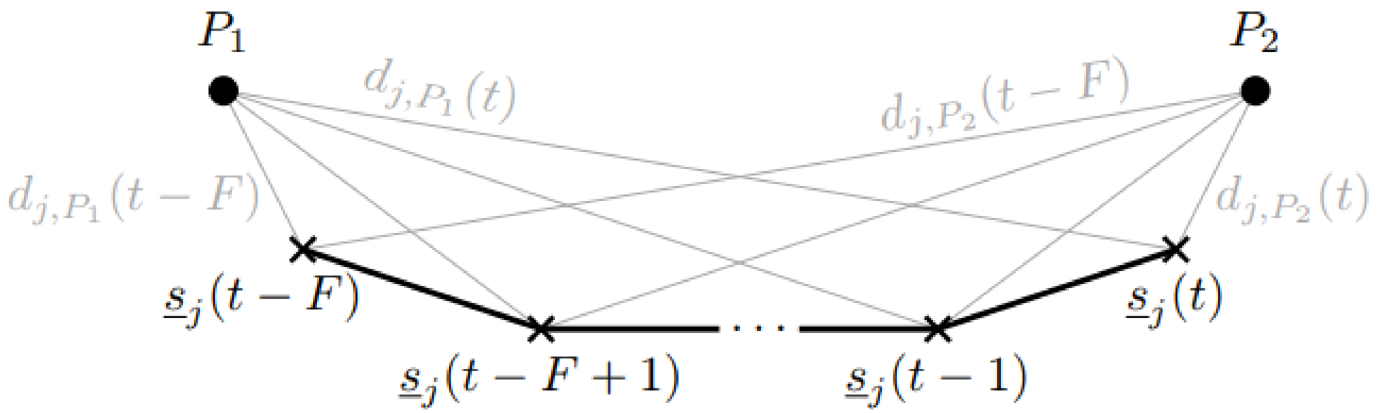
Algorithm for Online Semantic Annotation
→ based on Points of Interest (POI)

Idea: use $R_j(t, P_i) := \frac{1}{d_{oj,P_i}(t)} + \sum_{f=1}^{F} \frac{1}{w_f d_{o_j,p_i}(t-f)}$ as discriminator for the allocation of a measurement

- P_i refers to a location (x_i, y_i) on the shopfloor with semantic meaning *(e.g. machine or workplace)*
- $d_{o_j,P_i}(t)$ euclidean distance betwenn production order o_j and POI P_i
- pseudo probability: relating each current rating to the sum of all ratings at the time



Points of interest P_1 and P_2 with the trajectory of a production order o_j

Algorithm for Online Semantic Annotation
→ based on Areas of Interest (AOI)

Idea: allocate measurements to AOIs, if the majority of the last F measurements are inside

- A_i refers to an arbitrarily shaped area on the shopfloor that has a semantic meaning
  (e.g. work area around a machine or a storage)

$$PIA((x,y),A_i) = \begin{cases} 1 & \text{inside} \\ 0 & \text{on border} \\ -1 & \text{outside} \end{cases}$$

the discriminator is the point-in-area (PIA) test that checks if the measured point (x,y) is in A_i

- if the sum of all values returned by the PIA-test inside the *window size F* is greater or equal zero → location change

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Pseudocode can be found in the paper ;)

input : spatio-temporal trajectories $\underline{S}_j$ for each production order o_j, window size F, weighting factors $w_1, \ldots, w_F$, points of interest $P_i\ \forall i = 1 \ldots N$
output: semantic trajectory $\underline{S}_{a,j}$, event log

for each $t = 1 \ldots T$ **do**
  check plausibility constraints for measurement $s_j(t)$
  for each *production order* o_j **do**
    for each *point of interest* P_i **do**
      if $t \leq F$ **then**
        $R_j(t, P_i) := \frac{1}{d_{o_j, P_i}(t)}$; // initilization of first ratings
      else
        $R_j(t, P_i) := \frac{1}{d_{o_j, P_i}(t)} + \sum_{f=1}^{F} \frac{1}{w_f d_{o_j, P_i}(t-f)}$; // rating function
    assign P_i with $max\{R_j(t, P_i)\}$ to $\underline{s}_{a,j}(t)$; // chose most likely P_i
    if $P_i(t) \neq P_i(t-1)$ **then**
      save timestamp to eventlog ; // location has changed
return $\underline{S}_{a,j}(t)$, event log

Algorithm 1: Pseudocode for the allocation of measurements to points of interest (POI).

Choosing the “right” window size F

definition of POIs is easy
AOIs sometimes tricky

both definitions influence the results

input : trajectories $\underline{S}_j$ for each production order o_j, window size F, disjoint areas of interest $A_i\ \forall i = 1 \ldots N$
output: semantic trajectory $\underline{S}_{a,j}$, event log

for each $t = 1 \ldots T$ **do**
  check plausibility constraints for measurement $s_j(t)$
  for each *production order* o_j **do**
    for each *area of interest* A_i **do**
      if $(t > F)$ **then**
        if $PIA(\underline{s}_j(t), A_i) = 1$ **then**
          if $A_i(t) \neq A_i(t-1)$ **then**
            if $\sum_{f=1}^{F} PIA(\underline{s}_j(t-f), A_i) \geq 0$ **then**
              save event at $t - \lfloor \frac{F}{2} \rfloor$ to eventlog ; // location has changed
              A_i to $\underline{s}_{a,j}(t)$; // assign measurement
              A_i to $\underline{s}_{a,j}(t-1) \ldots \underline{s}_{a,j}(t - \lfloor \frac{F}{2} \rfloor)$; // update previous ones
            else
              assign previously identified area of interest A_i at $(t-1)$ to $\underline{s}_{a,j}(t)$
          else
            assign previously identified area of interest A_i at $(t-1)$ to $\underline{s}_{a,j}(t)$
        else if $PIA(\underline{s}_j(t), A_i) = 0$ **then**
          assign previously identified area of interest A_i at $(t-1)$ to $\underline{s}_{a,j}(t)$
      else
        if $PIA(\underline{s}_j(t), A_i) = 1$ **then**
          assign area of interest A_i to $\underline{s}_{a,j}(t)$; // initilization
return $\underline{S}_{a,j}(t)$, event log

Algorithm 2: Pseudocode for the allocation of measurements to areas of interests (AOI).

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Classification Problem (CP)

Idea: each measurement is assigned to a process class

- decision variable k_t for each position measurement $s_j(t)$ → process class $V_t \in V$
- two possible error functions: $e_j(t) = \begin{cases} 0 & PIA^\star(t) = k_t \\ 1 & PIA^\star(t) \neq k_t \end{cases}$ or $e_j(t) = 1 - p(t)$
- transistion function $u(k_t, k_{t+1}) = \begin{cases} 0 & \text{no change detected: } k_t = k_{t+1} \\ 1 & \text{change detected: } k_t \neq k_{t+1} \end{cases}$

$$\underset{k_t \in V^\star}{\text{minimize}} \sum_{t=1}^{T} e_j(t)$$

assignment error should be minimized w.r.t.

1st constraint

$$(k_t, k_{t+1}) \in Arc^\star$$

ensures that the sequence of processes is not violated

2nd constraint

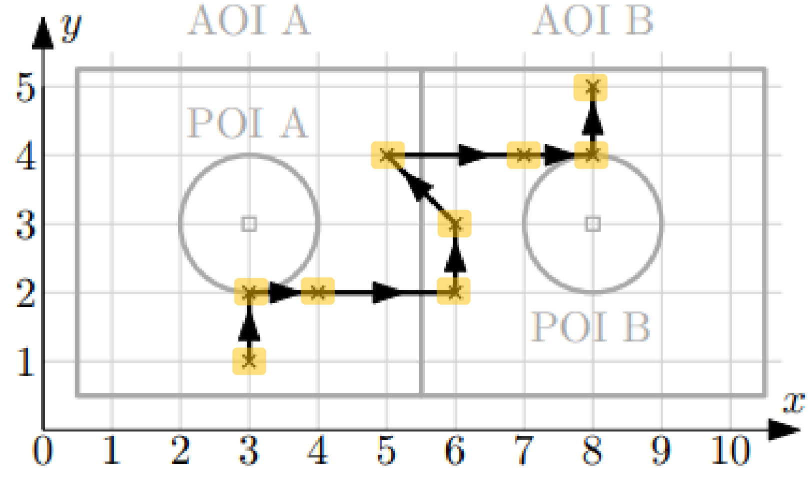
$$\sum_{t=1}^{T-1} u(k_t, k_{t+1}) = 2 \cdot |V^\star| - 1$$

is for the segmentation of trajectories in the number of allowed segments

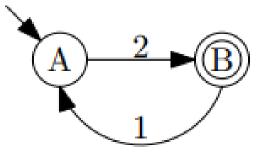
Contribution

Comparison of the Algorithms

Contribution

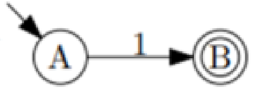


		Algorithm 1				Alg. 2	Classification Problem			
time t	(x,y)	PIA	POI	$R_j(t,P_A)$	$R_j(t,P_B)$	AOI	$\mathrm{CP_I}$	e	p_A or p_B	$\mathrm{CP_{II}}$
1	(3,1)	A	A	0,50	0,19	A	A	0	0,9	A
2	(3,2)	A	A	1,00	0,20	A	A	0	0,95	A
3	(4,2)	A	A	1,37	0,40	A	A	0	0,8	A
4	(6,2)	B	A	1,00	0,63	A $\rightarrow$ B	B	0	0,51	A
5	(6,3)	B	B	0,73	0,80	B	B	0	0,55	A
6	(5,4)	A	A	0,719	0,715	B	B	1	0,7	A
7	(7,4)	B	B	0,58	1,03	B	B	0	0,7	B
8	(8,4)	B	B	0,47	1,46	B	B	0	0,8	B
9	(8,5)	B	B	0,37	2,74	B	B	0	0,9	B



Non cycle-free graph

Cycle-free graph **only** because window size was sufficiently chosen



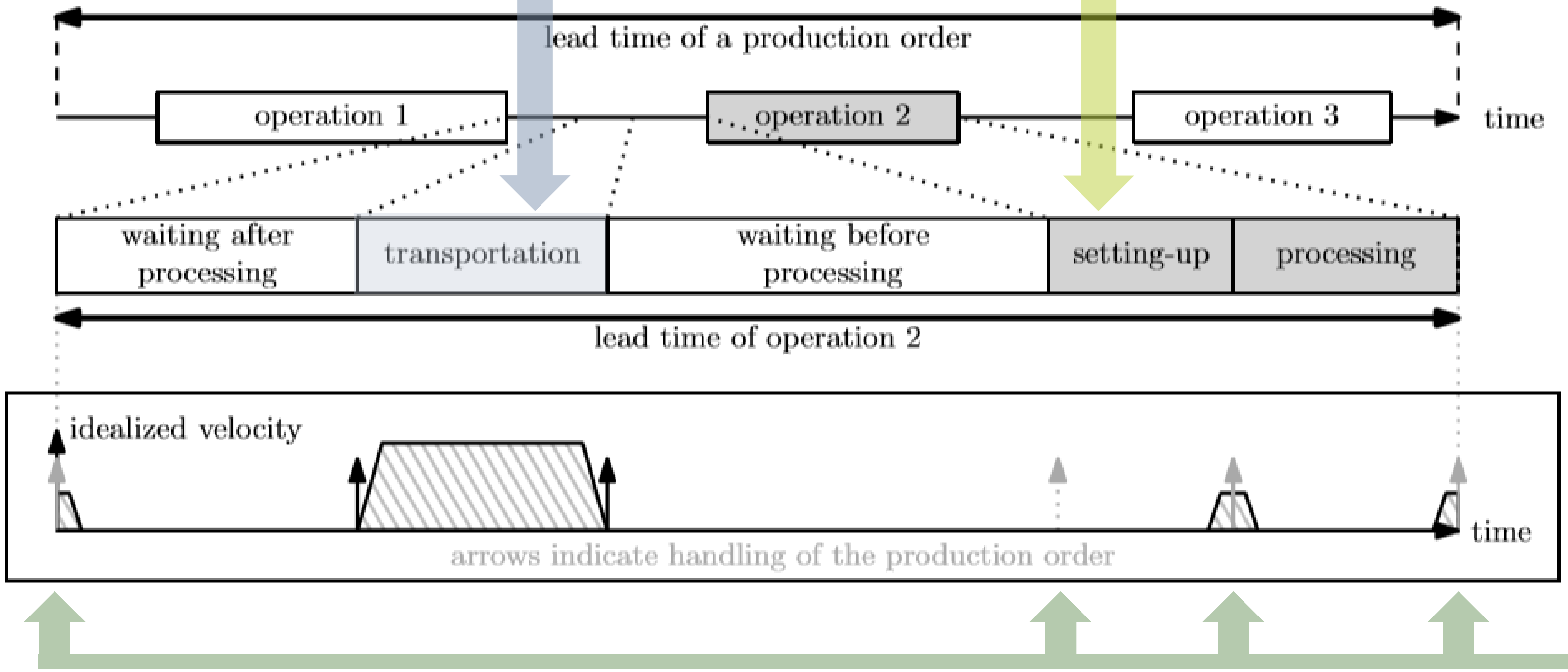
- cycle-free graph is guaranteed by design of the constraints
- can handle adjacency & overlapping
- rework can be identified → number of classes can be adjusted

Sensor Fusion Concept

combining knowledge from different sensor types

With existing approaches it is only possible to detect time shares between events that correspond to a change in location

Sometimes it is also of interest to split these times shares into smaller parts



Handling events can separate the trajectory into suitable segments

(e.g. accelerometer or magnetometer measurements)

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Summary

- introduction of semantic enrichment
- presentation of three approaches for semantic enrichment (online and offline)
- comparison of these algorithms
- presentation of a sensor fusion concept

Future work

use real-world data set for validation of proposed algorithms

derive other simulation inputs from RTILS data

Conclusion

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Conclusion

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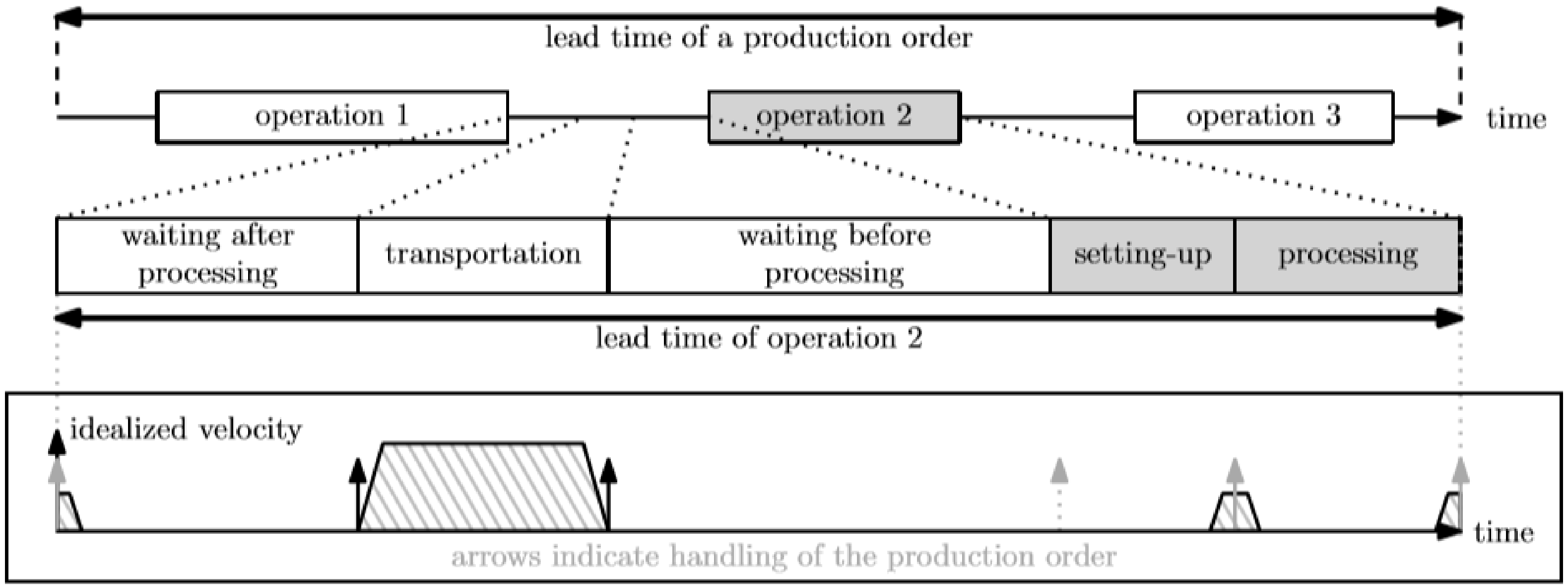
How to calculate lead time distributions from semantic trajectories



event	timestamp
laser cutting	2019-12-09 12:01:00
sorting	2019-12-09 12:10:00
transportation	2019-12-09 12:35:00
deburring	2019-12-09 12:36:30

$$(x, y, t, \mathrm{ID}_{marker}, \mathrm{ID}_{order}, \mathbf{C})$$

Domain ontology

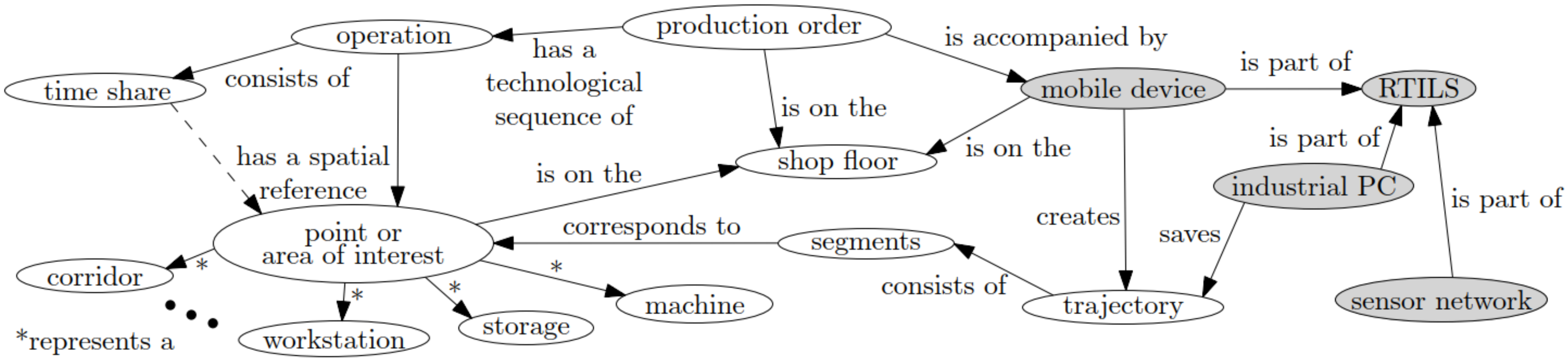


Figure 2: Manufacturing domain ontology for the semantic enrichment of trajectory from RTILS.

Graph of the production process

For a more reliable assignment of the measurements to the points or areas of interest, technological restrictions will be considered in the form of logical operation sequences. All possible operation sequences within the production system are part of a directed graph $G = (V, Arc)$. Each node V_i in the node set V represents an operation that is performed at the point or area of interest P_i or A_i, respectively. The arc set Arc contains all directed arcs (V_a, V_b) that always contain two logically sequentially executable production operations. A path $G_j \in G$ corresponds to a sequence of operations that a production order o_j passes through. Let $G^\star = (V^\star, Arc^\star)$ be an extension of G_j that results by adding edges that join each vertex of the path to itself (loops).

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