DICTION REPORT

WORK PACKAGE F

Real-Time Situational Awareness

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Introduction

Accurate, shared situation picture is essential to make operational decisions. During construction phase, it has been very difficult traditionally to achieve this because the main *data acquisition* methods have been based on manual observations by project participants. These observations have sometimes been manually entered to IT systems (e.g. scheduling applications). The normal way has been to communicate status information socially, in either ad-hoc or recurring meetings where the status is also compared to plans and corrective action is planned. However, the manually obtained status information is partial, asynchronous and subject to biases by humans making observations. Although status information is communicated in meetings, there is no guarantee that every stakeholder in the project is making decisions based on the same situation picture. Recent technological developments could allow at least partially automated, real time situation picture to be generated and shared. (Soibelman, 2018; Zhong, 2015; Golparvar-Fard, 2012)

Situation picture can be understood as integration between theoretical plans and actual progress on site. While the traditional process digitalizes information by human entry based on perceptions, new technology allows automated data acquisition by sensoring and computer vision and comparisons to theoretical plans. Situation picture emerges by comparing plans with reality and alerting decision makers of any deviations. Situation picture has a critical role because all the project stakeholders make decisions based on their knowledge of situation, which then impact the real situation in project environment. Figure 1 shows the theoretical plans (blue), actual situation (green), human-based situation picture (red) and automated situation picture (purple).

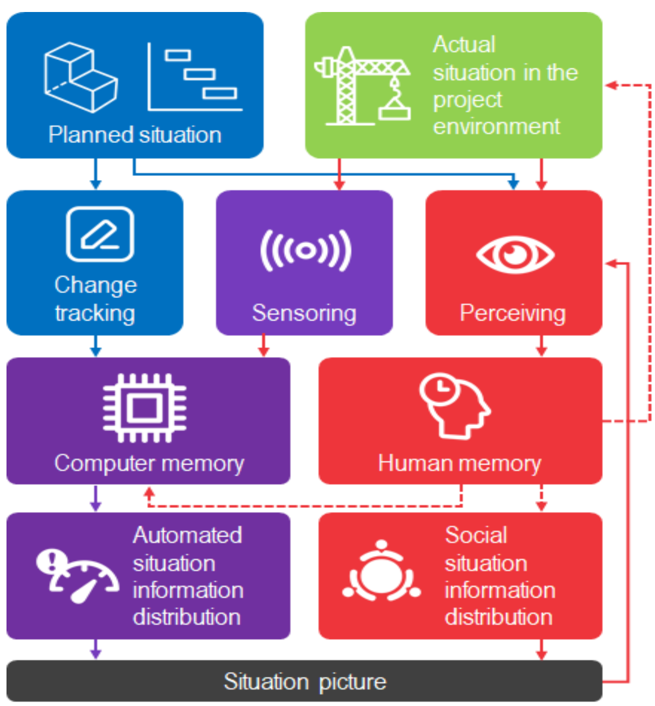

Figure 1. Creating situation picture socially vs. automatically (adapted from Kärkkäinen et al. 2019)

In previous research projects, the research group had investigated the use of indoor positioning (iCONS project, 2019) and computer vision (RECAP project, 2020). It was observed that the use of positioning and computer vision result in large amounts of data which can be helpful in creating situation picture but is not directly relevant for decision makers. On the other hand, computer vision techniques required a lot of training data for each different context and currently available approaches were not considered scalable. Therefore, in this project the challenge was to make situation picture role-specific, relevant and scalable by answering the following research questions:

- How should detailed situation picture be reflected back in plans?
- What kind of KPI's can be calculated based on situational awareness?
- What are the future processes and ways of working when digital situation awareness becomes available?
- What are the ways to use past experiences and situations to improve decision making in current situations?

Progress was made on all fronts. We evaluated indoor positioning results against plans in order to calculate important KPI's relevant for targeting lean interventions. Although computer vision development was not part of the scope, we defined how reality capture could become scalable by fusing multiple data sources. Construction process libraries could allow continuous industry-level learning. Additionally, we explored organizational learning based on situational awareness data and how ontologies could be used to improve situational awareness.

Automatic indoor work progress monitoring system for construction sites, case drywall work progress detection

Overview

We present here a proposal for a system of automatic detection of indoor work progress. The proposed system detects the progress of indoor work based on collected video material and design information. Additionally, it can be modified to automatically detect other visible things such as locations of material storages and equipment. The system can be divided to two parts: The first part does video material conversion to registered sets of video frames and point clouds. Here a critical tool is a Simultaneous Localization and Mapping (SLAM) algorithm. The second part of our proposed system detects progress from localized video frames and point clouds. This part combines a transfer learning approach using pretrained Convolutional Neural Network (CNN) models with successive AI tools allowing us to use it for the cases where standard deep learning algorithms fail due to the limited amount of case-specific training data. The actual implementation and validation of the proposed system will be done in future research.

A scalable system for progress detection is becoming easier and more attractive. Moore's (1965) law is still valid yielding continuously cheaper and more powerful hardware and cloud services. Improvements in deep learning algorithms, especially in deep CNN models for computer vision have given computers close to human capabilities to recognize patterns from images. The quality of open source projects has improved significantly, with projects often packaged in user-friendly formats like Keras and PyTorch for deep learning and OpenCV for computer vision. Many concepts from lean management, like takt production with short takt times, could benefit from easier, faster and automated generation of the situation picture of construction, which is why recent research has started to address this problem. For example, Kropp et al. (2018) developed a system for recognizing the indoor construction state with 4D BIM-registered image sequences and more recently, Braun et al. (2020) presented a method to monitor construction progress by fusing point clouds, semantic data and computer vision. Still, application of state-of-the-art deep learning methods to construction is an emergent field and there is much potential for improvement.

The proposed system uses BIM models and video material that is recorded from the indoors of the construction site. Currently, such recordings are done weekly as part of safety walks in several Finnish construction sites. In future, similar video material could be collected daily by indoor robots carrying the camera. While detecting the current stage of indoor work, the proposed system provides, as an additional result, a set of labelled and positioned as-built images as well as positioned point clouds from the video streams. Thus, the system makes possible to have fast queries of video snippets and images from required locations and times and it can be thought as an enabler for data search methods of all visible indoor elements.

In order to make the proposed system more concrete, we will describe the system in a drywall work progress detection context. The drywall case was selected because it is an important scope in indoor construction in terms of share of project budget. Drywall has clearly visible states, suitable for vision-based analysis. But the states cannot be evaluated by simply comparing captured geometry with design geometry because the design typically shows each wall as a composite element without detailing all the work phases. So, in this case, the pure geometry-based detection is not sufficient. Therefore, our proposal combines both geometry and 2D visual comparison.

Drywall progress status can be classified in these consecutive classes:

- not started
- studs installed
- backboard installed
- in-wall electrical
- drywall closed
- wall plastered
- wall painted

Figure 2 shows example inputs and output of the proposed system. Video inputs, BIM models and schedules are the same for all use cases but the stage examples, as well as the system training must be tailored for each case separately. The top of Figure 2 shows some labelled drywall stage images. Often computer vision algorithms need thousands of labelled example images before satisfactory accuracy can be achieved, but this proposed system will be designed to be able to classify current states with minimal amount of example images. In Figure 2, there is also an example of the output. The contents of the outputs depend on the availability of supporting data sources, like existence of indoor positioning data (e.g., Zhao et al. 2019) or schedules.

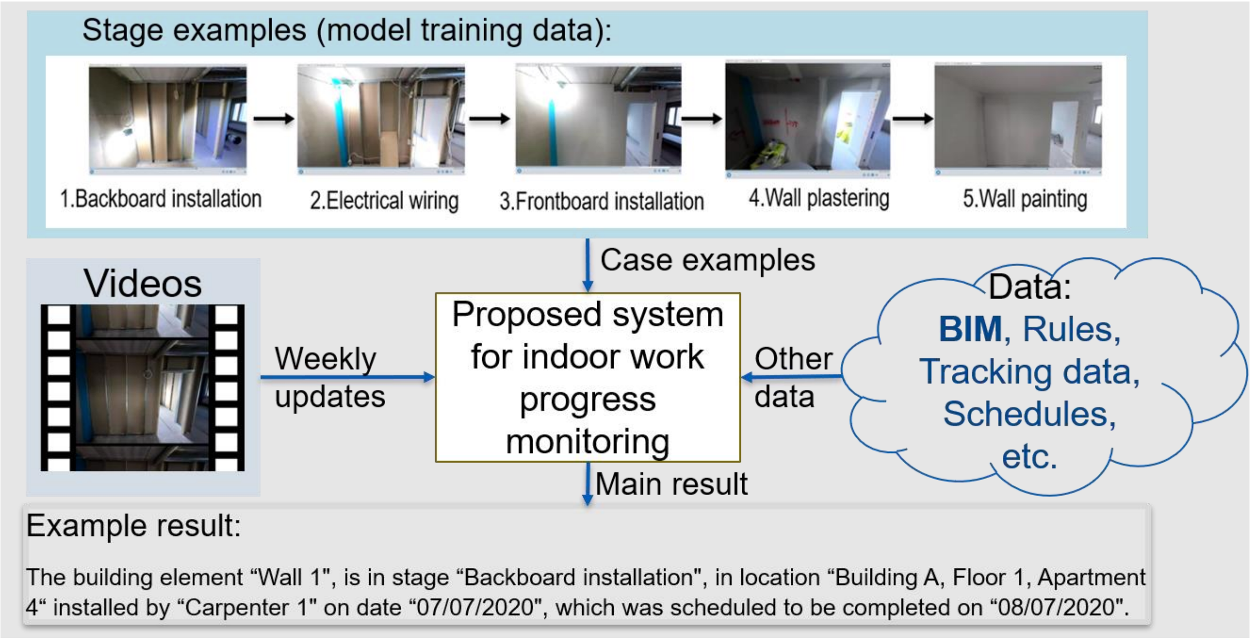

Figure 2. Main inputs and a result of the proposed progress detection system for the drywall case

Input data

The two necessary input data sources for this system are video recordings and the as-designed BIM model. Video recordings can be collected inexpensively and there are commercial services available which provide indoor videos. For our initial experiments we used data from 360 cameras mounted on helmets during weekly safety walk recordings. Videos provide visual material for the detection and BIM model geometrical information of construction site indoor areas as well as locations of the work areas the system is monitoring. Use of both video material and BIM requires some additional info. For example, SLAM algorithms need intrinsic camera parameters, like focal length, that can be sought from manufacturer specifications, or calibration may be done as a separate step in the beginning of the system setup. From BIM model one must specify, to which elements objects, like drywalls, we are focused on, and how those are labeled in the actual BIM data source, for example in an .ifc file.

In order to match the video path and point cloud to designed indoor area, some context data is required to limit the search. For example, a 4D BIM model could be used to filter out all elements which will be installed after the element of interest because they do not exist in the video material. For example, before drywall has been marked as complete, the comparison 3D model should not include floor coverings, fixed furniture floor covering material, or any doors attached to drywalls in question.

Other context data the system may use are Rules, Tracking data and Schedules. For the limited amount of the training examples, the visual analysis may benefit from the availability of some rules, like stage sequence order. For example, in the RECAP project (Seppänen et al., 2020), where bathroom and kitchen work progress were analyzed with computer vision, the use of stage sequence order yielded better classification result than classification without any sequential information (Byvshev et al., 2020). With indoor positioning data of workers, materials or tools, we can detect the active locations where work is most likely progressed. Tracking data and the schedules can be combined with computer vision result and this information can enrich the results as shown in Figures 2 and 3.

COMPUTER VISION

Which Ifc element?	Drywall 1
What stage of work?	Backboard installation

OTHER SENSORS (Ex: Bluetooth beacons)

What Location?	A-F1-ap004
Which worker(s)?	Carpenter 1
Start and End time?	*2020-07-07 T12:00* *2020-07-07 T16:00*

Figure 3: Fusion of computer vision and tracking data enabling productivity calculation by element

Table 1 lists the inputs for the system. Data sources and usages are same for all cases. Data format corresponds mainly to the data types that were collected during Diction project. Data is task specific, if it can be used only for single task progress detection, like for detection of drywall installation work. Of all inputs only video inputs are always updated, schedules are updated often, while BIM models and image labeling less often. If BIM or image labeling is updated, or camera model will be changed, it means practically need of update for the progress detection system.

Table 1. Input data types for the proposed work progress tracking system

Data source	Data usage	Data format (Diction data collection)	Task specific?
Video files, one set per week	Main input for the system, updated regularly, base for object images and point clouds	.360 Go Pro Max videos	Not
(Updated) Schedules (Optional)	Schedules are references for automatic detections (Alerts!). In addition, system might use schedules for searching the areas for time critical analysis.	Schedule files	Not
Tracking data (Optional)	Possibility for effectivity calculations, guidance for time critical analysis and initial labeling.	Time series, not collected in the case project	Not
BIM files	BIM provides general indoor area geometries as well as positions of the areas of interest.	.ifc files	Not
Labeled images / manual labeling or stage corrections	Teaching material for stage classification by images.	2D images and labels in table format	Yes
Rules for classification	Both stage order rules as well as some other rules for the point cloud analysis	Vary by rule type, not all specified yet	Yes

Initial supplementary data	Camera type and its calibration, BIM info of element names, construction order if not available 4D BIM, etc.	Varies	Not (necessary)

System architecture

Figure 4 shows an overview of the proposed system, which has two main parts. The first part of the system uses a SLAM-based algorithm, that generates point clouds and camera path specifications from video recordings. Depending on the selected SLAM method, the adjustment to BIM coordinates may be done inside the SLAM method or as a post processing step. With the accurately positioned camera path and orientation, it is possible to select desired object images from the video stream. The second part of the system uses novel tailored AI model for the detection of work progress of the task. It uses transfer learning approach with a pretrained deep CNN (Convolutional Neural Network) as an initial step to recognize general patterns and construction site objects from the selected images. After object detection, it uses additional neural network models or logical AI models for scene recognition.

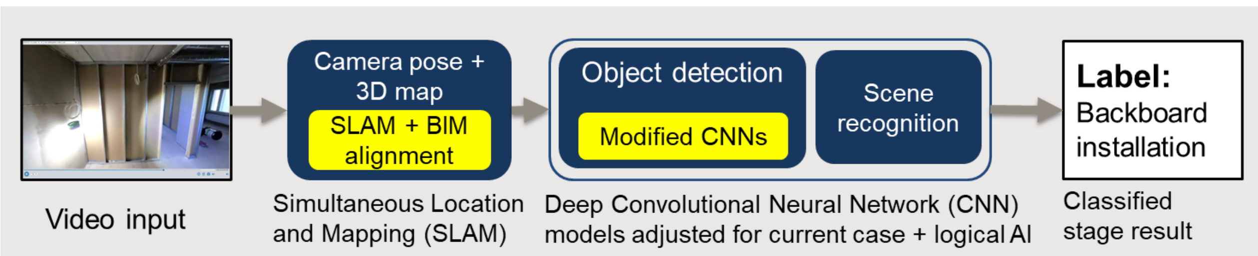

Figure 4: Overview of the stage detection system

For example, in the drywall case, the first part creates point clouds and image frame snippets around every possible drywall position area. Then, in the second part, those will be examined with a combination of deep neural network models and classical AI for classifying all drywall areas to pretrained class types, like: “Stage 1, Backboard installation”.

Overview in figure 4 is simplified and focuses more on the three most important analysis methods: SLAM, CNN and tailored logical AI. The automatized system needs some additional supporting algorithms, and the system provides some interesting intermediate results, like the as-built image library of the observed objects. Figure 5 shows the proposed system architecture in more detail. It shows data boxes in blue color and algorithms in yellow color. We assume that some of the algorithms are currently available, these are marked in solid line, while the others must be made or tailored for this system in the implementation part. Those are marked as yellow dashed line boxes.

Note that the generation of training data, i.e. labeled images, is part of the system. This does not mean that training data should be generated for every new site where system is used, but the costs of training data generation is often one of the main barriers that prevents the use of neural networks for image classification, so the system should support data labeling as well as possible. On the other hand, if the system finds a detection somehow contradictory or uncertain, it may ask confirmation and add this confirmed result automatically to the set of labeled images for further training of the neural network model. The main components of the proposed system are listed in the table 2 and they will be further discussed below.

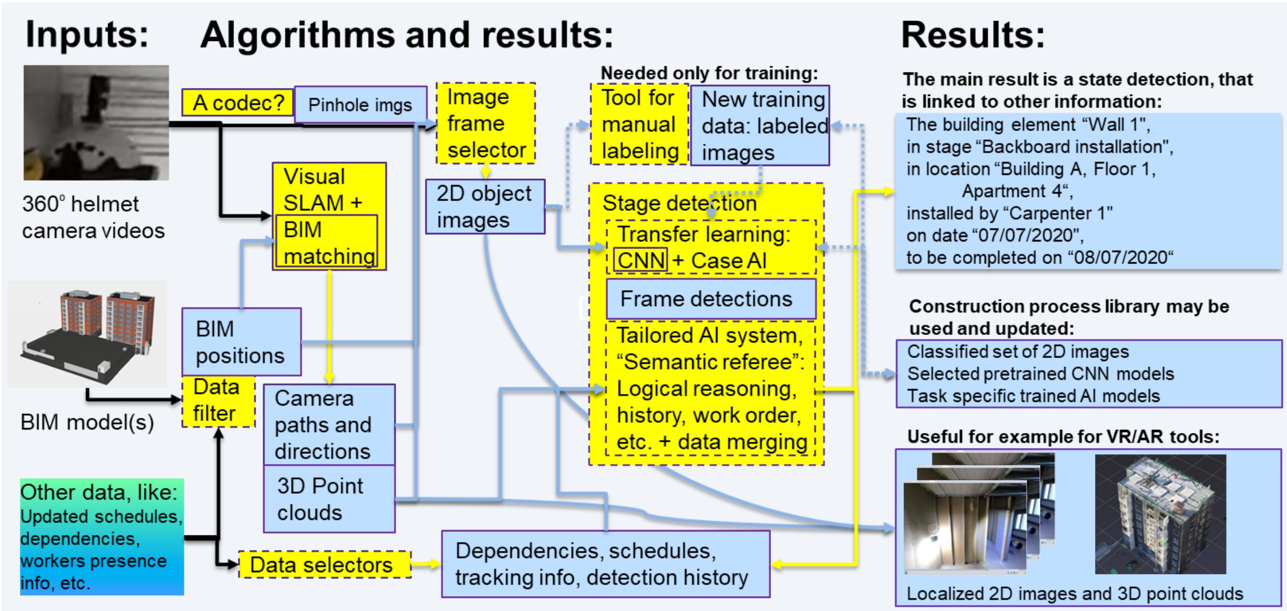

Figure 5: Detailed sketch of the proposed system. Yellow boxes are algorithms and blue boxes are intermediate and final data instances. Solid lines around yellow boxes mean that there are open source algorithms which might work without modifications while dashed line algorithms are methods that most likely need remarkable tailoring for this system.

Table 2. Some components needed for the proposed work progress tracking system

Component	Description	Ready tools available?
Main program	A Python file for running the system	Git project environment
SLAM tool	Infer camera path and area map from video + adjust it to BIM geometry	Several open source SLAMs, some with simultaneous BIM
Image frame selector	Clip "good" images of objects. Use camera pose, object location and visibility info. Take multiple views per video.	Computer vision libraries
Labeling tool	Tool to make labeling as easy as possible	Python image and GUI libraries
Object detections	Initial basic image analysis	Trained CNNs, Python libraries
Scene recognition	Combine analyses and other data, classify current state of an object	
BIM data provider	Opens .ifc file, selects proper data	IfcOpenShell for geometry
Data selectors	Tailored selectors for misc. data types	In future ontology-based tool?
Linker to CPL	Read and write to Construction Process Library (CPL)	

Testing codes	Ensure usability and quality of this project	

BIM and model data providers

Currently, design and other data (BIM model, original schedules, etc.) exists typically in files which will be read in the beginning of the project from the project folders and some analysis tools are needed to convert it usable for the proposed system.

As an initial step, static BIM model is read and analyzed by the system in order to have 3D representation of the building and the positions of the areas of the interest. The model geometry reading can be done, for example, with the open source IFCopenShell library tool or with some commercial tool like Tekla Open API application programming interface.

Because designs have all elements, those that do not exist at the time of video recordings must be filtered according to the installation order. Installation orders can be collected from 4D BIM data, if available. If it is not available, we may use general work order dependencies stored in the Construction Process Library (detailed later). The Digital Construction Ontologies (DICOs) could be used to link workflow information to BIM models to help with filtering.

SLAM method for 360° video streams

The system must be able to use monocular video streams for finding camera positions. One option for this are SLAM (Simultaneous Localization And Mapping) algorithms. Those provide, as an additional result to camera pose detection, a point cloud map around the viewed area. There are several published vision-based open source SLAM projects available and one key thing in this system development is to compare different implementations and to find an appropriate SLAM method for collected video material.

One advantage with open-source algorithms is that they can be modified whenever needed. For example, in practically all our sample recordings the start and end point locations on each floor are close to the stairways, and almost every time the camera path follows a “right turn first” principle. It could be later one research question, how these “rules” should be coded and test if those pieces of information could provide any advantage for SLAM mapping. It is also straightforward to follow a standard path during data collection, especially if robots or rovers are used to collect video data.

Main requirement for the SLAM algorithm is that the poses of all frames should be able to be registered correctly and the resulting point cloud map should be accurate enough for final registration with filtered BIM model. Some SLAM algorithms may map point clouds directly to BIM models thus removing the need of separate final registration and pose correction step. One challenge for BIM based mapping is that some elements that are not included in any BIM model (e.g. temporary elements) and there are elements in BIM models which are not yet installed or visible during construction phase. In the intended use case, no real time mapping is required, so it is possible to select a SLAM algorithm that uses computationally heavier methods for mapping.

Mapping should be done with the data available, in collected case data there are MP4 and 360° GoPro video streams of which intended focus is on the 360° videos. Mapping will be done with either solely according to visual video data or, if camera provides, for example, IMU unit information, these additional information sources can be used for mapping. If robots are not used, direct movement controls or measurements are not available for mapping. In addition, the GPS-signals inside buildings are not available or they are typically too unreliable for mapping. Indoor positioning technologies, such as BLE beacons, have been implemented in construction context but typically they do not necessary result accurate enough data for finding camera positions. There might exist also varying lighting conditions and strong shadows, so mapping should not be sensitive to these aspects.

Stage detection, Transfer learning and Tailored AI

The state-of-the-art in scene recognition uses Deep Learning (DL), a type of machine learning (ML) based on Deep Neural Networks (DNN). For example, architectures such as Convolutional Neural Networks (CNNs) have achieved excellent results in image classification. When combined with Long Short-Term Memory (LSTM) networks for processing sequences of images (so-called CNN-LSTM networks), videos can be classified effectively. However, deep networks are data-greedy, requiring 1000's of images for accurate modeling.

For a specific case, such as detection of construction indoor work progress in a particular project, the amount of training material that can be collected may be limited. This can be addressed by transfer learning, which refers to using previously created models as starting points. Knowledge contained in old models can be imported into new models, or new models can be concatenated on old ones. The system is designed to be modular so that different pretrained models and different modification methods are tested in the implementation phase. There are several trained open source models available, such as VGG-Net (Simonyan, 2014), GoogleLeNet (Szegedy, 2015; Szegedy, 2016) and Resnet (He, 2016) and it is possible, and computationally not so expensive, to use even several models simultaneously.

In addition to single image analysis, we might need several images and other data for a reliable result. For example, in the drywall work progress detection case, walls are in some states open from one side and closed on other side, so it is often impossible to know the actual state from just one image. In such cases, analysis of image sequences may be critical, which can be achieved by CNN-LSTM networks or a tailored combination of pretrained models.

Additionally, further analysis will be required to incorporate a priori information of state sequences, which could help detect logical errors made by machine learning, such as suggesting states out of their planned sequence. We will also have to consider rare cases of disassembly due to rework, in which the planned sequence may in fact be reversed.

Implementation of the proposed indoor state monitoring system

The actual implementation will be done as part of future research. The initial model will be developed using the raw data that was collected in this Diction project and it will be tested and refined with the data collected in upcoming research projects. The first designed test case will be the detection of drywall installations, but the extensive data set collected allows also progress detection of several other interior work processes and the detection of temporary objects like building material storages and tools. The main limiting factor here is the need of training data and the amount of work and computational resources needed for finding a suitable AI model for a particular task. This data only becomes available well into the running of the project and thus a DL model can only be deployed at the tail-end of a project, or even not at all. Additionally, data from past projects may be used as an initial solution, but needs to be organized in a common, open-source and machine-readable database so we can automatically retrieve relevant data for a current project. This is the motivation behind the Construction Process Library, which could enhance the collection of the training data as well as pretrained models for different tasks and makes it easier to develop similar AI systems in the future.

Data Organization with the Construction Process Library

The Construction Process Library (CPL) is envisioned as a database that contains visual data, machine learning models and construction sequencing knowledge to facilitate automatic recognition of construction processes. The aim of the CPL is to enable transfer learning across projects and aid in automatic reasoning of construction progress from images. The CPL will be populated with existing DL models that have shown to perform well in construction contexts. The library will be open to updates from the research community. The CPL eventually aims to capture DL models built specifically for the construction context, spanning diverse construction scenarios. Additionally, robust DL models will be imported from other domains and added to the CPL. For example, the Mask-RCNN has been shown to perform well in object recognition in many domains and was recently successfully used for recognizing construction objects from videos.

Additionally, while DL models have been successful at object recognition, they are not as effective at learning the relationships between recognized objects since they lack high-level context, which is a barrier to scene understanding. This problem can be addressed by incorporating domain knowledge in the reasoning mechanism, which can be used to detect errors obvious to a domain expert but not to the DL model. In this project, the Digital Construction Ontologies (DICOs) developed in Work package A and E (see the DA.1 and DE.1) will be populated with construction sequencing information for drywalls. Then, constraints defining the relationships between objects will be added to characterize each step in the sequence. The ontology will then be linked to the CPL so that a reasoning framework can retrieve the sequencing information. One promising reasoning framework is the Semantic Referee, which supervises the training of a DL model based on a domain ontology.

Task progress monitoring based on a real-time tracking system

Background and motivation

In previous research related to the iCONS research project (Seppänen et al. 2018; Zhao et al. 2019) we developed an indoor positioning system and used it to detect uninterrupted presence on project level. It could be used to determine overall flow on construction projects but was not yet enough to target lean interventions. In this work package, our aim was to extend our results to give task-level guidance and KPI’s that could result in actionable data for production management. In order to accomplish the aim, we first developed heuristics for identifying actual task start and finish times based on resource location and then analyzed the events between the start and finish dates in order to calculate the required new KPI's.

Method (Based on Zhao et al. in review)

We used a Bluetooth low energy (BLE) based tracking system, which has been described in a previous publication (Zhao et al., 2019). A residential apartment renovation project was selected in Helsinki, Finland. The tracking period was from March to June 2018. The BLE beacons were assigned to eight workers who agreed in advance to be monitored by the system. The simplified floor plan with gateways marked is shown in Figure 6. Because there was a lack of power supply on floor 2, we were unable to place a gateway there.

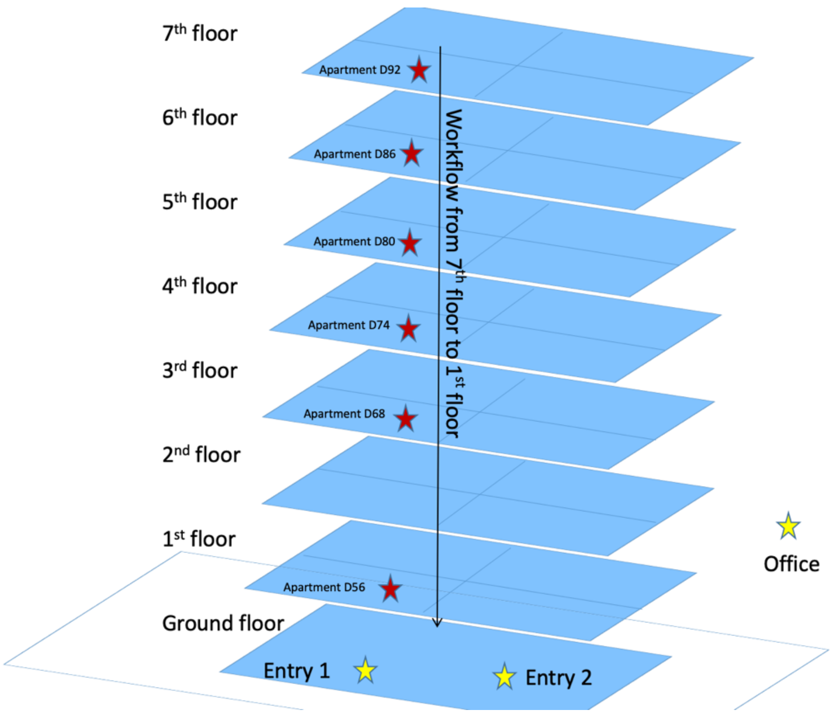

Figure 6: Gateways were placed on vertical line of apartments and at entrances

Overall, there were 12 tasks covering three different trades in 6 work locations. The tasks can be divided into two groups: a bathroom workflow and a kitchen workflow. In the bathroom, the selected tasks had to be completed in the following sequence: masonry of shafts -> preparation of concrete floor pours and pouring -> waterproofing -> tiling -> joints -> suspended ceiling -> caulking of the suspended ceiling -> painting of the suspended ceiling -> furnishing -> finishing. Second, the kitchen workflow is a set of tasks that are not technically dependent on the tasks of the bathroom workflow but have resource dependencies, including shaft drywall and kitchen furnishing. A summary of tracked workers in the selected project is shown in table 3.

Table 3: Tasks, trades and workers assigned to tasks

Tasks (Abbreviations)	Work trade	Workers assigned to the task
Masonry of shafts (MS)	Carpentry	Carpenter 1 Carpenter 2
Preparation of concrete floor pours and pouring (PP)	Carpentry	Carpenter 1
Waterproofing (WP)	Tiling	Tiler 1
Tiling	Tiling	Tiler 1
Joints	Tiling	Tiler 2
Suspended ceiling (SC)	Carpentry	Carpenter 1 Carpenter 3
Caulking of suspended ceiling (CSC)	Painting	Painter 1 Painter 2
Painting of suspended ceiling (PSC)	Painting	Painter 1 Painter 2
Furnishing (Fu)	Carpentry	Carpenter 1
Finishing (Fi)	Carpentry	Carpenter 1
Shaft drywall (SD)	Carpentry	Carpenter 2

Kitchen furnishing (KF)	Carpentry	Carpenter 1 Carpenter 4

Results (Based on Zhao et al. in review)

First, we need to develop the heuristics for automated detection of task start and finish dates based on the raw tracking data from the system. The method to turn the raw data to actual start and finish dates was based on the following steps:

1. For both workflows, the first detected uninterrupted presence on each floor was compared with the scheduled of the task that was closest to that time period. Uninterrupted presence was defined as a continuous presence of the same worker in same work location for at least 10 consecutive minutes without moving to another location (Zhao et al. 2019). This was done in order to find out which was the first task in each workflow on the floor.
2. The next task is to identify when the next task in the workflow starts and the previous finishes. This is done by evaluating the periods of uninterrupted presence.
    - IF the task's successor is done by the same worker: Workflow switches to the next task if there was a significant absence after the last presence of worker had been detected. For the purposes of this study, we put the absence time at four hours which happened to be also the most common scheduled duration of tasks in the project. If we could not find any long absences, task switch was determined based on planned start time and looking at an uninterrupted presence closest to the planned task switch. When determining absence, we did not count the absence time outside the standard construction hours: (1) the workday would start at 7:00 a.m.; (2) the workday would end at 3:30 p.m.; and (3) a lunch break would be between 11:00 a.m. and 11:30 a.m.
    - If the given task's successor was planned for different workers, task switch happened when the first uninterrupted presence of the successor task was detected, regardless of the length of the absence time between the two tasks.
3. The start time of the task is the start of the first detected period of uninterrupted presence after task switch, and the finish time was the end of the last uninterrupted presence of that task until the task switch.

Based on the steps, Table 4 presents the plans and tracking results of the tasks in the sequence of how work was actually performed, from the tasks "masonry of shafts" (top) to "painting of suspended ceilings" (bottom). There is a discrepancy between the tracked and planned start and end times. However, this is expected because in practice, workers do not or cannot follow their plans all the time.

Table 4: Plans and tracking results of tasks

TASKS	LOOK-AHEAD PLAN		TRACKING RESULT	
	Start time	End time	Start time	End time
MASONRY OF SHAFTS	March 20 7:00	March 20 11:00	March 20 12:42	March 20 15:12
PREPARATION OF CONCRETE FLOOR POURS AND POURING	March 21 7:00	March 21 11:00	March 21 7:31	March 21 11:04
WATERPROOFING	March 22 7:00	March 22 11:00	March 22 8:01	March 22 12:05
TILING	March 23 7:00	March 23 11:00	March 23 8:07	March 23 15:55
JOINTS	March 27 7:00	March 27 11:00	March 26 9:31	March 27 14:38
SUSPENDED CEILING	April 03 7:00	April 03 11:00	April 03 7:32	April 03 12:13
CAULKING OF SUSPENDED CEILING	April 04 7:00	April 04 11:00	April 04 7:24	April 04 10:09
PAINTING OF SUSPENDED CEILING	April 05 7:00	April 05 11:00	April 05 7:29	April 05 9:56
SHAFT DRYWALL	March 21 7:00	March 21 11:00	March 21 7:31	March 21 13:11
KITCHEN FURNISHING	March 22 13:30	March 23 8:00	March 22 9:50	March 23 13:06

Next, we visualized the uninterrupted presence of workers in tracked tasks and work locations, in order to get a big picture of worker movements and task progress. Figure 7 illustrates the two workflows of the tracked tasks in one timeline.

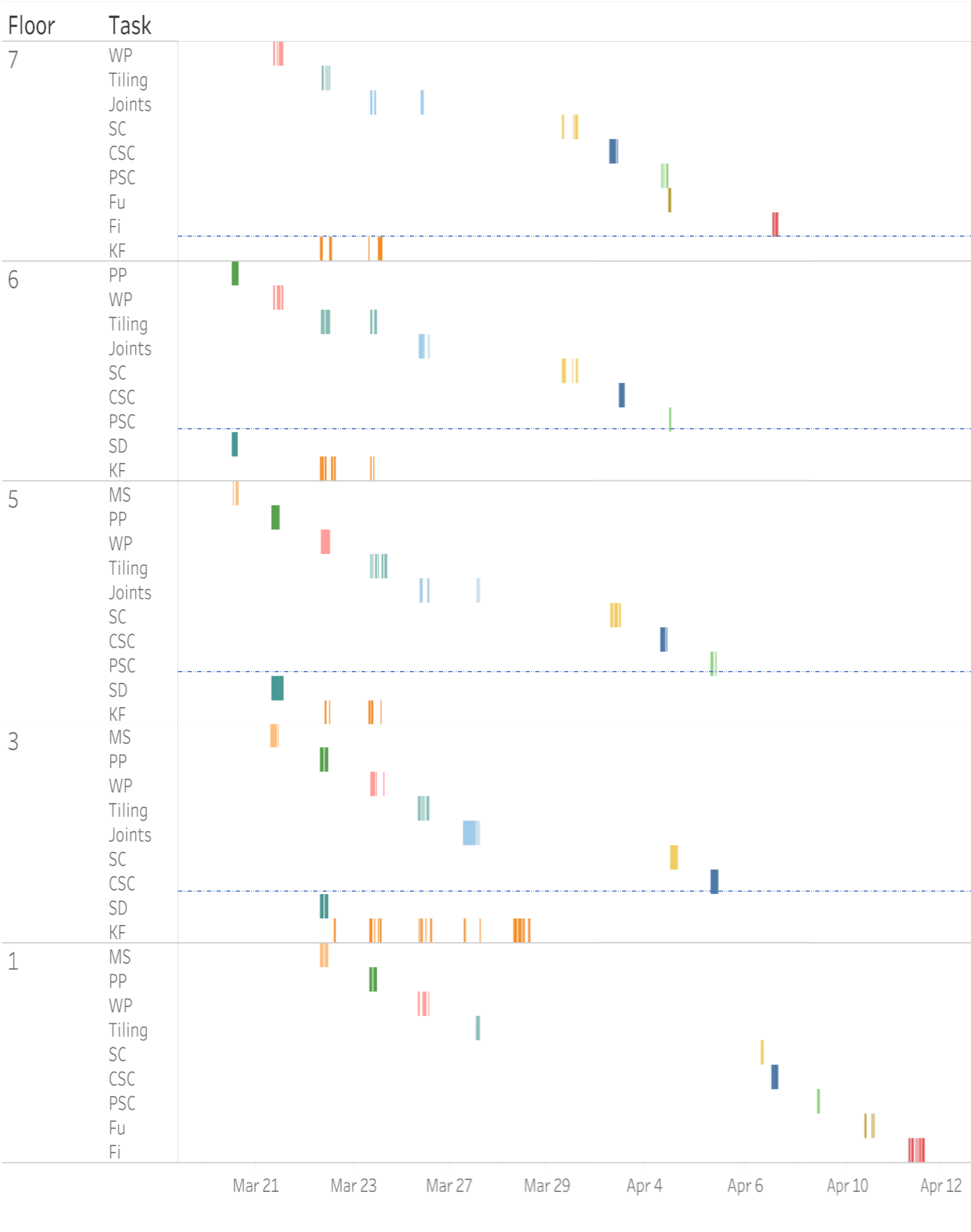

Figure 7: Patterns of uninterrupted presence in work locations and tasks. Tasks below the dotted line on each floor belong to the kitchen workflow

After obtaining the start and end times of tracked tasks, it is possible to analyze worker presence on task level. We first followed the method proposed by Zhao et al. (2019) for calculating the indices for workers' uninterrupted presence for each task. The task-level presence indices (PIs) of the workers were calculated by dividing the total uninterrupted presence in a location between the start and finish times of the task by the actual duration of the task. The actual duration of the task was defined as the duration between the first detected time and the last detected time of the task, excluding breaks and hours outside of standard working hours (evenings, weekends, and holidays).

Equation 1: Task-level presence indices (PIs) $= \frac{\text{uninterrupted presence time during task}}{\text{actual duration of the task}}$

Table 5 shows the task-level PI for each location and the mean and standard deviation across all work locations. During the observation period, tasks were not detected or self-reported in all locations. Locations with missing data have been marked N/A (not available) in the table.

Table 5: Task-level PI for each location and means and standard deviation across work locations

Tasks	floor 7	floor 6	floor 5	floor 3	floor 1	Mean	Standard deviation
Masonry of shafts	N/A	N/A	8% (13/150)	26% (108/424)	28% (125/440)	21%	9%
Preparation of concrete floor pours and pouring	N/A	26% (142/549)	55% (117/213)	54% (114/212)	64% (129/202)	50%	14%
Waterproofing	26% (71/277)	41% (107/262)	39% (94/244)	23% (94/413)	33% (102/306)	34%	7%
Tiling	13% (30/235)	34% (132/389)	31% (143/468)	22% (71/317)	46% (30/65)	29%	11%
Joints	21% (43/208)	15% (41/267)	14% (43/315)	81% (377/463)	N/A	33%	28%
Suspended ceiling	13% (53/411)	8% (32/420)	42% (107/251)	36% (130/356)	49% (102/208)	30%	16%
Caulking of suspended ceiling	25% (53/215)	75% (116/155)	36% (120/330)	69% (287/418)	12% (41/336)	43%	25%
Painting of suspended ceiling	12% (54/456)	64% (51/80)	17% (25/147)	N/A	35% (40/116)	32%	20%
Furnishing	32% (47/150)	N/A	N/A	N/A	14% (31/225)	23%	9%

Finishing	25% (32/129)	N/A	N/A	N/A	31% (134/434)	28%	3%
Shaft drywall	N/A	91% (138/151)	46% (154/340)	59% (114/194)	N/A	65%	19%
Kitchen Furnishing	26% (195/754)	28% (154/542)	22% (106/479)	25% (403/1632)	N/A	25%	2%

By comparing the actual worker presence in a specific work location and the expected level of presence from the construction plans, it is possible to identify opportunities for productivity improvement interventions. Thus, we are introducing another metric to evaluate the conformance between plan and realized work:

Equation 2: Presence-to-plan ratios (PPs) $= \frac{\text{uninterrupted presence time during task}}{\text{planned duration of the task}}$

The PPs show how much presence is required compared with the planned duration to complete the task; therefore, it measures the buffer included in the duration of the task to account for waste and variability. Table 6 shows the results of PPs in comparison with PIs in all tracked tasks.

Table 6: Presence-to-plan ratios and its relation to task presence index

	Task presence indices (PIs)	**Presence-to-plan ratios (PPs)**	**Actual duration / Planned duration (PPs/PIs)**
Masonry of shafts	21%	18%	8%
Preparation of concrete floor pours and pouring	50%	34%	68%
Waterproofing	34%	39%	115%
Tiling	29%	34%	117%
Joints	33%	53%	161%
Suspended ceiling	30%	26%	87%
Caulking of suspended ceiling	43%	33%	77%
Painting of suspended ceiling	32%	10%	31%
Furnishing	23%	11%	48%
Finishing	28%	34%	121%
Shaft drywall	65%	57%	88%
Kitchen furnishing	25%	57%	228%
Average	34.4%	33.8%	98%

The proposed KPIs can be important for several reasons:

1. The KPIs allow for quantitative analysis of task-level uninterrupted presence of workers. The findings indicated that the task-level uninterrupted presence of workers varied to a large extent, task by task and location from location. This variability is a symptom of waste.
2. PIs indicate how much actual uninterrupted presence of workers in work locations was needed to complete a task. Between 43% up to 90% of the time during task execution had no workers in the location.
3. PPs indicate how much buffer is included in task duration. In this case, on average 66% of the task durations could be compressed if there were no interruptions of workflow. Therefore, PP revealed that there is still a massive improvement opportunity for productivity gains and elimination of waste in these tasks.

In summary, the results show that workers' real-time monitoring information allows for detection of task progress status such as start and end times, based on the task-level uninterrupted presence. This enables the possibilities of enhancement for production planning and control in construction. The KPI's could be used to target lean interventions to tasks with high variability of PI and to focus lean interventions to those tasks with lowest PPs (highest in-task buffers).

Combinations with reality capture approaches explored in the previous section will be evaluated in future research. Ultimately, indoor positioning could be used to filter the elements in the BIM model based on uninterrupted presence patterns in locations and tasks in sequence and uninterrupted presence could be allocated to individual elements by using the progress detection system. Multiple sources of information could result in quite accurate picture of what happened and could be instrumental in creating a digital twin of the construction process.

Heat map applications for workspace detection in construction site based on a real-time tracking system

Overview

In this section, we investigated possibilities of applying heat maps for workspace detection in construction sites. Heat maps can contribute to enhancement of situational awareness in construction for example by giving real time alerts of possible workspace congestions and work disturbance. In this research, our aim was to generate heat maps of workers presence based on workers' coordinates and to explore various use cases of workspace heat maps. The indoor positioning system initially developed in iCONS project (Seppänen et al. 2018) was augmented to provide x,y-coordinate-level information.

In this section, we analyze the successful implementation of the system in a project in China. The results suggest that heat maps which use dimensional and temporal positioning data, could be a feasible and convenient way to define workspaces of crews in jobsite and could potentially help in work density calculations of takt planning.

Method (Based on Zhao et al. 2020)

Case description

We conducted a single case study and the location of the case was in a Chinese city near the capital Beijing. We were monitoring MEP workers in a shopping mall project. We installed the BLE-based real-time tracking system on the second floor where the MEP workers were planned to do ductwork installation (Figure 8)

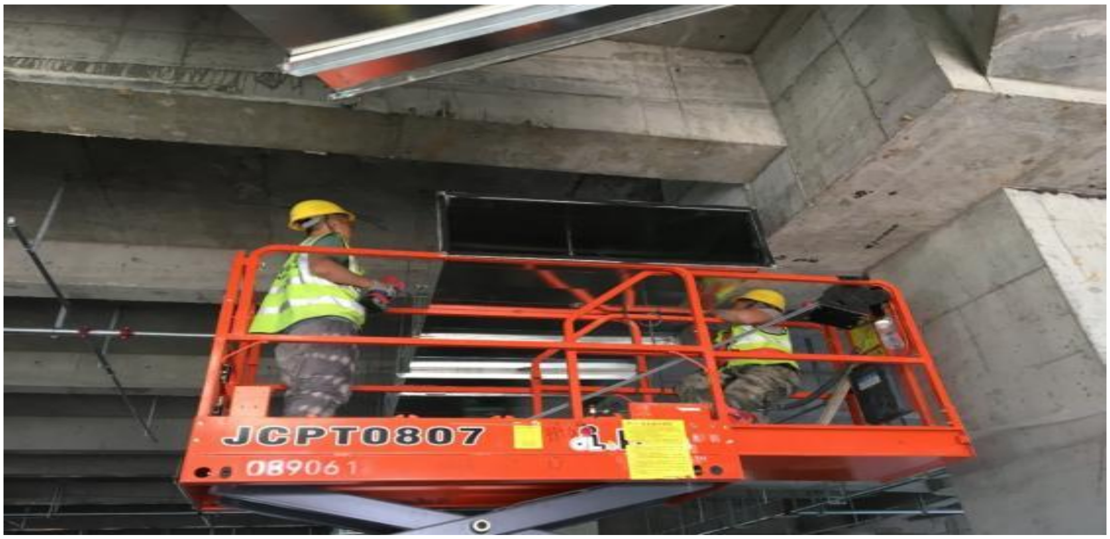

Figure 8: ductwork installation in case project

Our tracking area was the second floor which was an open workspace. The space had a regular grid of load-bearing pillars onsite and each pillar was about nine meters away from each other. We tracked the task of ductwork installation which followed a single direction from west to east in the jobsite. The environment of having a grid of pillars with fixed distance enabled good conditions for indoor positioning with the feature of coordinate detection and generation of heat maps.

Heat map validation

First, we conducted validation of heat map calculation routine to see how accurate of heat map reduction of movement of workers is. We had one researcher simulate a worker’s possible site routine and obtained his coordinates from the system compared with the real location of his movement. The test routine is displayed in figure 9 and the researcher stayed each test point (the red dot) for two minutes before moving to the next test point. A round of validation took about 40 minutes.

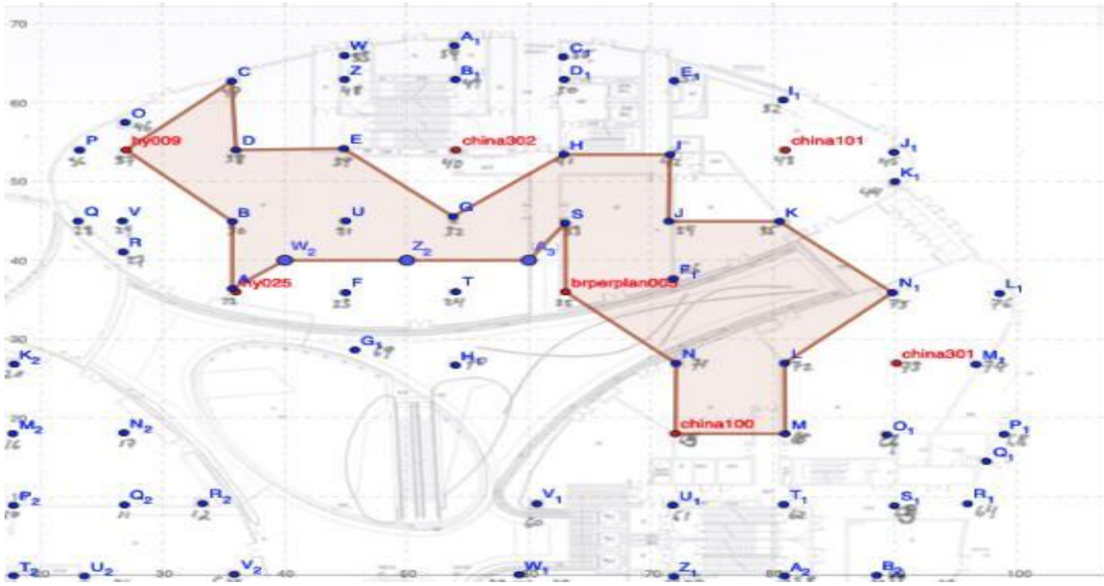

Figure 9: validation route and the position of gateways

The heat map of a researcher's simulated work path was visualized in Figure 10. The movement line (deeper-coloured area) can be displayed by the heatmaps based on the density of system detected points. Although individual coordinates calculated by the system are not very accurate, the heat maps can show general areas of movement in real situations. Therefore, it provides evidence that heat maps can be an efficient approach to define overall workspace during any given time of the day. After the test with researcher data, we then calculated heat maps for mechanical workers.

Figure 10: HEat map of researcher's path

Result (Based on Zhao et al. 2020)

Heat maps enable making conclusions about workers' activities. For instance, figure 11 is a heat-map change figure on May 30, 2019 onsite for MEP worker 16. The figure gives the following information:

- A large amount of presence of this worker was found from 9am to 11am to the east of the site, from 2pm and 4pm in the middle and east side of the site, while no presence was detected between 12pm to 1pm which indicates that the worker had left the site.
- During the time 2pm to 3pm, the highlighted area was indicated as a straight line in the figure, matching the ductwork assembly direction in practice. During the time 3pm to 4pm, the worker seemed to be working in many dispersed locations at the east corner.
- This dynamic change of heat maps with hourly time intervals provides possibilities in real-time to check workers' actual workspace in any given hours. Since the system supports multiple resource tracking at the same time, the image visualization can be used for alerting site managers for potential work congestions.

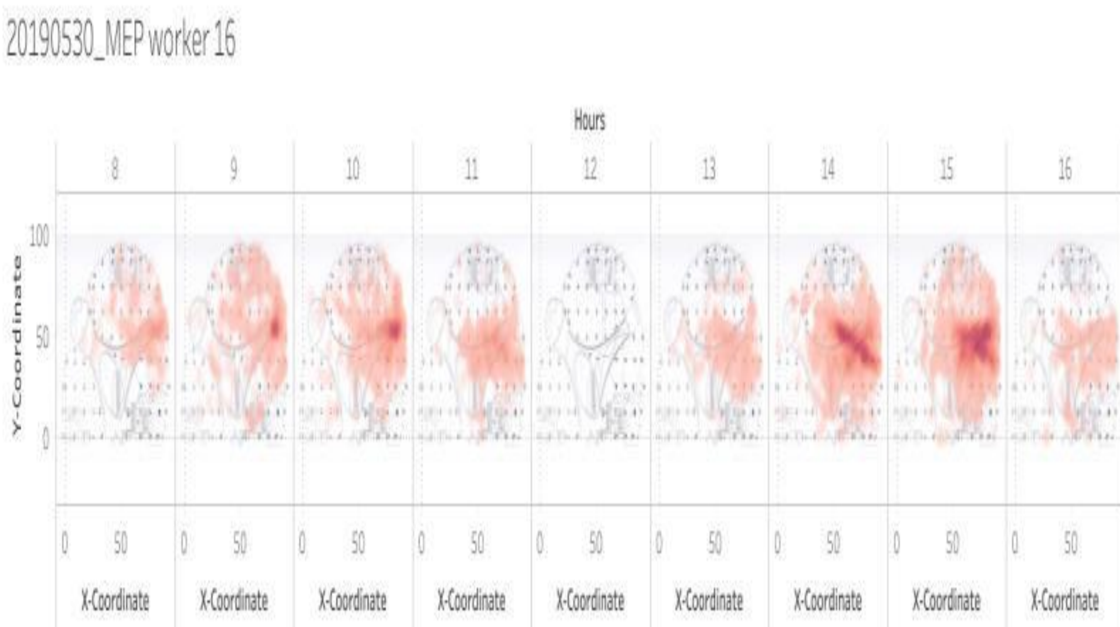

Figure 11: Heatmap of a mechanical worker

Another possible use of heat maps is to compare the actual heat maps to work density calculations related to takt planning (Jabbari et al. 2020; Singh et al. 2020) and evaluate conformance with takt plans. Analysis of heat maps compared to takt plans could enable continuous improvement in takt projects. Alerts could be provided when actual heat maps are different from theoretical plans.

Integration of material and labor tracking based on a linked-data framework

In this section, we used the indoor positioning system to monitor resource flows of material and labor, aiming to introduce new KPIs considering the relationships of material and worker locations, and to establish a linked-data model which can connect tracked data of resources with an automated process.

The real-time resource tracking in construction for production control has focused mainly on labor or materials but few studies have reported results considering both labor and materials. In this work package in the Diction project, we tried to integrate material monitoring into the labor tracking for evaluation of conformance of workers and materials in work locations based on their detected uninterrupted presences. This information can be used to support site managers with quicker identification of workers' presence onsite without access to relevant materials which can indicate waste. This could provide a clearer situation picture related to work where workers are working on tasks requiring specific, tagged materials or tools. To connect all available site resources from a centralized database, a new linked-data framework is proposed amid the identification of conformance levels of workers' and materials' location information. New KPIs are also suggested to enhance situational awareness in construction regarding the integration of labor workflow and material flows.

A description of the case study

A renovation project in Helsinki, Finland was selected as the case study. The renovation work was undertaken in a three-floor building during June 2018. We placed one gateway in each apartment, in total nine gateways. Eight workers including carpenters, plumbers, plasterers and bricklayers were given the beacons and eight material kits which included materials of all trades for an individual apartment were also attached with beacon tags for monitoring. Each of eight material pack was designated for each apartment shown in the simplified floor plan in Figure 12. We wanted to investigate if monitoring the material flows can bring additional value to labor tracking in terms of revealing waste and needs for lean interventions.

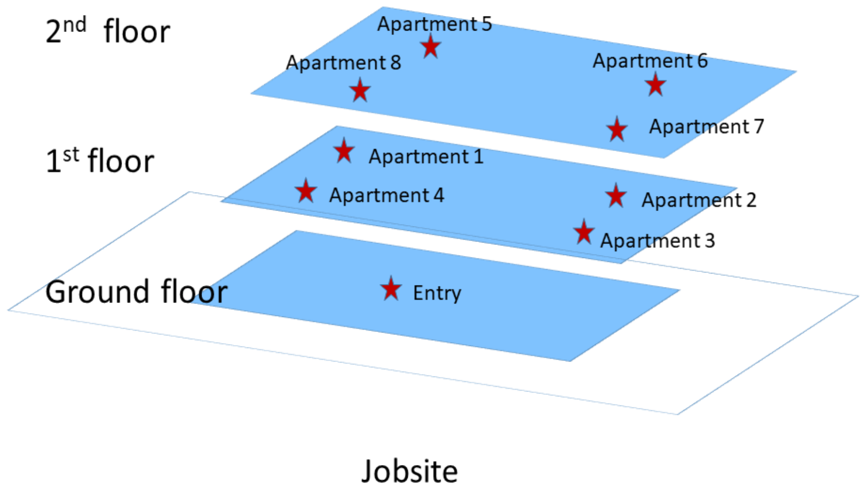

Figure 12: Simplified floorplan with gateways marked with asterisks

Calculation of conformance level of workers and materials

Based on the automatically obtained tracking data including materials' and workers' location information, the following steps were taken to calculate the time-matching level of workers and materials for each apartment. We used uninterrupted presence (Zhao et al. 2019) with threshold time of 10 minutes. All tracked workers were assumed to conduct material-related work in each apartment.

1. We looked for uninterrupted presences of a worker during the same time as the material pack for that assigned apartment was detected present. We aggregated and summed up all found time intervals as time T1.
2. We aggregated all uninterrupted presence of a worker at one work location during the time when the material pack for the designated apartment was undetected but any other material packs were detected present. We summed up all this type of time intervals as T2.
3. We aggregated all uninterrupted presence of a worker at one work location during the time when no material packs were detected present. We summed up all this type of time intervals as T3.
4. The ratio of T1/(T1+T2+T3) denotes the workers time in an apartment with the material pack designated to that apartment. We abbreviated the ratio as TMD.
5. The ratio of (T1+T2)/(T1+T2+T3) denotes the workers time in an apartment with any material package (even if not assigned to that apartment). We abbreviated the ratio as TMA.

6. The ratio of T3/(T1+T2+T3) denotes workers time without an associated material in the apartment. We abbreviated the ratio as NAL.

It should be noted that although the case study was using kits of materials per apartment, the KPI's could also be calculated with general materials although it is impossible to differentiate between T1 and T2 if the materials are not assigned to particular locations.

A linked data-based framework

In order to handle the complex data from the indoor position system to support the calculation and analysis of the KPIs, a linked-based framework was designed to support the automatic identification of the labor and material interaction. The architecture for the linked data framework of the KPI calculation is shown in Figure 13. This framework is intended to be a general framework of implementing the linked data method to manage and process the indoor positioning data to enable KPI calculations. Moreover, the proposed framework is designed to provide an automatic identification of the labor and material KPIs with limited human intervention to support the stakeholders to understand the situation of the on-site operation.

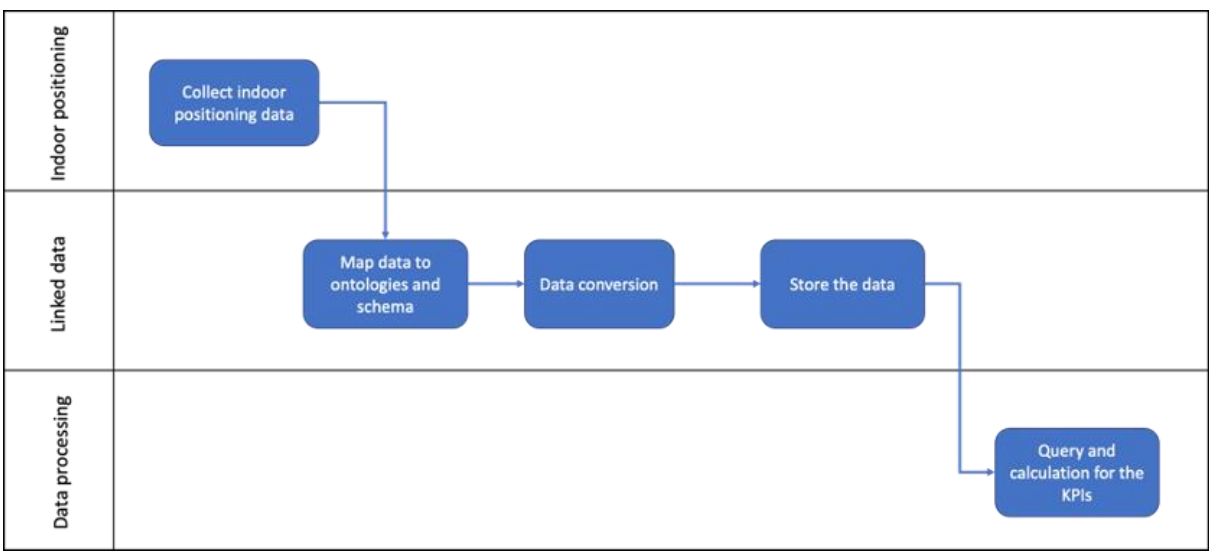

Figure 13 The architecture of the linked data-based framework

There are three tracks designed in this framework:

Indoor positioning: This track obtains the indoor positioning tracking data of the labor and material.

Linked data: The major objective of this track is to prepare, convert and link the data collected from the indoor positioning systems based on the linked data method to create an integrated database that holds the comprehensive indoor positioning data. In this track, first the data of the tracking labor and material collected from the indoor position system are mapping to an ontology for formalizing and creating the interlinks. In this research, the Digital Construction Ontologies (DICOs) developed in Work package A and E (tasks DA.1 and DE.1) is used as the foundation of the linked data. The mapping of the indoor positioning data to the DICOs is shown in Figure 14.

Every record of the indoor positioning system is considered as an Event, which are observed by a Beacon and a Gateway during a time interval when the Gateway capture the signal from the beacon. Both beacons and gateways are considered as sensors that beacons are hosted by worker and material, which are known as the instance of Person and Material Batch classes in DICOs. While the gateways are hosted by apartment, which is considered as a Location. Subsequently, the original data formed as spreadsheet is converted into Resource Description Framework (RDF) graphs. The conversion in this case is achieved by a Python script utilizing RDFlib Python library. After the conversion, the generated RDF graphs are stored in the Graph DB store. Graph DB is one of the most popular RDF stores for storing and managing the for semantic information serialized in RDF format. In the Graph DB environment, users can also conduct SPARQL queries to the process, search and retrieve the information from the database.

Data processing: This track aims to process and query the linked data to 1. identify the worker and material interaction time (T1, T2 and T3) determined in previous part 2. support the calculation of the KPIs based on the principles we define in the previous part. To achieve this, the RDF graphs converted from the indoor positioning data should be stored in the RDF store and then it would be accessible for SPARQL queries. In this case, the generated RDF graphs are stored in the Graph DB store. Graph DB is one of the most popular RDF stores for storing and managing the for semantic information serialized in RDF format. In the Graph DB environment, users can also conduct SPARQL queries to the process, search and retrieve the information from the database.

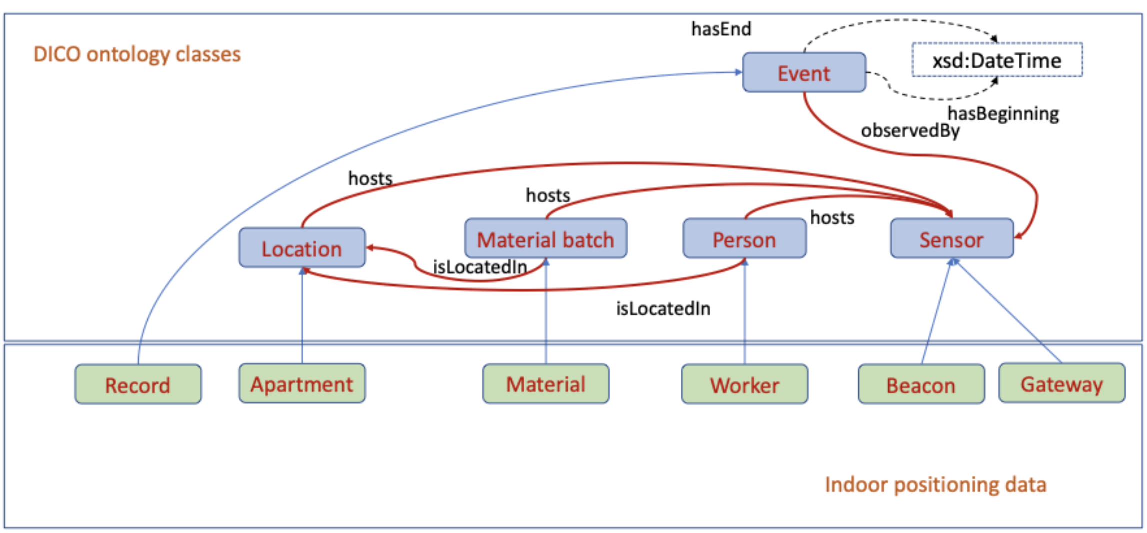

Figure 14 The data mapping with DICOs

The developed linked data framework can formalize and integrate the labor and material data to enhance the data processing and automate the process of calculation. The linked data is achieved by using the DICOs ontologies to map and formalize the indoor position data. This creates an integrated database of the material and labor tracking data with clear data structure and interrelations, which can be used for specific semantic queries for identifying the labor and material interaction time thus support the automated calculation of the KPIs based proposed principles. This framework thus can be further developed in the future to provide a systemic solution for investigating and monitoring the performance of onsite labor and utilization of material to support creating the shared situation picture from labor and material aspect.

Data analysis

First, we calculated and summarized the proposed KPIs grouped by each worker (Table 7).

Table 7. Summary of the conformance level for each individual worker (all number in minutes except percentages)

WORKERS	OPERATIONAL TIME	T1	T2	T3	PRESENCE INDEX	TMD	TMA	NAL
BRICKLAYER 1	10375	1111	381	125	15,6 %	68,7 %	92,3 %	7,7 %
BRICKLAYER 2	9539	1785	82	93	20,5 %	91,1 %	95,2 %	4,8 %
CARPENTER 1	10938	1135	160	209	13,7 %	75,5 %	86,1 %	13,9 %
CARPENTER 2	9391	1107	102	193	14,9 %	78,9 %	86,3 %	13,7 %
PLASTERER 1	5737	937	85	42	18,6 %	88,0 %	96,0 %	4,0 %
PLASTERER 2	6815	1089	98	103	18,9 %	84,4 %	92,0 %	8,0 %
PLUMBER 1	6117	723	34	112	14,2 %	83,2 %	87,1 %	12,9 %
PLUMBER 2	6793	993	75	48	16,4 %	89,0 %	95,7 %	4,3 %
SUM	65705	8879	1018	925	16,5 %	82,0 %	91,5 %	8,5 %
STANDARD DEVIATION	1928	285	101	56	2,3 %	7,1 %	4,0 %	4,0 %

The material based KPI’s bring additional dimension to just looking at the PI presented in previous section. A significant share of uninterrupted presence was spent in apartments with either incorrect material or no material at all. The results could be used to evaluate the level of logistics performance in the project and they also indicate that even during uninterrupted presence there can be waste in the process. It is hard to assume value-adding work, when the worker is in a work location without materials.

Avenues for organizational learning aided by situational awareness

To systematically reap the benefits of acquired situational awareness, organizational learning over single projects is crucial. The provided situational awareness (for example, through real-time indoor monitoring systems) provides an unprecedented opportunity to accelerate the learning processes in construction organizations, which has not been previously possible. In this section, we propose a conceptual framework for organizational learning that exploits the opportunities provided by situational awareness development.

Background

Traditionally, construction organizations have been inefficient learners. Temporarily formed project organizations generate vast amount of situational knowledge within projects, however, after the project ends, most of the information and knowledge is dispersed and lose its usefulness (Almeida 2014). Even though individuals might be able to effectively learn and increase their capabilities and tacit knowledge, learning of teams and organizations is at the moment slow, inefficient and burdensome (Dave & Koskela 2009).

The main reason for the dispersion of knowledge and resulted inefficiency in learning is mostly due to the inability to effectively collect, analyze, store and re-apply the generated information and knowledge in projects. On the contrary, the information merely leaks through anecdotes (Henderson et al. 2013). As very limited amount of information flows from construction production to upstream stages (such as preliminary design and production planning; Carrillo & Chinowsky 2006), construction production often appears as “black box” for the parties that actually plan and form the prequisities for successful production. When the individuals and teams operating with the upstream activities only see a glimpse of what happens inside of the "black box of production", holistically learning from the previous experiences is, indeed challenging.

However, providing an adequate situational awareness and extracting the information through it also to the parties outside of the production, could form a basis for more efficient organizational learning. Obtaining information that is backed up by accurate data and combined with the tacit knowledge of the project participants, could ultimately form an avenue for more efficient learning processes.

Learning process in construction

Carrillo et al. (2013) and Bartsch et al (2013) distinguish three fundamental steps in organizational learning in project based-settings:

1) Data collection & structuring data to information. Data from the project can be collected from so-called personalized sources (such as from interviews, observations and meeting minutes), or from so-called codified sources (such as measurements from indoor tracking, camera tracking, or observing site progress in real-time; strongly related to automated situational awareness) (e.g. Hansen et al. 1999). Preferably, both form of sources are used to allow triangulation. In addition, the data should be structured in a meaningful manner (for example, as adequate visualizations, calculations and metrics such as PP and PI that aid understanding of indoor tracking data) to allow further analysis. For example, in takt production, heatmaps formed from indoor tracking data could be visualized similarly to work density maps, allowing to insightfully compare planned and actual work density.

2) Information analysis, transforming information to knowledge & storing the knowledge. The information is analyzed and reflected upon with an adequate group that has interest and knowledge in solving problems in the mentioned area. These kind of problem-solving groups – called communities of practice – can be formed as project-based or cross-organizational (Wenger 1999). Problem solving should not only focus on tackling immediate issues, but reach to the root causes and aim to produce fundamentally important knowledge for the organization's future practices. Problem-solving should be based on rigorously analyzing the provided information, but also the intuition of the participants should guide the process. The process should provide a solution that is applicable in the organization's setting, and easily utilized in the future for increased performance. The created solution of the analysis should be stored, again in both personalized (in a form of announcements and stories) and codified (in a form of guidelines and structured instructions) manners to the organization. Storing the knowledge should enhance the organizations social capabilities (organization's ability to collectively perform) and technical capabilities (organization's ability to technically perform effectively).

3) Knowledge exploitation in the future projects. For the stored knowledge to be useful for the organization, it should be actively utilized in the future projects. The knowledge should be exploited in multiple stages of the new projects, depending on its use case. In optimal settings, the solutions and their benefits cumulate in the upcoming projects, ultimately reducing the amount and magnitude of future root-cause problems. However, for effectively to happen, adequate resources and change management is needed.

The presented learning process is an example of so-called double-loop learning process (Argyris & Schön 1996), which can be accompanied with so-called single-loop learning. Single-loop learning demonstrates a process where problems are analyzed and swiftly utilized to control the process, enabling fast and efficient production control with in a project. While single-loop learning focuses on solving immediate problems during the production and is necessary for production control, double-loop learning demonstrates a process where root causes of the problems are analyzed thoroughly, and actions that affect the whole way of conducting operations in a deeper level are conducted. In an optimal setting, both single and double loop processes are continuously utilized, enabling learning on different levels. While single-loop learning can be utilized even daily, double-loop learning should be utilized at least between production stages and after every production.

The proposed learning process for organizational learning aided by situational awareness

With the presented possibilities of situational awareness, we propose the following learning process for effective organizational learning in construction projects and organizations. While exploiting the best practices of project-based organizational learning processes, the aim of the model is to most effectively utilize the potential of situational awareness and resulted information flow for learning. More specifically, codified data collection and storage can be enhanced by situational awareness tools and processes.

The model presented in Figure 15 is based on a learning model by Lehtovaara et al. (2019), which was also created as a part of the DiCtion project in early 2018. The model is primarily inspected from project/production management point of view, thus, mainly concerning general contractors, clients and project management consultants.

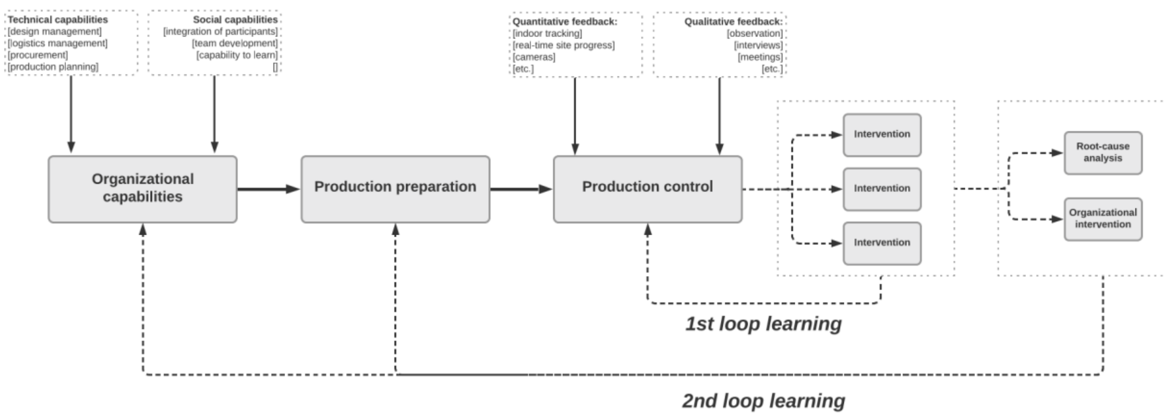

Figure 15: The proposed conceptual learning process

The proposed model consists of three rough steps: 1) Production preparation, 2) Production control and single-loop learning, with 3) After-action review & double-loop learning.

Step 1. Production preparation (Figure 16)

Organization’s ability to prepare and conduct production are roughly formed by technical capabilities (such as competency for design management, logistics management, procurement, production planning) and social capabilities (such as competency for participant integration, team development, and capability to learn). With these capabilities production preparation consists of steps such as conceptual, preliminary and detailed design, procurement, team building and production planning.

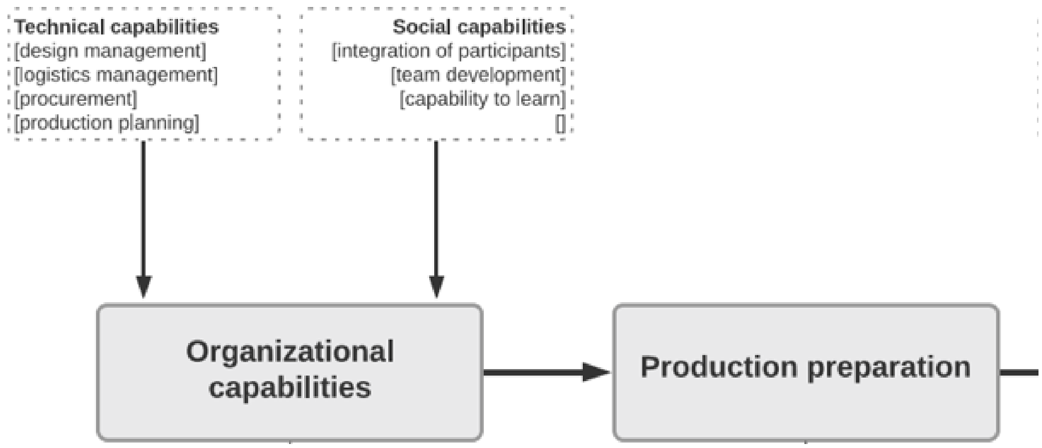

Figure 16: Production preparation

2) Production control & single-loop learning (Figure 17)

While production is controlled by steering daily, weekly and monthly activities, single-loop learning is utilized to more effectively improve production within the project. Single-loop learning is enabled by collecting and analyzing both codified/situational awareness (quantitative; such as indoor tracking, camera observation, observation of real-time site progress) and personalized (qualitative; such as interviews) feedback from the production. The feedback should be structured in a meaningful manner (for example, as adequate visualizations, calculations and metrics) to allow effective further analysis.

The collected feedback is analyzed through specified interventions in project-based communities of practice, in which problems are solved and the solutions are applied in production in swift and agile manner. Interventions can be as small as five minute problem analysis-solution-implementation sessions with site personnel, or larger entities with bigger group, depending of the nature of the solved problem. These interventions form the continuous single-loop learning process within a production.

Interventions could include issues such as

- determining in which tasks presence index (PI) is especially low, and analyzing could improving PI improve production
- developing logistics and task-level planning of work; further analysis of whenever PI was improved

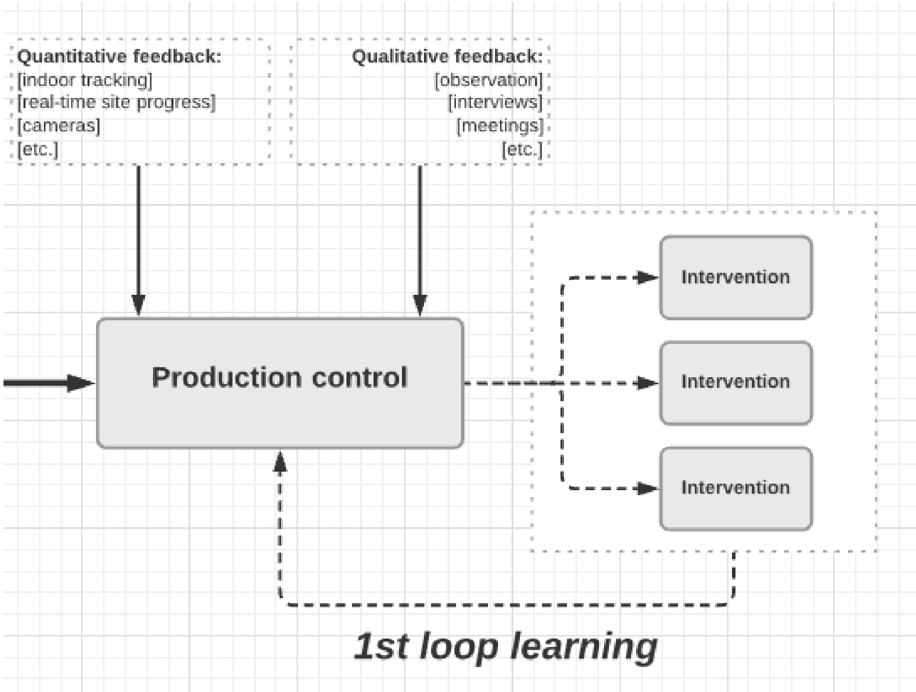

Figure 17: Production control & single-loop learning

Step 3: After-action review & double-loop learning (Figure 18)
Optimally, after-action review is formed at least between every project phase to enable efficient double-loop learning process. Within larges cross-organizational communities of practice, the information gained from production and from single-loop level interventions is analyzed and reflected upon with an adequate group that has interest and knowledge within the given area of expertise. In after-action review, the most prevalent problems and lessons are extracted and further analyzed and reflected through root-cause analysis, providing fundamentally important solutions and knowledge for the organization's future practices. The process should provide a solution that is applicable in the organization's setting, and easily utilized in the future for increased performance. As an example, in a production setting where takt production is utilized, learning from worker movement heatmaps could aid learning on how work density estimations could be improved in the forthcoming projects.

The created solution of the analysis should be stored, again in both personalized (in a form of announcements and stories) and codified (in a form of guidelines and structured instructions) manners to the organization. Storing the knowledge should enhance the organizations social capabilities (organization's ability to collectively perform) and technical capabilities (organization's ability to technically perform effectively), forming an organizational-level intervention(s), and further, to organizational learning as the practices are utilized in the following projects. In an optimal settings, the solutions and their benefits cumulate in the upcoming projects, ultimately reducing the amount and magnitude of future root-cause problems. However, for effectively to happen, adequate resources and change management is needed.

After-action reviews could include issues such as

- was low PI / PP due to project or organizational level issue?
- how root causes of low PI/PP are eliminated by improving technical and/or social capabilities?

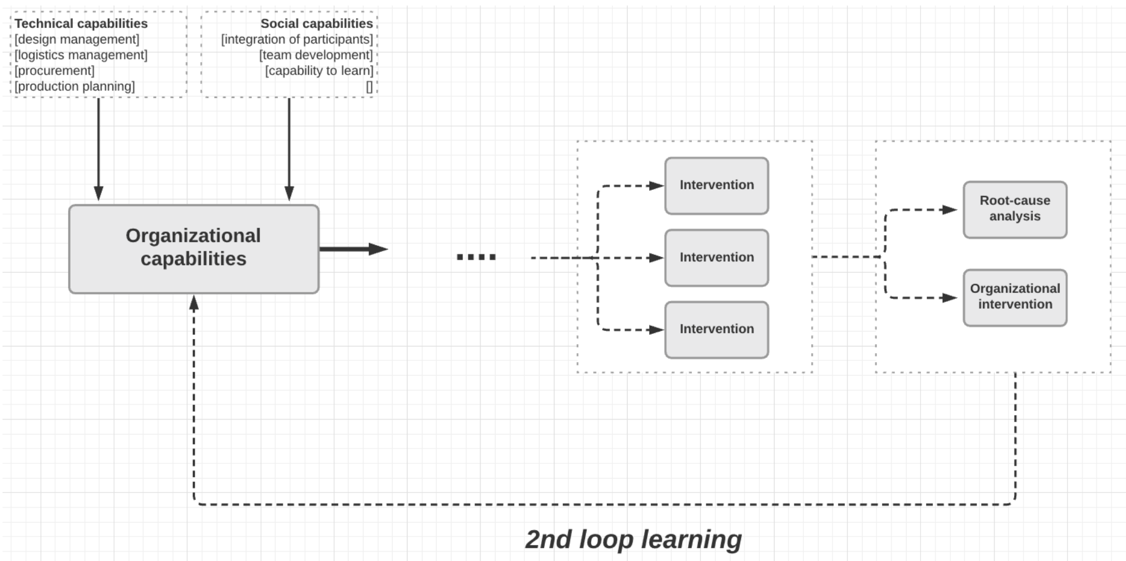

Figure 18: After-action review & double-loop learning

Further development

The model has been developed and validated in DiCtion with one intervention and one validation workshop. However, in the intervention mainly personalized knowledge was utilized. To further develop the model to utilize situational awareness most effectively, further validation is needed.

Conclusions

In this work package, our goal was to investigate how Reality Capture technologies and positioning could be used together to come up with relevant KPI's for production management.

We ended up proposing a scalable way to implement automated progress monitoring based on 360 videos. The unique part of that proposal was augmenting traditionally used approaches with rich context data from other data sources, such as indoor positioning and task relationships using an ontology. Rather than training the models separately for each project, it should be feasible to implement Construction Process Libraries which codify standard dependencies and include collections of images of elements in various stages of progress. Combined with indoor positioning approaches, it is feasible to get element-level productivity. Combined with construction ontology, it is possible to get an element-level library of images which could have huge potential in AR applications.

We extended our previous work related to indoor positioning, particularly focusing on KPI's on task level. It turned out to be feasible to estimate start and finish dates of tasks based on evaluating the uninterrupted presence of assigned workers. This could be very powerful when combined with machine vision approaches. Task-level Presence indices and Presence-to-plan indices can be used to identify tasks with greatest potential for productivity improvements and schedule compression. Heat maps based on positioning could be used to learn about the actual behavior of production systems. Additional information can be integrated related to material logistics and the combination of labor and material tracking can provide even more granularity to the proposed KPI's. Finally, we proposed a process how this situational awareness data could be used in organizational learning using a double-loop learning process.

In future research, we will implement the proposed automated progress monitoring system and collect data from case studies where we can augment the progress monitoring with indoor positioning data. We will calculate task-level KPI's and conduct action research trying to help management to achieve better outcomes using the proposed KPI's.

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