An On-body Sensor-based Visual Management Tool for Work Task Progress Monitoring

Emil L. Jacobsen[1], Jochen Teizer[2], Søren Wandahl[1]
[1]Department of Civil and Architectural Engineering, Aarhus University, Denmark
[2]Department of Civil and Mechanical Engineering, Technical University Denmark, Denmark
elj@cae.au.dk

Abstract. This study proposes a visual management tool to communicate progress of construction projects. The method utilizes state-of-the-art kinematic classification algorithms to infer the type of work from on-body inertial measurement units. The work type is combined with location data collected through a local positioning system and is imported to a shared environment in which the 3D model is used as the basis for conveying the information. The tool constructs spatial artifacts representing workspaces to append information to the relevant 3D objects. The spatial artifacts are created through the intersection of wall buffering and a Dirichlet tessellation created from the line segments representing the walls of the 3D model. The proposed framework enables a more simplistic and transparent understanding of the current state. This research further contributes by defining a spatial artifacts *workspace* which is used to ensure points are appended correctly.

1. Introduction

This paper presents a framework for monitoring construction labor productivity (CLP) in a spatiotemporal manner. The framework utilizes machine learning models to estimate the current and future states of the production system. It furthermore uses location data of workers to append the work to elements in the model. CLP has, over the past decades, fallen behind other industries. Collecting data for measuring productivity and progress on-site is time-consuming and often requires extensive post-processing to estimate its state (Jacobsen et al., 2023a). Furthermore, in the industry, the result is often given in day curves or solely by a single number when looking at productivity. This information is usually only available for the project as a whole. Therefore, the level of detail is inadequate to optimize on-site labor productivity, as limited valuable information can be extracted by a dataset representing the construction project at the highest level. CLP is an important metric when monitoring construction projects, as labor accounts for up to 40% of the total projects' budgets (Kazaz et al., 2008). CLP and Progress monitoring is a spatiotemporal problem in the sense that information must be collected over time and with spatial granularity. Having a high level of spatial detail gives valuable information about troublesome areas of the construction project and could lead to actionable knowledge regarding the layout or scheduling of the construction project.

Visual management (VM) is a way of presenting information visually that simplifies the communication of data often used in lean construction. Concepts such as "Obeya" (Big room in English) and 5S are well-established VM concepts, which allows for a simple and fast overview of potentially very complex data. The VM tools range from very simple concepts, such as putting posters on the construction site with the sequence of the takt-train to more elaborate concepts such as establishing an Obeya. Managing a construction project, can today suffer under information overload as multiple streams of complex data are given as the basis for decision-making. The inputs expected to be a foundation for decisions can be messy and in several different modalities. The current VM tools on construction projects are often manually updated and mainly focus on giving insights into the planned project. Therefore, the questions can be asked: (1) how can autonomous monitoring systems improve visual management methods? Furthermore, (2) how can progress be efficiently conveyed through model environments? To answer these questions, several objectives are defined: to (a) create spatial reasoning of when work belongs to an element, (b) create an open-source framework for visualizing work in a 3D environment utilizing kinematic-based algorithms to estimate work, and (c) establish a simple and transparent way of conveying work information.

2. Related works

Monitoring of productivity and progress has been extensively studied. Several paths have been investigated (Jacobsen and Teizer, 2022), from manual data collection (Wandahl et al., 2021) to vision-based autonomous systems (Wang et al., 2021). The data output can be overwhelming for managers on large construction projects, even with autonomous processes. The use of visual inputs such as dashboards when managing construction projects has seen an increased interest both in research and practice (Tezel et al., 2016). This section will introduce the related works to the processes and methods used in this study. Starting with why and how visual representations of data have been used to manage complex systems effectively and, after that, how to connect sensor information to the virtual model through different methods.

Visual management

Conveying the state of a construction project can be difficult, but the information is essential as current progress give critical information needed for managing the project. VM is an essential tool within lean construction (Koskela et al., 2018) and has been shown to lead to an increase in productivity (Lerche et al., 2020). Classical VM tools range from signs and labels on the construction site (Tezel et al., 2011) to dedicated kanban systems in the offices. VM has previously been defined through nine functions (Tezel et al., 2016). Among them are both transparency and simplification, which for a digital tool, are critical aspects for adoption in a construction setting.

Several initiatives have been done to create VM tools, but most focus on tools in which stakeholders are to create the data or information that are put into the VM tools through manual activities (Conte et al., 2022; Lerche et al., 2021; Grönvall et al., 2021; Pedo et al., 2020). Not only do the tools require manual efforts for the analysis or information gathering, but they often also require manual efforts in the visualization parts, through printing cards, for instance (Tezel et al., 2011). As more and more processes give access to data streams, automatically creating visuals based on these is seen as a natural next step in managing construction projects through lean principles.

Model enrichment

A relation to the model needs to be established to infer progress from sensor information. This connection between reality (and its sensor data) and the virtual model has previously been established for vision-based systems (Golparvar-Fard et al., 2009). In the work of Golparvar-Fard et al. (2009), the model is superimposed onto images of the construction project to infer progress by comparing the as-planned model (4D) to the as-built taken from the 3D representation created through progress photographs. By superimposing the two using geo-registered images, the proposed framework can detect whether or not an element from the as-planned exists in the as-built, thereby inferring progress. However, this method is only viable due to the input-data being images. To infer progress from sensor data, such as from inertial measurement units, work needs to be related to an element in the model in a different way through shared spatial information. Furthermore, the use of vision-based technologies has several limitations, such as occlusions and being difficult to use for indoor activities, as this requires cameras covering every room of a project, potentially leading to hundreds of cameras.

For reasoning based on model geometric information, spatial artifacts have been used in construction for purposes other than progress monitoring. Bhatt et al. (2009) present four spatial categories (object space, operational space, functional space, and range space). Understanding these spatial categories makes it possible to automatically find design issues, for instance, the intersection of an object space and an operational space. Furthermore, Johansen et al. (2023) propose a hazard ontology using spatial artifacts to define fall-hazard spaces (an intersection between a walkable space and a fall space) for safety requirement analysis. This gives valuable information to the area of the spatial artifact, in this example, where the safety requirements are not fulfilled in the model. The idea of using spatial artifacts as a method to reason about the spatial information in the model could be translated to the area of productivity and progress, here defining workspaces rather than hazard spaces.

To summarize, VM systems are mostly physical visualizations on posters or whiteboards. This hinders the accessibility of the information when not in, for instance, the Obeya. Model enrichment can be a tool to improve the VM tools by allowing access through model viewers. This would enable everyone with a smart device to access the information from the VM system.

3. Methodology

This work relies on past work in which a classification model has been developed using inertial measurement units (IMUs) as the input (Jacobsen et al., 2023a). IMUs are kinematic sensors which give angular velocity and acceleration in a 3D space. The overall process is depicted in Figure 1.

The algorithms in this work are set up to be an input to the proposed monitoring system alongside a location module that collects the workers' location on the construction project as well as the model of the project given in an IFC format. The algorithms are essential to the overall process, as they enable seamless high-frequency data collection. The algorithms developed for the input will not be explained in detail in this work, and the reader is therefore referred to the original implementations by Jacobsen et al. (2023a).

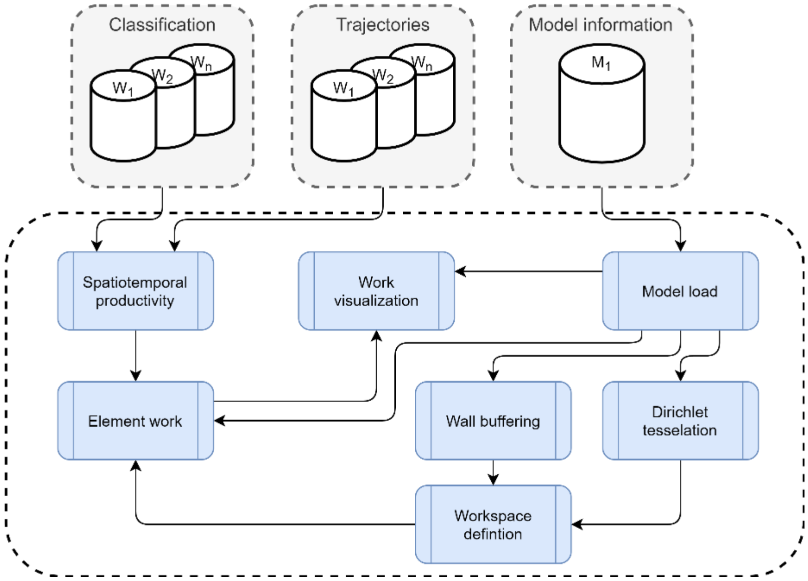

Figure 1: Flowchart for the backend module of the proposed solution

Inputs

Three inputs are needed for the analysis. The first (classification) is taken directly from the algorithm described in earlier works (Jacobsen et al., 2023a). The algorithm gives an output every 3.5 seconds. The trajectories are for this implementation collected through a local positioning system which is part of the IMUs developed by XSENS and gives location with a frequency of 60Hz. The location data is down-sampled to the frequency of the classification algorithm to be able to pair them 1:1. The IMUs have a limited range, and the positioning system is therefore limited to work in a 30m proximity to the receiver. However, the VM tool developed is not limited to this one type of location sensor, so the limitations of the chosen sensor can be mitigated by using more robust location systems, which have already seen successful implementations in construction research (Teizer et al., 2022; Cheng et al., 2013). However, the data format is locked. This means that if the data is collected through GPS and therefore formatted according to NMEA, a translation of the latitude and longitude is needed. The fourth and final input to the backend framework is the 3D model in an IFC format. For the implementation presented in the following case study, the IFC 4 schema is used.

The frontend has four interactions available. Two of them are used to upload the required data. *Upload model* allows uploading and visualizing the IFC model in the browser-based framework. This process uses a JavaScript library built on top of Three.js named IFC.js. This JavaScript framework is chosen because it is open-source and requires no license. This is an important feature, as it will enable everyone on the construction project to access the information regardless of their affiliation. The model is added to the scene, and the schema is saved in an object for further analysis. *Upload activities* takes a .csv file consisting of a combination of trajectories and classification. This combination is done by synchronizing the two datasets explained earlier. The synchronization is done by down-sampling the trajectory dataset to give a mean value of the 3.5 seconds between the classification points. An investigation could be done in which the reverse process was used by up-sampling the classification by appending the same classification to all trajectory points in the 3.5 seconds window. For this study, the first option is chosen, as this will create the least number of points and is, therefore, more simplistic in the visualization. As the intent is a VM tool, simplicity is one of the most critical metrics. This gives a .csv file where every line is a spatial point (x,y,z) where one of three classes (direct work, indirect work, or waste) is appended. When uploading the file, the information is stored for further analysis, and the trajectories can be visualized as spheres color-coded as either red (waste), green (direct work), or blue (indirect work).

Workspace definition

A spatial understanding of the workers' activities must be established to append work to elements in the IFC model. This is done by creating areas of the spatial scene, which are defined as workspaces. When a point from the activities file is within a workspace, the algorithm will append that activity to the wall to which the given workspace belongs. For each wall element in the IFC model, a spatial artifact is created using the model's geometry. Two parallel geometric processes are done, and the intersections of these are defined as workspaces, at least one for each element in the model. The two approaches and their combination are shown in Figure 2.

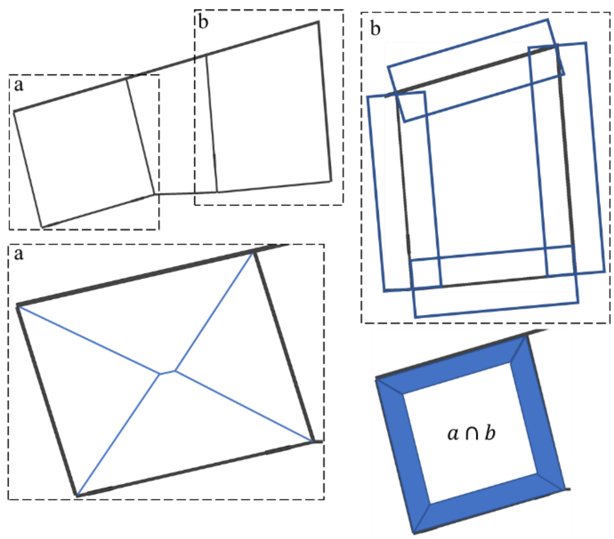

Figure 2: The process of creating the workspaces from a plan view. (a) shows the polygons created using the Dirichlet tessellation, and (b) shows the buffering of the line segments representing walls. Taking the intersection between (a) and (b) for each room gives the workspace, as shown in the bottom left. The intersection will for the rooms presented in this figure lead to four workspaces in each room.

The basis of both processes is a line segment calculated for each IFC element using the location, the direction ratios, and the element length. The Dirichlet tessellation is used for the first of the two processes, as it is an efficient distance-based method. It is used to create subdivisions of surfaces representing areas of influence. The Dirichlet tessellation can be described by a set of points, P, on a Euclidean plane. For each point, P_k, a cell is created consisting of all elements on the plane whose distance to P_k is less than any other points of P. The Dirichlet tessellation can be seen in Figure 2(a). The reason not to use the Dirichlet tessellation as the workspace definition is that all points on the plane will be part of a cell. This becomes problematic as trajectories far from any element will also be appended to one of the elements. A logical constraint is that if the trajectory is further away from any element than a threshold distance, no progress can be made on any element, regardless of the classification of that trajectory point. If the points are still classified as direct work, it is likely a misclassification. This means that a logical constraint regarding the distance of the element will be an algorithmic feedback loop to the classification algorithm to find misclassifications and ensure that direct work far from any element is not appended as work. To create this logical constraint, buffering of the line segments representing the IFC walls is done, as seen in Figure 2(b). The buffering is done using the normal vector of the line segment and a threshold distance of 2.5 meters. When the two spaces are computed, the intersection is found through the Sutherland-Hodgman algorithm, which defines the workspace.

Element work and visualization

For all workspaces, a connection needs to be established to an element. By using the element IDs from IFC.js, a relationship between workspaces and IFC elements is established by making each workspace a child of a wall element in the IFC file. An IFC element can have more than one workspace as a child, as the interior walls usually have a workspace on both sides. All points from the trajectory located within a workspace are accumulated and appended to the information of the wall. These accumulated metrics are visually displayed by coloring the wall element based on the distribution between direct work, indirect work, and waste. The color scheme for the walls is a simple RGB scheme, where the value for red is directly calculated based on the waste class of the distribution, green is calculated from direct work, and blue from indirect work. The distribution by itself is not always an ideal way to visualize the information, as 1 point in the workspace would mean 100% of one of the three categories. To ensure an understanding of the number of points appended to the wall, the transparency of the coloring is defined by the number of points, where the maximum number of points for any wall will be 0% transparent, and 0 points will be 100% transparent. This configuration keeps the initial visualization simple and ensures a fast overview of the current state. If an area or a specific wall is of interest, the full details can be extracted (number of points appended, average of all classes, and distribution of classes), as they are all stored in the object representing all walls.

4. Case study

To showcase the framework, a case study is done using a model of part of the Department of Civil and Architectural Engineering at Aarhus University. The general interface is displayed in Figure 3.

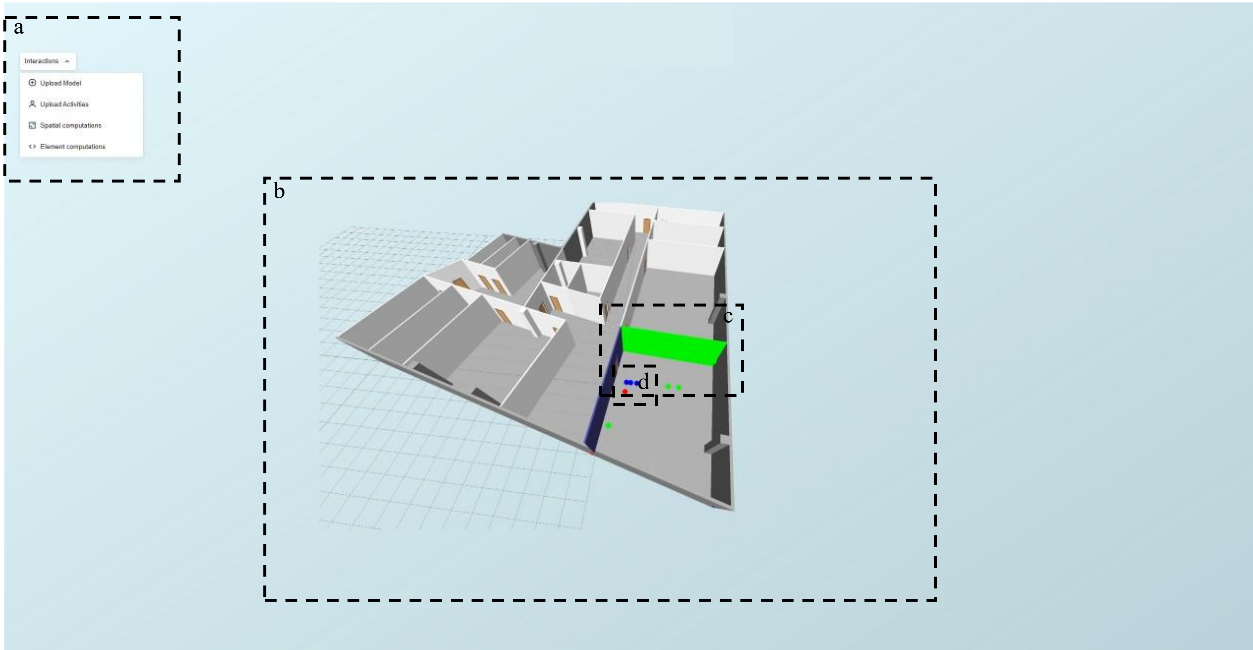

Figure 3: The browser-based frontend of the framework. (a) shows the dropdown menu in which the four interactions are located, (b) is the model visualization canvas, where the IFC model, the trajectories, and the coloring of the walls are displayed, (c) is the wall for which work has been done, hence it is colored as opposed to the other walls, and (d) is a snippet of trajectory points colorized based on their class.

A laboratory experiment setup of painting walls is used for collecting the trajectory and classification dataset, described in more detail in Jacobsen et al. (2022a). The tool is hosted in a Chrome browser and can thus be opened on most devices. This is done as it ensures that the tool lives up to the simplistic function of a VM tool. The requirement of a simplistic function is further met by conveying work class distribution information through a color scheme rather than numbers. To showcase this, six different examples of coloring the same wall are shown in Figure 4.

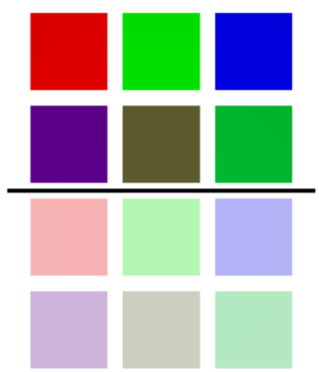

Figure 4: The color scheme. The first rows is the wall coloring if only one class is appended (from left to right: waste, direct work, indirect work). The second row is an example of class combinations (from left to right: 40% waste and 60% indirect work; 40% waste, 40% direct work, and 20% indirect work; 80% direct work and 20% indirect work). The two rows below the horizontal line are the same representations, but with only 30% of the points of the wall with the most points.

This method of conveying work information makes it easy to quickly see the dominating type of work for the walls and how much work has been appended to the given wall through the opacity. Some colors are still difficult to understand instantly, for example, the second color of the second row in Figure 4. The colors challenging to distinguish from each other are often found when more than two classes are present. This could be further optimized, either by splitting each wall into segments where each of the three color components would be visualized or by changing one of the three classes to be represented by a custom fill on top of the two colors, as colors consisting of two of the three components are easier to comprehend. A closer look at the developed tool can be seen in Figure 5.

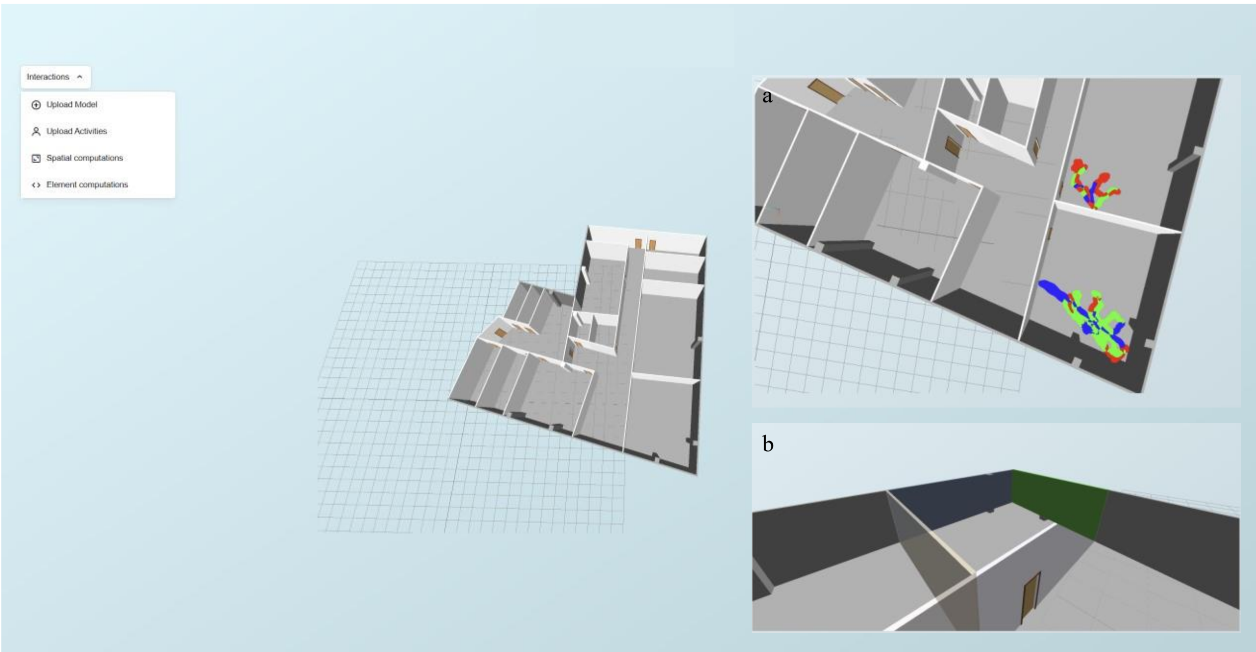

Figure 5: Screenshots from the developed tool using data collected from a laboratory experiment at the Department of Civil and Architectural Engineering, Aarhus University's building. (a) shows the two trajectories from the experiment colorized by the three classes, and (b) shows the coloring and opacity of the walls with the trajectory filtered out of the view.

Conclusion and outlook

This work presents a VM tool using autonomously generated information to convey states of work areas and the type of work in those areas. The framework has been created to ensure construction managers have the best decision-making conditions. It follows the most important functions when conveying data in VM tools and enables simplistic and transparent visualizations of work and the ability to dive deeper into data on element levels. This is done through a combination of color coding and opacity of elements to ensure a quick overview is possible to understand both type and amount of work. The method is shown through a case study of painting of an office building. Where the walls are given information regarding work in its workspace. This information is used to colorize the wall to create a VM tool for progress monitoring. To further assist the managerial tasks on construction projects through VM, several initiatives are seen as important next steps. Integrating the schedule to infer if the as-built is behind the as-planned would be beneficial for understanding the state, not only by seeing troublesome areas in terms of direct work as the solution is now but also if and how far they are behind schedule. This could be combined with previous works of the authors where methods were created to forecast productivity metrics (Jacobsen et al., 2023b), which is seen as a valuable addition to the solution, as this could give a simplistic overview of what to expect in the future states of the production system. The current method appends all work to walls, but by developing a better reasoning algorithm, it would be possible to append work to floors, slabs, or ceilings. For instance, this could be the space left empty in the middle of all rooms after intersecting the buffering and the Dirichlet tessellation. If the workspace reasoning was improved, this could be combined with information on the type of work the classification and trajectory were collected from, as this information would allow the algorithm to append the information to the correct type of object. Other granularities could then be created to create a hierarchical structure of information, where workspaces both belonged to elements and rooms or sections of the construction project.

References

Bhatt, M., Dylla, F., Hois, J. (2009). Spatio-terminological Inference for the Design of Ambient Environments, *Proc. 9th International Conference on Spatial Information Theory (COSIT)*, pp. 371-391, https://doi.org/10.1007/978-3-642-03832-7_23.

Cheng, T., Teizer, J., Migliaccio, G. C., Gatti, U. C. (2013). Automated task-level activity analysis through fusion of real time location sensors and worker's thoracic posture data, *Automation in Construction*, https://doi.org/10.1016/j.autcon.2012.08.003.

Conte, M., Trentin, B., Pedó, B., Etges, B. M. B. da S., Navarrete, S. (2022). Exploring the Use of Digital Visual Management for Last Planner System Implementation, *Proceedings of the 30th Annual Conference of the International Group for Lean Construction (IGLC30)*, pp. 645-656. https://doi.org/10.24928/2022/0172.

Golparvar-Fard, M., Peña-Mora, F., Savarese, S. (2009). Application of D4AR – a 4-dimensional augmented reality model for automating construction progress monitoring data collection, processing and communication, *Journal of Information Technology in Construction (ITcon)*, Vol. 14, pp. 129-153, https://www.itcon.org/paper/2009/13.

Grönvall, M., Ahoste, H., Lehtovaara, J., Reinbold, A., Seppänen, O. (2021). Improving Non-Repetitive Takt Production with Visual Management. *Proc. 29th Annual Conference of the International. Group for Lean Construction (IGLC29)*, pp. 797–806. https://doi.org/10.24928/2020/0195.

Jacobsen, E. L., Teizer, J. (2022). Deep learning in construction: Review of applications and potential avenues, *Journal of Computing in Civil Engineering*, Vol. 36, Issue 2, https://doi.org/10.1061/(ASCE)CP.1943-5487.0001010.

Jacobsen, E. L., Wandahl, S., Teizer, J. (2023a). Work estimation of construction workers for productivity monitoring using kinematic data and deep learning, *Automation in Construction*, Vol. 152, https://doi.org/10.1016/j.autcon.2023.104932.

Jacobsen, E. L., Teizer, J., Wandahl, S., Brilakis, I. (2023b). Probabilistic Forecasting of Metrics for Construction Labor Productivity Monitoring, Manuscript submitted for publication.

Johansen, K. W., Schultz, C., Teizer, J. (2023). Hazard ontology and 4D benchmark model for facilitation of automated construction safety requirement analysis, *Computer-Aided Civil and Infrastructure Engineering*, https://doi.org/10.1111/mice.12988.

Kazaz, A., Manisali, E., Ulubeyli, S. (2008). Effect of basic motivational factors on construction workforce productivity in Turkey, *Journal of Civil Engineering and Management*, Vol. 14, Issue 2, https://doi.org/10.3846/1392-3730.2008.14.4.

Koskela, L., Tezel, A., Tzortzopoulos, P. (2018). Why visual management?, *Proc. 26th Annual Conference of the International Group for Lean Construction (IGLC)*, pp. 250–260, https://doi.org/10.24928/2018/0527.

Lerche. J., Neve, H. H., Ballard, G., Teizer, J., Wandahl, S., Gross, A. (2020). Application of Last Planner System to Modular Offshore Wind Construction, *Journal of Construction Engineering and Management*, Vol. 146, Issue 11, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001922.

Lerche, J., Neve, H., Gross, A., Wandahl, S. (2021). A Model to Link Takt Schedules and Operations in Construction, *Proc. 29th Annual Conference of the International Group for Lean Construction (IGLC29)*, pp. 667–676, https://doi.org/10.24928/2021/0111.

Pedo, B., Brandalise, F.M.P., Viana, D.D., Tzortzopoulos, P., Formoso, C.T., Whitelock-Wainwright, A. (2020). Digital Visual Management Tools in Design Management, *Proc. 28th Annual Conference of the International Group for Lean Construction (IGLC28)*, pp. 901-912, https://doi.org /10.24928/2020/0071.

Teizer, J., Neve, H., Li, H., Wandahl, S., König, J., Ochner, B., König, M., Lerche, J. (2020). Construction resource efficiency improvement by Long Range Wide Area Network tracking and monitoring, *Automation in Construction*, https://doi.org/10.1016/j.autcon.2020.103245.

Tezel, A., Koskela, L., Tzortzpoulos, P. (2011). An examination of visual management on finnish construction sites, *Proc. 19th Annual Conference of the International Group for Lean Construction (IGLC)*, https://iglc.net/Papers/Details/1103.

Tezel, A., Koskela, L., Tzortzpoulos, P. (2016). Visual management in production management: a literature synthesis, *Journal of Manufacturing Technology Management*, Vol. 27, Issue 6, https://doi.org/10.1108/JMTM-08-2015-0071.

Wandahl, S., Neve, H. H., Lerche, J. (2021). What a Waste of Time, *Proc. 29th Annual Conference of the International Group for Lean Construction (IGLC)*, pp. 157-166, https://doi.org/10.24928/2021/0115.

Wang, Z., Zhang, Q., Yang, B., Wu, T. (2021). Vision-Based Framework for Automatic Progress Monitoring of Precast Walls by Using Surveillance Videos during the Construction Phase, *Journal of Computing in Civil Engineering*, Vol. 35, Issue 1, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000933.