Trajectory Prediction: A Review of Methods and Challenges in Construction Safety

Chronopoulos C.[1], Teizer J.[2], Esterle L.[3]
[1]Department of Civil and Architectural Engineering, Aarhus University, Denmark
[2]Department of Civil and Mechanical Engineering, Technical University of Denmark, Denmark
[3]Department of Electrical and Computer Engineering, Aarhus University, Denmark
chrichr@cae.au.dk

Abstract. This review focuses on methods for trajectory prediction of moving entities (i.e., pedestrian workers and heavy construction equipment) in construction. To the authors' knowledge it is the first review on trajectory prediction devoted to construction safety. Through a bibliometric analysis of the relevant literature, it examines the input data and prediction models used for trajectory prediction in dynamic and complex construction environments. Several techniques are available to perform prediction and their performance varies widely. Various types of data is being used, however, so far vision-based data is the major input to the models. Hence, computer-vision techniques are deployed for object tracking to infer the locations of the construction resources in almost entirely outdoor environments. This review concludes with an overview of the gaps, challenges, and future research steps for trajectory prediction relevant for researchers as well as practitioners working on reducing occupational health and safety hazards on construction sites.

1. Introduction

Construction sites are highly dynamic and constantly evolving environments. Due to the irregular environment, workers are prone to accidents mainly attributed to four key hazards, namely falls from height, struck-by heavy objects, caught-in or –between, and electrocutions. Furthermore, many construction accidents involve pedestrian workers in the proximity of static or dynamic hazards, such as unprotected leading edges, moving heavy construction equipment, or lifted crane loads. In 2019, nearly two-thirds of all construction fatal accidents in the U.S. were caused by those types of hazards also known as the 'Construction Focus Four' (CPWR, 2021). This is a reason why construction in the US remains at the top of the list of fatal accidents as it observes a 25%-share of all fatalities for the year 2019 (U.S. Bureau of Labor Statistics, 2020).

Trajectory prediction literature in the field of construction contributes mainly towards two directions. First, is the development of proactive real-time safety systems based on proximity monitoring for accident prevention. Those systems aim to provide relevant stakeholders (e.g., workers, equipment operators, safety managers) information for identifying static or dynamic hazard zones and performing safety decision-making, as well as enough response time for preventing imminent potentially hazardous events. Second, is the transition of construction to automation and autonomy where trajectory prediction is critical for safety planning and collision avoidance in human-robot collaboration.

Proximity monitoring and detection in construction sites have been a major research area, and various location tracking methods have been adopted for acquiring spatio-temporal data of onsite moving workers and equipment. For instance, radio frequency identification (RFID) technology has been adopted in proximity warning systems (Schiffbauer, 2001; Teizer et al., 2010), as well as ultra wideband (UWB) (Cheng et al., 2011; Teizer and Cheng, 2015), Bluetooth low-energy (BLE) (Lin et al., 2015; Teizer et al., 2017), Global Navigation Satellite Systems (GNSS) (Li et al., 2013; Zhang et al., 2015) and Long Range Wide Area Networks

https://doi.org/10.7146/aul.455.c233

(LoRA) (Teizer et al., 2020) for indoor and outdoor localization accordingly. More recently, vision-based systems that take advantage of modern computer vision techniques have been developed to identify the location of objects in construction site environments (Nahangi et al., 2018; Kim et al., 2020). Those studies investigated and validated the applicability of such location tracking technologies in various construction site environments and demonstrated high accuracy. However, the uncertainties in the dynamic construction environment affect the accuracy of proximity warning systems and alert frequency, reducing users' trust and potentially limiting their situational awareness (Ruff, 2006).

Regardless of when the construction sector will eventually achieve the envisioned level of autonomy, both directions are significant to ensure and reinforce the safety of workers in the dynamic and complex construction environment. The remainder of this paper is structured as follows, (a) an introduction to the methodology of the literature review, (b) quantitative results on the applications of trajectory prediction in construction as well as what input data and prediction models are used, and (c) discussion of the challenges and future directions. The main contributions of this paper are (i) identification of applications and methods for trajectory prediction used in construction, (ii) limitations and challenges of the existing studies, and (iii) future research steps in trajectory prediction for safety in construction.

2. Method

The literature review and the bibliometric analysis are based on the Scopus and Web of Science (WoS) scientific databases because of the extensive coverage of literature, the ability to export the search results as comma separated values (CSV) file for further analysis, and the support of Boolean (i.e., "AND", "OR") and proximity operators (i.e., "W/", "NEAR/") in search strings for advanced queries. The selected scientific databases have been successfully used in previous state-of-the-art review papers (Jacobsen and Teizer, 2022; Kim et al., 2019). The yielded search results have been exported in CSV file format and used for further analysis. The export contains the citation information (e.g., authors, title, and year) and, abstract and keywords.

The literature search is performed as a keyword search query by using keywords and, Boolean and proximity operators to limit the yielded results to the intended focus area. The search string consists of two parts. The first part contains the keywords "trajector*", "move*", "path" and "motion" followed by "predict*" and "forecast*" combined with the proximity operator "W/2" (or "NEAR/2 in WoS)", that is for combinations of sets of keywords within two words space. The "or" operator is used to include all keyword sets variations. The asterisk wildcard is used to indicate a character that may or may not be present in the term. The second part is focused on yielding results that are relevant to the construction sector and therefore, it includes the keyword "construction" followed by keywords such as, "worker", "site", "safety", "project" and "environment". The results are limited to publications written in English.

3. Data

The publications that were yielded from the search were first filtered by eliminating the duplicate records in the two databases. Subsequently, the results were screened to only include relevant publications. The screening was done by searching in the titles and abstracts for topics and research fields that are not in the scope of the review. These topics include for instance soil mechanics and geotechnical engineering, offshore engineering, cost estimation, and labour ergonomics, and therefore, the corresponding papers were excluded from the publications database. This resulted in a total of 49 papers that were further assessed for eligibility.

The overall review process can be described by the following stages, (i) identification of the records from the selected digital databases and duplicate elimination, (ii) screening of the initial results, (iii) eligibility assessment of the publications, and (iv) inclusion of the relevant studies (as shown in Figure 1). The analysis of the current state-of-the-art for the trajectory prediction in construction aims to shed light on two main questions: What models or methods have been used for trajectory prediction in construction in previous studies, and what type of input data are utilized? For this, the abstracts and full text of the selected publications were reviewed.

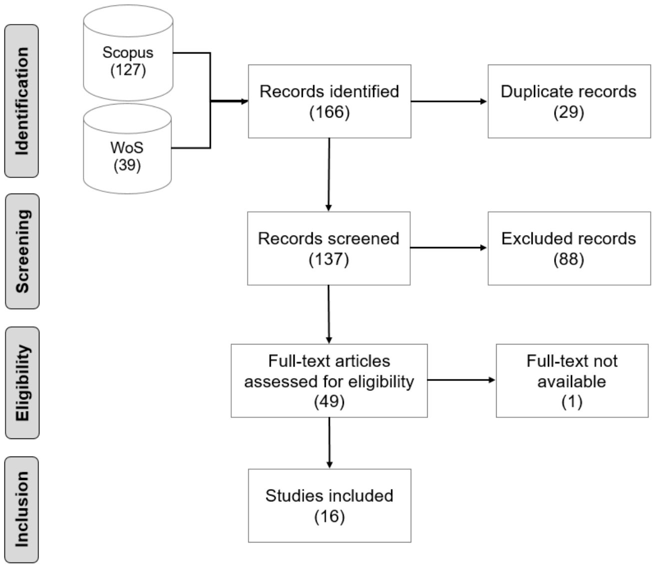

Figure 1: Stages and flow of the review process (number of publications in parentheses).

3.1 Input Data

Each publication on the topic of trajectory prediction in construction has been categorized based on the type of input data that are used by the corresponding predictive method to perform the prediction task. Regardless of the technology used, trajectory prediction requires either acquiring raw location tracking data (i.e., x, y, z coordinates over time) or inferring the location of the tracked entities indirectly, for instance, through the analysis of video-recorded footage and the application of object tracking techniques.

Therefore, the input data could be grouped into three main categories, (i) vision-based data, (ii) raw location tracking data, and (iii) point clouds. In the analysed publications, the most frequently used type of input is vision data, namely camera footage from construction sites. The cameras used in the corresponding studies are mostly stationary and less frequently embedded in moving vehicles, such as unmanned aerial vehicles (UAVs). Another type of input data used is location tracking data from GNSS devices. Lastly, 3-dimensional point cloud data from Light Detection and Ranging (LiDAR) sensors which are combined with kinematic data from inertial motion units, stroke sensors, and rotational encoders that measure force, angular rate and displacement of objects. Figure 2 shows the number of publications per type of input data.

3.2 Model

To understand how the trajectory prediction of moving workers and equipment is performed in the construction safety literature, the adopted models and methods for trajectory prediction have been investigated in the publications dataset. Deep neural networks (DNN) are commonly used for trajectory prediction. A sub-genre of DNN is recurrent neural networks (RNN) in which long short-term memory (LSTM) models are the most common for trajectory prediction problems. In other publications, Kalman filtering (KF) and hidden Markov models (HMM) are used for the prediction of workers and equipment motions. An illustration of the distribution of adopted methods in the identified publications is presented in Figure 3.

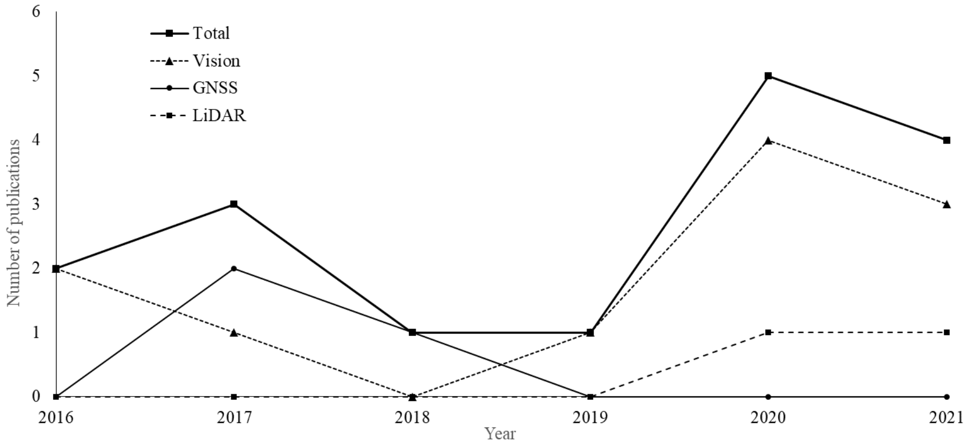

Figure 2: Publications per year and type of input data used for trajectory prediction.

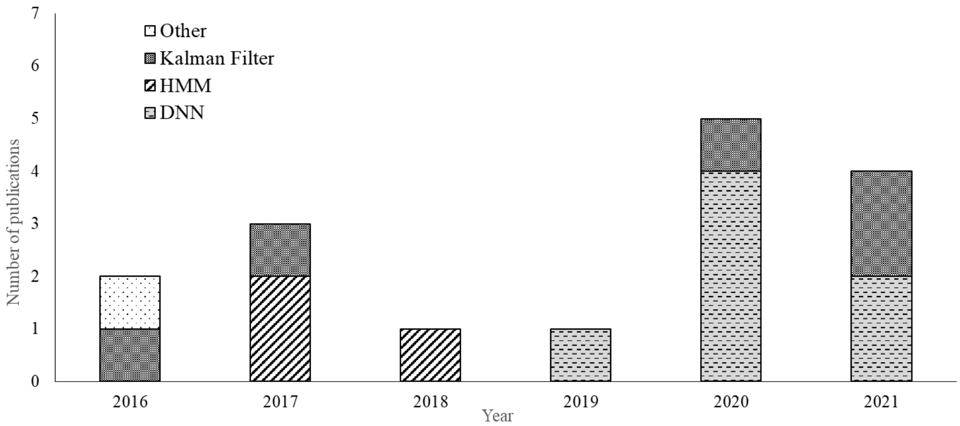

Figure 3: Publications per year and method used for trajectory prediction.

4. Results

Trajectory prediction is a critical topic in other relevant research fields, motivated and enhanced by the rapid technological advancements of the computational power as well as of the availability and cost-effectiveness of computational, sensory and data acquisition technologies.

4.1 Trajectory Prediction in Construction

Trajectory prediction in construction refers to the short-term prediction of the path followed by a moving object within 1 to 10 seconds ahead and focuses on two main directions. First, the development of proactive real-time safety systems based on proximity monitoring for accident prevention (Golovina et al., 2019), and second, the transition of construction to automation and autonomy where trajectory prediction is critical for safety planning and collision avoidance in human-robot collaboration. Although the future of automation and robotics in construction is promising (Garcia de Soto and Skibniewski, 2020), the majority of the identified publications focus on proximity monitoring for accident prevention rather than on construction automation.

Three categories of input data were found to be used for trajectory prediction in construction literature: vision-based data, raw location tracking data, and 3-dimensional point cloud data from LiDAR sensors. Similar to Jacobsen and Teizer (2022) the average time of publication (ATP) is used as a bibliographic metric. Table 1 shows the ATP for the different types of input data, prediction methods and applications in the construction literature. The most common input type, namely the vision-based data have an ATP of 2019.2, whereas the LiDAR data have the highest ATP with very limited publications. DNN models are the most commonly used and have the highest ATP contrary to the other predictive models that have also developed in the previous decades. This is arguably showing a trend in the application of DNN for trajectory prediction in construction. The three types of input data and models adopted for trajectory prediction in the identified construction literature are depicted in Table 2 and further discussed in the following sub-sections.

Table 1: Average time of publication (ATP) and number of papers for different types of input data and model adopted for trajectory prediction in construction.

Input data	ATP	Publications	Method	ATP	Publications
Vision	2019.2	11	DNN	2020.1	7
GNSS	2017.3	3	Kalman Filter	2019.0	5
LiDAR	2020.5	2	HMM	2017.3	3
			Other	2016.6	1

Table 2: Model adopted for different types of input data for trajectory prediction in construction.

Input data	DNN	Kalman Filter	HMM	Other	References
Vision				x	Rezazadeh Azar, (2016)
	x (ConvLSTM)				Bang et al., (2021)
	x (Seq2Seq LSTM)				Cai et al., (2020)
		x			Deng et al., (2021)
	x (Seq2Seq LSTM)				Hu et al., (2020)
	x (Social LSTM+GAN)				Kim et al., (2019)
	x (Social LSTM+GAN)				Kim et al., (2020)
	x (Social LSTM)				Kong et al., (2021)
		x (UKF)			Papaioannou et al., (2017)
	x (LSTM+MDN)				Tang et al., (2020)
		x			Zhu et al., (2016)
GNSS			x		Rashid and Behzadan, (2017)
			x		Rashid et al., (2017)
			x		Rashid and Behzadan, (2018)
LiDAR		x (EKF)			Rasul et al., (2020)
		x (UKF)			Rasul et al., (2021)

Vision-based Data

Video recorded footage is used for predicting the movement of workers and equipment in construction sites through vision-based object recognition. The tracked objects (i.e., workers and equipment) are identified in the frames using computer vision and the motion vector is then calculated. Short-term prediction is commonly performed based on NN models and KF, whereas HMM are less frequently applied. Zhu et al. (2016) proposed a framework for computer vision-based estimation of position and short-term prediction of workers and mobile equipment. The researchers assumed functionality with clear and of acceptable quality videos with limited occlusions, which makes the framework susceptible to input of inferior quality. To solve the tracking limitations in construction environments, Rezazaddeh Azar (2016) developed a vision-based equipment tracking algorithm for automated camera control with predictive capability by estimating the motion vector and speed of the tracked object.

To increase the accuracy of the predictive models semantic and contextual information is used combining input from other sensory technologies. Papaioannou et al. (2017) introduced a system that uses footage from CCTV camera infrastructure and data from the inertial sensors embedded on modern smartphones and applied the Social Force Model (SFM) to consider obstacles and other people in the scene, assuming that they affect the behaviour of human motion, and represent their effect as repulsive forces. Cai et al. (2020) designed an LSTM model to predict worker trajectories in construction environments, considering additional contextual information, namely the distance to the nearest neighbour, the relationship between that neighbour and the tracked worker, and the distance to destination. An LSTM network combined with mixture density network (MDN) for construction workers and equipment path prediction towards right time intervention of collision and intrusion was constructed by Tang et al. (2020). The model considers two contextual cues, namely the distance between moving and static objects and the type of objects (i.e., worker and vehicle) to predict up to 2 seconds in the future. Although the model outperforms other existing models, it is still limited by the dynamic visual occlusions due to other moving construction resources. Semantic information in the form of predefined hazard zones is also considered in the literature. Deng et al. (2021) used KF to predict the movement of workers in construction sites and the estimated trajectory is checked against a set of artificial danger zone boundaries to determine whether the prediction point lies inside or outside of the zones. Considering the occlusion limitations, the researchers performed multi-angle detection which however, is limited by the camera resolution, especially when the workers are far from the camera position. Kong et al. (2021) proposed a framework for workers' trajectory prediction in construction sites based on the Social LSTM architecture. The framework takes into consideration the workers' unsafe behaviour, defined as any movement towards predefined hazardous areas, and corrects the predicted trajectories using KF. One important shortcoming of that study is related to the validation of the pre-trained model, performed on their own dataset with limited scenarios, preventing it from being generalizable.

Only two of the identified publications focused on the future construction, where human workers and robots co-exist and collaborate. Kim et al. (2019) proposed a framework based on social generative adversarial network (S-GAN) for trajectory prediction to tackle contact-driven hazards in construction between workers and autonomous trucks. Their results showed that longer observation periods do not necessarily lead to higher prediction accuracy, due to inclusion in the prediction of less relevant time steps. In a later study, they evaluated the model on a controlled testbed, including a worker and a truck following three predefined movement patterns (Kim et al., 2020). Hu et al. (2020) expanded the application of the LSTM model developed by Cai et al. (2020), by implementing the A* path planning algorithm for autonomous robots in construction sites. However, the study validates the worker trajectory and path planning algorithms separately assuming flat ground surface.

Location Tracking Data

GNSS are satellite-based navigation technologies that depend on the satellites orbiting around the earth. Existing studies have deployed low-cost GNSS technology for tracking construction resources to enhance construction safety, planning and management (Pradhananga and Teizer, 2013; Zhang et al., 2015). GNSS data have also been used as input to trajectory prediction models in construction applications. Rashid and Behzadan (2017) developed a smartphone-based application for trajectory prediction of workers to prevent contact-driven accidents in construction sites. The underlying model is based on HMM. A risk factor is introduced and ranges between 0 and 1 depending on the angle between the trajectory and the centre of one stationary and user-defined hazard zone (Rashid et al., 2017). The model was further developed to consider one static or dynamic hazard (i.e., moving between two points) and validated it by comparing to a benchmark Polynomial Regression model, showing better prediction accuracy (Rashid and Behzadan, 2018). Both models however, are error-prone in predicting trajectories with sharp turns and are limited to a single pedestrian worker and a predefined hazard. Furthermore, the application considers outdoor construction activities due to the limitations of GNSS technologies in indoor environments. Another shortcoming is related to the large number of detected close-call events (n=369) and potential collisions (n=77) in a 30-minute experiment, which could hinder the users' situational awareness and trust in the warning system and lead to delays.

Point Clouds

Point clouds are sets of data points in space that can represent 3-dimensional objects, where each point has its own set of x, y and z coordinates. In a recent study, a LiDAR sensor was utilized to acquire point cloud data to track the positions of heavy machinery and obstacles in a construction site (Rasul et al., 2020; Rasul et al., 2021). The raw point cloud data were analysed to first detect the heavy machinery (i.e., excavator) and then perform detection and clustering of other objects (i.e., workers and machinery) of a width greater than 0.4m, which is the average chest width of a human being. The Extended Kalman Filter (EKF) was adopted for predicting the position and velocity of the moving objects, whereas the excavator's predicted working area was calculated based on kinematics analysis and data from embedded stroke sensors and a rotational encoder (Rasul et al., 2020). In a later study, they used unscented Kalman filtering (UKF) to predict the non-linear motion dynamics of the moving objects. In both studies two safety indices are defined and used, namely the time to collision (TTC), and the warning index (x) defined as the degree of potential collision risks.

5. Gaps, Challenges and Future Research

This paper reviews the problem of trajectory prediction in dynamic and complex construction environments and discusses the current applications, prediction methods and input data used for the predictive task. The following summarizes the gaps, challenges and directions for future research for trajectory prediction with a specific focus on the construction site applications:

1. Predicting the future trajectories of moving objects while incorporating human behaviour is a highly complex problem and hence it is limited to short-term prediction typically for 1-10 seconds ahead with decreasing performance when the prediction horizon increases. Previous studies improved the models' accuracy by correcting the predicted trajectories with KF, whereas other methods include construction semantic (i.e., static hazard zones) and contextual information (e.g., distance from hazards, risk factor) to achieve better performance. Trajectory prediction of moving construction resources should not neglect

pedestrian workers and their contribution to potentially hazardous events. Future research should focus on both construction heavy equipment and pedestrian workers while integrating additional construction semantic information. For instance, construction semantic information such as dynamic hazard areas, work order and construction site layout information (Chronopoulos et al., 2021) could potentially further improve the prediction performance and thus, increase the impact of the developed architectures in real construction applications.

2. Currently, trajectory prediction in construction aims to support the development of proactive real-time safety systems for accident prevention. Increasing the accuracy of prediction models is a common goal among all identified publications. However, it is important to consider the time dimension in proactive warning systems and the feedback must be shared at the desired level-of-detail at the right-time instead of in real-time (Teizer, 2016). Frequent warnings can limit the situational awareness and trust in the warning system of workers and operators (Ruff, 2006). Novel systems focusing on construction safety though trajectory prediction should ensure not only high prediction accuracy but also right-time warning functionality.
3. The current state-of –the-art of trajectory prediction in construction mostly utilizes vision-based data as input to computer-vision methods for object recognition and tracking. For this, recorded videos from cameras on-board UAVs, stationary commercial cameras, existing CCTV infrastructure and public datasets (Lerner et al., 2007) are used to train or validate the developed models. This introduces three significant issues that need to be considered in future research studies. First, is the comparability of performance metrics between models that are validated on different datasets. Second, is the absence of publicly available datasets for the construction sector to be used as benchmark for validating the developed models. Third, the use of camera-based systems in dynamic and rough construction environments is susceptible to various limitations, such as occlusions (Zhu et al., 2016), camera equipment resolution (Deng et al., 2021) and limited field-of-view (Jacobsen and Teizer, 2021), dust, weather conditions, malicious acts, and vandalisms.
4. The trajectory prediction literature in the context of construction focuses primarily on outdoor applications and thus the proposed methods including the tools, models, training and validation are structured based on that spatial assumption. However, several types of private or public construction projects take place in indoor environments, for instance buildings, underground and tunnelling projects with additional constraints (e.g., limited luminosity, dust, no network, signal or GNSS coverage) that further constrain the applicability and scalability of those methods in the aforementioned projects. Future research efforts should also include indoor or hybrid construction environments in developing and validating trajectory prediction models for construction safety.

6. Conclusion

This review paper is, to the authors' knowledge, the first that presents an overview of the trajectory prediction models for complex and dynamic construction environments. Deep neural networks are commonly used in recent studies to perform prediction compared to other methods. To increase the performance of the models, linear estimation models have been applied and integration of limited contextual and semantic information is performed. Various limitations exist and are related to the applied technologies as well as the dynamic and complex characteristics of the construction environments. The paper discusses those limitations and proposes future research steps in trajectory prediction for safety in construction. For instance, the integration of additional construction semantic information (e.g., dynamic hazard areas, work order and construction site layout information) to further improve the prediction accuracy and the consideration of right-time proactive warning systems not only in outdoor construction environments but also in indoor or hybrid construction projects.

References

Bang, S., Hong, Y. and Kim, H. (2021). Proactive proximity monitoring with instance segmentation and unmanned aerial vehicle-acquired video-frame prediction, *Computer-aided civil and infrastructure engineering*, 36(6), pp. 800–816. doi: https://www.doi.org/10.1111/mice.12672.

Cai, J., Zhang, Y., Yang, L., Cai, H. and Li, S. (2020). A context-augmented deep learning approach for worker trajectory prediction on unstructured and dynamic construction sites, *Advanced engineering informatics*, 46(101173), p. 101173. doi: https://www.doi.org/10.1016/j.aei.2020.101173.

Cheng, T., Venugopal, M., Teizer, J. and Vela, P.A. (2011). Performance evaluation of ultra wideband technology for construction resource location tracking in harsh environments, *Automation in Construction*, 20(8), pp. 1173–1184. doi: https://www.doi.org/10.1016/j.autcon.2011.05.001.

Chronopoulos, C., Johansen, K.W., Teizer, J., Schultz, C. and Esterle, L. (2021). Towards a holistic self-organised safety framework for construction, in *2021 IEEE International Conference on Autonomic Computing and Self-Organizing Systems Companion (ACSOS-C)*. IEEE. doi: https://doi.org/10.1109/ACSOS-C52956.2021.00060.

CPWR - The Center for Construction Research and Training (2021). *Fatal injury trends in the construction industry*. https://www.cpwr.com/wp-content/uploads/DataBulletin-February-2021.pdf.

Deng, H., Ou, Z. and Deng, Y. (2021). Multi-angle fusion-based safety status analysis of construction workers, *International journal of environmental research and public health*, 18(22), p. 11815.

Garcia de Soto, B. and Skibniewski, M.J. (2020). Future of Robotics and Automation in Construction. In Sawhney, A., Riley, M., and Irizarry, J. (eds.) *Construction 4.0: An innovation platform for the built environment*. Routledge, pp. 289–306.

Golovina, O., Perschewski, M., Teizer, J., König, M. (2019). Algorithm for Quantitative Analysis of Close Call Events and Personalized Feedback in Construction Safety, *Automation in Construction*, Elsevier, 99, 206-222, doi: https://doi.org/10.1016/j.autcon.2018.11.014.

Hu, D., Li, S., Cai, J. and Hu, Y. (2020). Toward intelligent workplace: Prediction-enabled proactive planning for human-robot coexistence on unstructured construction sites, in *2020 Winter Simulation Conference (WSC)*. IEEE.

Jacobsen, E.L. and Teizer, J. (2022). Deep learning in construction: Review of applications and potential avenues, *Journal of computing in civil engineering*, 36(2). doi: https://www.doi.org/10.1061/(asce)cp.1943-5487.0001010.

Kim, D., Jebelli, H., Lee, S. and Kamat, V.R. (2020). Enhancing deep neural network-based trajectory prediction: Fine-tuning and inherent movement-driven post-processing, in *Construction Research Congress 2020*. Reston, VA: American Society of Civil Engineers.

Kim, D., Lee, S. and Kamat, V.R. (2020). “Proximity prediction of mobile objects to prevent contact-driven accidents in co-robotic construction, *Journal of computing in civil engineering*, 34(4), p. 04020022. doi: https://www.doi.org/10.1061/(asce)cp.1943-5487.0000899.

Kim, D., Liu, M., Lee, S. and Kamat, V.R. (2019). Trajectory prediction of mobile construction resources toward pro-active struck-by hazard detection, in *Proceedings of the 36th International Symposium on Automation and Robotics in Construction (ISARC)*. International Association for Automation and Robotics in Construction (IAARC).

Kim, M.-K., Wang, Q. and Li, H. (2019). Non-contact sensing based geometric quality assessment of buildings and civil structures: A review, *Automation in Construction*, 100, pp. 163–179.

Kong, T., Fang, W., Love, P.E.D., Luo, H., Xu, S. and Li, H. (2021). Computer vision and long short-term memory: Learning to predict unsafe behaviour in construction, *Advanced engineering informatics*, 50(101400), p. 101400. doi: https://www.doi.org/10.1016/j.aei.2021.101400.

Lerner, A., Chrysanthou, Y. and Lischinski, D. (2007). Crowds by example, *Computer graphics forum: journal of the European Association for Computer Graphics*, 26(3), pp. 655–664. doi: https://www.doi.org/10.1111/j.1467-8659.2007.01089.x.

Li, H., Chan, G. and Skitmore, M. (2013). Integrating real time positioning systems to improve blind lifting and loading crane operations, *Construction management and economics*, 31(6), pp. 596–605.

Lin, X.-Y., Ho, T.-W., Fang, C.-C., Yen, Z.-S., Yang, B.-J. and Lai, F. (2015). A mobile indoor positioning system based on iBeacon technology, *Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference*, 2015, pp. 4970–4973. doi: https://www.doi.org/10.1109/EMBC.2015.7319507.

Nahangi, M., Heins, A., McCabe, B. and Schoellig, A. (2018). Automated localization of UAVs in GPS-denied indoor construction environments using fiducial markers, in *Proceedings of the 35th International Symposium on Automation and Robotics in Construction (ISARC)*. International Association for Automation and Robotics in Construction (IAARC). doi: https://www.doi.org/10.22260/isarc2018/0012.

Papaioannou, S., Markham, A. and Trigoni, N. (2017). Tracking people in highly dynamic industrial environments, *IEEE transactions on mobile computing*, 16(8), pp. 2351–2365.

Pradhananga, N. and Teizer, J. (2013). Automatic spatio-temporal analysis of construction site equipment operations using GPS data, *Automation in Construction*, 29, pp. 107–122. doi: https://www.doi.org/10.1016/j.autcon.2012.09.004.

Rashid, K.M. and Behzadan, A.H. (2017). Enhancing motion trajectory prediction for site safety by incorporating attitude toward risk, in *Computing in Civil Engineering 2017*. Reston, VA: American Society of Civil Engineers.

Rashid, K.M. and Behzadan, A.H. (2018). Risk behavior-based trajectory prediction for construction site safety monitoring, *Journal of construction engineering and management*, 144(2), p. 04017106.

Rashid, K.M., Datta, S. and Behzadan, A.H. (2017). Coupling risk attitude and motion data mining in a preemtive construction safety framework, in *2017 Winter Simulation Conference (WSC)*. IEEE.

Rasul, A., Seo, J. and Khajepour, A. (2021). Development of sensing algorithms for object tracking and predictive safety evaluation of autonomous excavators, *Applied sciences (Basel, Switzerland)*, 11(14), p. 6366. doi: https://www.doi.org/10.3390/app11146366.

Rasul, A., Seo, J., Oh, K., Khajepour, A. and Reginald, N. (2020). Predicted safety algorithms for autonomous excavators using a 3D LiDAR sensor, in *2020 IEEE International Systems Conference (SysCon)*. IEEE.

Rezazadeh Azar, E. (2016). Active control of a pan-tilt-zoom camera for vision-based monitoring of equipment in construction and surface mining jobsites, in *Proceedings of the 33rd International Symposium on Automation and Robotics in Construction (ISARC)*. International Association for Automation and Robotics in Construction (IAARC).

Ruff, T. (2006). Evaluation of a radar-based proximity warning system for off-highway dump trucks, *Accident; analysis and prevention*, 38(1), pp. 92–98. doi: https://www.doi.org/10.1016/j.aap.2005.07.006.

Schiffbauer, W.H. (2001). An Active Proximity Warning System for Surface and Underground Mining Applications, in *SME Annual Meeting*.

Tang, S., Golparvar-Fard, M., Naphade, M. and Gopalakrishna, M.M. (2020). Video-based motion trajectory forecasting method for proactive construction safety monitoring systems, *Journal of computing in civil engineering*, 34(6), p. 04020041. doi: https://www.doi.org/10.1061/(asce)cp.1943-5487.0000923.

Teizer, J. (2016). The role of automation in right-time construction safety, in *Proceedings of the 33rd International Symposium on Automation and Robotics in Construction (ISARC)*. International Association for Automation and Robotics in Construction (IAARC).

Teizer, J., Allread, B.S., Fullerton, C.E. and Hinze, J. (2010). Autonomous pro-active real-time construction worker and equipment operator proximity safety alert system, *Automation in Construction*, 19(5), pp. 630–640. doi: https://www.doi.org/10.1016/j.autcon.2010.02.009.

Teizer, J. and Cheng, T. (2015). Proximity hazard indicator for workers-on-foot near miss interactions with construction equipment and geo-referenced hazard areas, *Automation in Construction*, 60, pp. 58–73. doi: https://www.doi.org/10.1016/j.autcon.2015.09.003.

Teizer, J., Neve, H., Li, H., Wandahl, S., König, J., Ochner, B., König, M. and Lerche, J. (2020). Construction resource efficiency improvement by Long Range Wide Area Network tracking and monitoring, *Automation in Construction*, 116 (103245). doi: https://www.doi.org/10.1016/j.autcon.2020.103245.

Teizer, J., Wolf, M., Golovina, O., Perschewski, M., Propach, M., Neges, M. and König, M. (2017). Internet of things (IoT) for integrating environmental and localization data in building information modeling (BIM), in *Proceedings of the 34th International Symposium on Automation and Robotics in Construction (ISARC)*. Tribun EU, s.r.o., Brno.

U.S. Bereau of Labor Statistics (2020). *Number and rate of fatal work injuries, by industry sector*. Available at: https://www.bls.gov/charts/census-of-fatal-occupational-injuries/number-and-rate-of-fatal-work-injuries-by-industry.htm (Accessed: January 10, 2022).

Zhang, S., Teizer, J., Pradhananga, N. and Eastman, C.M. (2015). Workforce location tracking to model, visualize and analyze workspace requirements in building information models for construction safety planning, *Automation in Construction*, 60, pp. 74–86. doi: https://www.doi.org/10.1016/j.autcon.2015.09.009.

Zhu, Z., Park, M.-W., Koch, C., Soltani, M., Hammad, A. and Davari, K. (2016). Predicting movements of onsite workers and mobile equipment for enhancing construction site safety, *Automation in Construction*, 68, pp. 95–101. doi: https://www.doi.org/10.1016/j.autcon.2016.04.009.