Proceedings of the 2020 Winter Simulation Conference
K.-H. Bae, B. Feng, S. Kim, S. Lazarova-Molnar, Z. Zheng, T. Roeder, and R. Thiesing, eds.

TOWARD INTELLIGENT WORKPLACE: PREDICTION-ENABLED PROACTIVE PLANNING FOR HUMAN-ROBOT COEXISTENCE ON UNSTRUCTURED CONSTRUCTION SITES

Da Hu
Shuai Li

Department of Civil and Environmental Engineering
The University of Tennessee
851 Neyland Drive
Knoxville, TN 37996, USA

Jiannan Cai

Department of Construction Science
The University of Texas at San Antonio
501 W César E Chávez Blvd
San Antonio, TX 78207, USA

Yuqing Hu

Department of Architectural Engineering
Pennsylvania State University
104 Engineering Unit A
University Park, PA 16802, USA

ABSTRACT

Construction robot path planning is critical for safe and effective human-robot collaboration in future intelligent workplaces. While many studies developed methods to generate paths for construction robots, very few, if any, have integrated the worker trajectory prediction on the jobsite. The objective of this research is to find a safe and efficient robot path, meanwhile, taking into account the predicted movement of construction workers. To this end, we propose a context-aware Long Short-Term Memory (LSTM)-based method to predict worker's trajectory. Based on the predicted trajectory, the A* and Dynamic Window Approach (DWA) are used to find an optimal path for the robot. The efficiency and effectiveness of the proposed method are manifested by simulated and field experiments. The proposed method will contribute to the body of knowledge for prediction-based construction robots path planning and provide the potential to be integrated into existing robot platforms to enhance their performance.

1 INTRODUCTION

Automation and robotics are the future of the construction industry. The global construction robot market is projected to increase to $186.6 billion by 2024 from $78.6 billion in 2018 (The Robot Report Staff 2019). Approximately 49% of construction tasks can be automated or be substituted by robots (Manzo et al. 2018). Robots are expected to solve the labor shortage issue and boost productivity in the construction industry. In the near future, humans and robots will coexist on the intelligent construction sites to conduct a variety of tasks, posing new challenges on robotics-related safety. Construction robots are expected to autonomously navigate on the dynamic and unstructured jobsite while avoiding collisions with other site entities, which, however, remains an unaddressed challenge. Therefore, there is a critical need to create effective algorithms for collision-free path planning of robots to enable efficient and safe human-robot collaboration at construction sites.

In some existing studies, methods have been developed to plan paths for construction robots on construction sites. For example, Kim et al. (2003) proposed a *SensBug* algorithm to generate a path for a mobile construction robot from its initial position to a target position. The *SensBug* algorithm can navigate robots in a 2D planar unknown environment with stationary and moving obstacles. However, this method requires a high-level positioning accuracy of robots which is not achievable at urban or crowded construction sites. In addition, the generated path by the SensBug algorithm is close to the obstacle, which is not safe and efficient. Kayhania et al. (2018) presented a methodology to automate path planning for heavy construction equipment. The proposed method can find the shortest path and avoid obstacles at construction sites. However, this method is not suitable for moving obstacles such as construction workers.

To address these challenges, we proposed a novel robot path planning method by integrating the worker trajectory prediction in construction sites. The proposed method can generate paths for robots without collision with moving workers. Our contribution is twofold. First, this research develops a new algorithm to predict worker's trajectory with context information. Second, this research develops a new workflow that integrates worker trajectory prediction to robot path planning to generate safe and efficient robot paths.

2 LITERATURE REVIEW

2.1 Related Studies on Human Trajectory Prediction

Human trajectory prediction is an essential yet challenging task in computer vision. Traditionally, tracking filters, such as Kalman filter and Particle filters, are used to predict the future steps in a trajectory (Hermes et al. 2009; Liu et al. 1998). However, because only the continuity of movement is considered, such approaches may either result in physically impossible locations (e.g., behind walls, within obstacles) or degrade into random walks of feasible motion over large time horizons (Ziebart et al. 2009). Some researches (Rudenko et al. 2018; Ziebart et al. 2009) adopted planning-based approaches, where entities are treated as intelligent agents who actively plan their path to achieve a goal. The problem is formulated as a path planning or optimal control task, such as the Markov decision process (MDP). One main drawback is that the planning-based approach relies heavily on prior knowledge, and it still uses hand-crafted features to model states and reward functions that are specific to particular settings. Recently, data-driven approach has been increasingly used given that it does not require to explicitly model movement dynamics and the ability to be generalized to various scenarios. Long short-term memory (LSTM) network is the most widely used deep learning method for human trajectory prediction (Alahi et al. 2016; Xue et al. 2018).

In the construction domain, Zhu et al. (2016) proposed a novel Kalman filter to predict the movements of workers and mobile equipment using positions obtained from multiple video cameras. Although the methods achieved a submeter accuracy when predicting the next-step movement in 0.03s, the accuracy decreases to about 1.5m when predicting the movement in 1.5s. Instead of using conventional tracking filters, Dong et al. (2018) and Rashid et al. (2018) modeled the worker movements as a Markov process to predict their trajectories based on historical records. More recently, Kim et al. (2019) and Tang et al. (2019) attempted to predict the construction entity trajectory through a data-driven approach given the advances in deep learning techniques. Most existing studies only consider individual movements while predicting a worker's trajectory, which is insufficient to capture worker behavior under different scenarios. In reality, multiple entities co-exist on the construction site, forming various working groups to accomplish different activities (Cai et al. 2019). Workers' behavior will be influenced by each other and the specific activities they are involved in. Jobsite contextual information such as entity interactions and ongoing activities must be incorporated in order to better predict entity movements, which, however, has been overlooked by existing studies in the construction domain.

Some studies on pedestrian behavior analysis have recognized the significance of context information and considered various contextual features to predict pedestrian trajectory and intention on the road. For instance, Kooij et al. (2019) found that incorporating pedestrian situational awareness, situation criticality, and spatial layout of the environment increases the prediction accuracy. Alahi et al. (2016) proved that the pedestrian trajectory can be better predicted by incorporating the interaction among multiple pedestrians. These studies show the great promise of contextual features in improving the performance of movement prediction. Motivated by the above achievements, this study proposes a context-aware deep learning method for worker trajectory prediction on unstructured and dynamic construction sites.

2.2 Relative Studies on Robot Path Planning

With the emergence of robot application in different industries, such as construction (Bogue 2018) and manufacturing (Paryanto et al. 2015), to automate tasks and enhance worker safety, mobile robotics field has attracted increasing attention from many researchers, in which robot path planning problem is one of the important and challenging research themes. Path planning is used to identify a sequence of actions to transform robots from a start to a goal position. Existing studies on robot path planning can be classified as classical and heuristic approaches (Atyabi and Powers 2013). Classical approach commits to prove whether an optimal path for the robot exists or not (Masehian and Sedighizadeh 2007). This method requires intensive computational power and is sensitive to uncertainty, which limits their application in the real world. The approaches such as Subgoal Network, Cell Decomposition, Potential Field, and Road Map are common classical path planning methods. The heuristic approach is developed to solve complex optimization problems in real-world scenarios, which integrates probabilistic algorithms such as Probabilistic Roadmaps (PRM) to achieve a high-speed implementation (Mac et al. 2016).

Many heuristic-based path planning approaches have been developed to navigate robots in a partially known or dynamic environment. For instance, graph-based methods such as Dijkstra's (Dijkstra 1959) and A* (Hart et al. 1968) algorithms have been utilized to find an optimal path from the start position to the goal position. The two methods plan paths on a given graph $G = (S, E)$ that represents the environment of the robot. Where S is a set of robot states in the graph and E is a set of edges connecting pairs of vertices in S. The edge cost is defined as the transition cost between the two endpoints of the edge. The optimal path represents a path that has minimal transition costs leading from initial state to goal state. Rapidly-Exploration Random Tree (RRT) is a typical sampling-based algorithm (Lavalle 1998). This method is suitable for planning in a high-dimensional space. However, all the above approaches were designed for static environments, which do not involve path re-planning after the path is calculated. Thus, they may not work well in a dynamic environment with moving obstacles. To address this issue, the incremental re-planning algorithm like the D* algorithm (Stentz 1994) was developed. The D* algorithm is based on the A* algorithm, which offers an efficient re-planning in changing environments like adding a new obstacle.

The heuristic-based approach was also widely adopted in robot path planning on construction sites. Soltani et al. (2002) evaluated the performance of Dijkstra's, A*, and Genetic algorithms regarding their application in construction sites based on the distance, risk, and visibility of the path. The study concluded that the A* algorithm can find an optimal solution more efficiently for a large-scale problem. In Ali et al. (2005), the Genetic algorithm was used to automate a collision-free path planning of cooperative crane manipulators. The generated path achieved a shorter distance and less computational time compared to the A* search. Chang et al. (2012) proposed a fast path-planning method for crane erection, where the PRM algorithm was incorporated. The developed method was validated in virtual experiments, which can generate erection paths efficiently for operating. The main drawback of these studies is that a static environment was assumed, which ignores dynamic nature at construction sites where multiple entities conducting various activities simultaneously on the jobsite.

3 METHODOLOGY

Figure 1 shows an overview of the proposed method, which consists of two steps. In the first step, an LSTM-based method is created to predict the worker's trajectory considering contextual information on the jobsite. In the second step, the robot path planning method is devised based on predicted worker trajectories to avoid potential collisions. The next two sections elaborate on the technical details of our method.

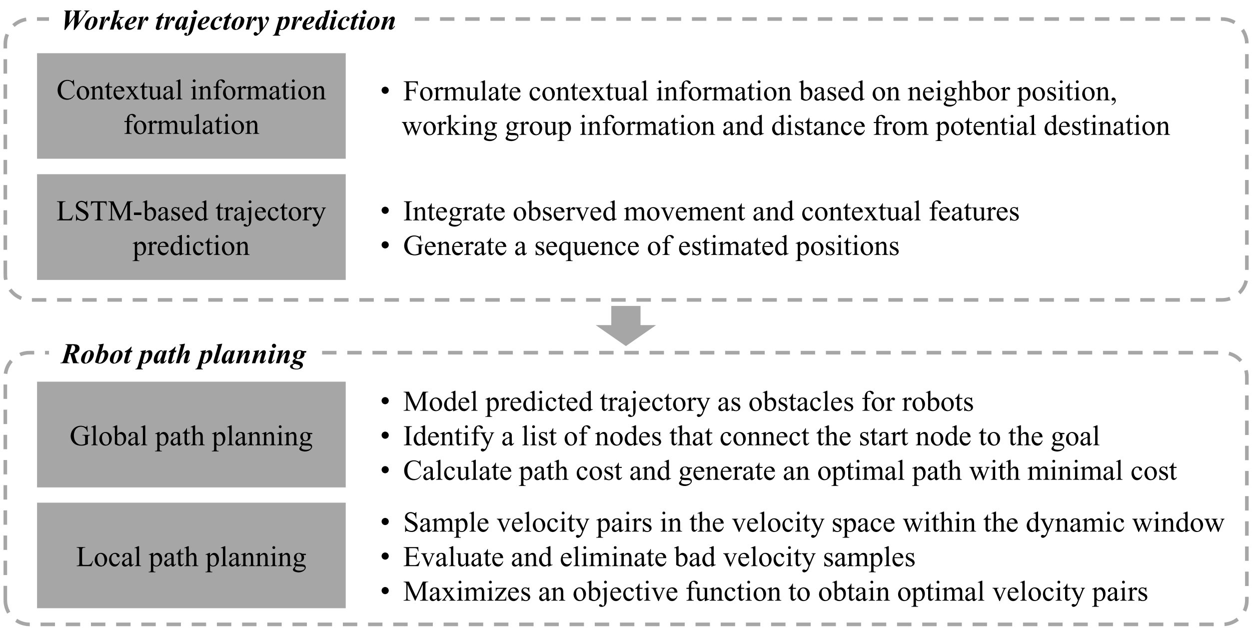

Figure 1: Methodology overview.

3.1 Worker Trajectory Prediction

This study proposes a context-aware LSTM-based method for accurate worker trajectory prediction using construction video data based on Cai et al. (2020). The method incorporates both individual movement and workplace contextual information regarding movements of neighboring entities, working group information, and potential destination information. Entity movement and contextual information are incorporated in the LSTM-based sequence-to-sequence (seq2seq) neural network for trajectory prediction. Figure 2 illustrates the framework.

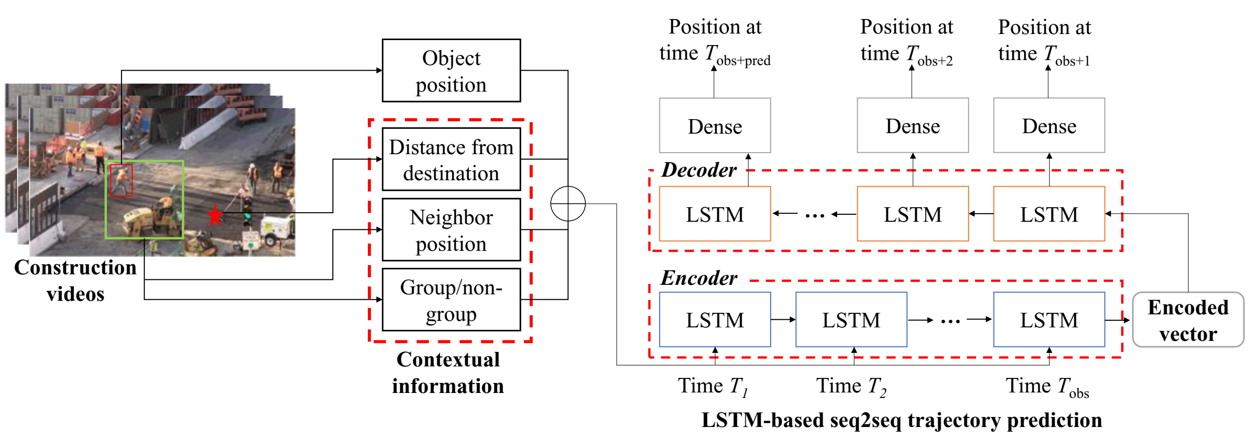

Figure 2: Context-aware LSTM-based model for trajectory prediction.

It is assumed that construction videos are first preprocessed to obtain entity positions and contextual features, consistent with most of the related studies (Alahi et al. 2016; Tang et al. 2019; Xue et al. 2018). We use the mid-bottom point of entity's bounding box to represent their position. As a result, at time step t, the i^{th} entity is denoted by its pixel coordinates on the image plane, i.e., (x_t^i, y_t^i). The objective is to predict entity positions from time step T_{obs+1} to $T_{obs+pred}$ based on the observation of site dynamics, including both the positions of all entities and the jobsite contexts from time step T_1 to time step T_{obs}. Different from previous studies (Alahi et al. 2016; Tang et al. 2019) which only observe entity positions and implicitly incorporate the interactions among entities using hidden states learned from deep neural networks, we explicitly models the contextual information on the jobsite based on the methods developed in our previous study (Cai et al. 2019).

3.1.1 Contextual information formulation

Construction workers co-exist and collaborate with other entities to conduct various tasks on the jobsite. Their behavior is purposeful and will be influenced by involved activities and their surrounding entities. It is expected that construction workers tend to avoid obstacles to prevent potential collisions, while stay close to their co-workers or group members to conduct the activity collaboratively. In addition, workspaces, where workers locate and move, are typically defined by specific activities, which will indicate their potential destination. Therefore, the specific contextual features considered in this study include neighbor position, working group information, and distance from potential destination.

Neighbor position. Worker behavior can be influenced when they interact with other entities, especially with their neighbors. Different from previous studies that use occupancy map to represent the existence of other entities (Alahi et al. 2016; Tang et al. 2019), we directly use neighbor position information as one contextual feature to capture the temporal dynamics of neighbor's movement. Note that, to ensure features in different scenarios have the same dimension, we only consider the position of entity's nearest neighbor. It is reasonable because an entity is more likely to be affected by others who are spatially closer to them.

Working group information. The working group information, i.e., the relationship between an entity and its neighbor in terms of whether they belonging to the same working group, also influences entity movement. For instance, workers tend to avoid entities that are not in the same group to prevent potential conflict, while they tend to have similar movement patterns with their co-workers. Therefore, the group relationship between an entity and its nearest neighbor is considered as a second contextual feature. If they belong to the same working group, the feature value is 1, otherwise, it is 0. The group information can be obtained using the LSTM-based method created in our previous study (Cai et al. 2019) by integrating positional and attentional cues on the jobsite.

Distance from potential destination. The distance between construction workers and the potential destination is considered as a third contextual feature because construction worker behavior is typically goal-based and influenced by their involved activities. In this study, we simplify the potential destination as prior knowledge. In practice, it can be inferred from the involved activity and the corresponding workspace, where ongoing activity can be automatically learned from visual data and workspace can be extracted from site layout or BIM model.

3.1.2 LSTM-based trajectory prediction

This study adopts the LSTM encoder-decoder architecture (Sutskever et al. 2014) (see Fig. 2), which allows the generation of a sequence with arbitrary length from a given sequence. In the method, the entity position during observation time and the corresponding contextual features are concatenated into time-series feature vectors and fed in LSTM encoder. The encoder outputs an encoded vector that incorporates the information from the observed movements and jobsite context. The encoded vector is used to initialize the states in LSTM decoder which allows the integration of previous information for better prediction of future trajectory. The hidden state of each LSTM cell in the decoder is considered as the output of the corresponding time step, which is further fed into a dense layer with two nodes. The dense layer performs a linear regression, resulting in estimated positions from time T_{obs+1} to $T_{obs+pred}$. The network is trained to minimize one of the most commonly used loss functions, i.e., mean squared error (MSE) loss function (Lee 2007). The MSE is computed as $MSE = \sum_{i=1}^{N}(\hat{Y}_i - Y_i)^2/N$, where N is the size of training data, $\hat{Y}_i$ and Y_i are the predicted and actual i^{th} trajectory.

3.2 Robot Path Planning

Robots must avoid construction workers to ensure safe operation on construction sites. In this regard, Construction workers are treated as obstacles for robot path planning. As such, robots can avoid potential collisions with workers who are moving and conducting a variety of tasks along the trajectory. We adopt a hierarchical planning approach which includes global and local planning. The global planner is used to find an optimal collision-free path from the start to the goal without considering differential or dynamic constraints. In the local planning stage, the local trajectory tries to smooth path with dynamic constraints and stay close to the global path.

The A* algorithm is used as the global planner in this study, which was developed by Hart et al. (1968). The algorithm is an improvement of the Dijkstra's algorithm (Dijkstra 1959) designated to find the shortest path with high-efficiency. A heuristic function $h(n)$ is used to direct the robot toward the goal position. The h function acts as a critical role in the performance of the A* algorithm. In this study, the Manhattan distance heuristic function is defined in Eq. (1) to calculate distance from any node, n (x_n, y_n), to the goal, g (x_g, y_g) in the graph.

$$h(x_n, y_n) = |x_n - x_a| + |y_n - y_a| \tag{1}$$

The search cost is defined in Eq. (2), where $g(n)$ represents the cost from starting point to any node n, $f(n)$ is the total cost. The objective is to minimize the total cost. Using this equation, the A∗ algorithm will direct toward the goal and try to find the most direct path.

$$f(n) = g(n) + h(n) \tag{2}$$

Given a global path to follow, the local planner produces linear velocity v and angular velocity w for the robot. The Dynamic Window Approach (DWA) algorithm proposed by Fox et al. (1997) is used for local robot planning. Constraints regarding robot dynamics (e.g., the maximum velocity) are considered in the DWA algorithm. The algorithm directly samples velocities in the robot's control space within a given time window. The bad velocity samples that intersect with an obstacle are eliminated. The DWA will find an optimal pair of (v, w) for the robot based on its local condition by maximizing a cost function that depends on (1) proximity to the global path, (2) proximity to the goal, and (3) proximity to obstacles. Eq. (3) gives the weighted cost function to find the optimal trajectory. The trajectory with minimal cost is selected.

$$\text{cost} = \alpha f_a(v,w) + \beta f_d(v,w) + \gamma f_c(v,w) \tag{3}$$

Where $f_a(v, w)$ represents the distance between global path and the endpoint of the trajectory, $f_d(v, w)$ is the distance to the goal from the endpoint of the trajectory, $f_c(v, w)$ is the grid cell costs along the trajectory, α is the weight representing that how much the controller should stay close to the global path, β is the weight for how much the robot should attempt to reach the goal, and γ is the weight for how much the robot should attempt to avoid obstacles.

4 IMPLEMENTATION AND RESULTS

In the proposed framework, the moving workers are treated as obstacles for robots in a dynamic environment. The predicted worker trajectories obtained in module 1 (Section 3.1) can be used to determine the potential locations of obstacles for robot path planning (Section 3.2). We conducted two experiments to validate each module of the proposed method and analyzed the results. Note that, the worker trajectory prediction and robot path planning method were evaluated separately in this study. Specifically, field videos were collected to evaluate the performance of worker trajectory prediction. A robot simulation platform was developed to demonstrate the robot path planning method. Using the robot simulation to replicate the scenarios in real construction sites is justified in two aspects. First, with the simulation platform, various construction scenarios can be arranged for testing, which allows us to fully assess the performance of the robot path planning method. The workers' trajectories can also be simulated in the robot simulation platform to reflect different construction activities in real world. The potential safety issue in real construction sites prevents such experimentation. Second, the simulated scenario is built based on photos and videos from real construction sites to ensure its authenticity and validity.

4.1 Implementation

We collected ten construction videos from three projects to validate the proposed worker trajectory prediction method: a hospital construction project from the Hospital Construction (2019), and two teaching building projects videotaped by authors. The videos consist of a total of 84 workers in different construction scenarios, conducting various activities in different working groups. All videos were down-sampled to 2fps, similar to other studies (Alahi et al. 2016; Xue et al. 2018) on video-based pedestrian trajectory prediction. Figure 3 illustrates some images from the dataset. Visual data were pre-processed to extract entity positions and contextual features, serving as inputs of the prediction model.

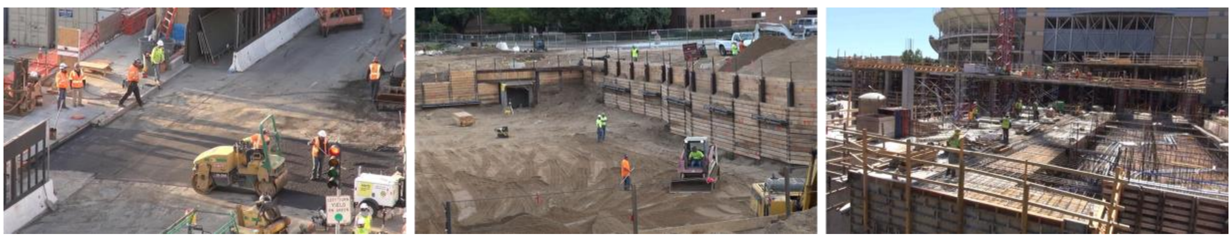

Figure 3: Sample images.

In this study, we observed worker movements and contextual information for 3s (i.e., 6 frames) and predicted for 5s (i.e., 10 frames), consistent with relevant studies (Alahi et al. 2016; Xue et al. 2018) on pedestrian trajectory prediction. The proposed method was implemented on a desktop with 3.6GHz Intel i9-9900K CPU, 32GB, and NVIDIA GeForce GTX 2080 Ti GPU using Keras library on top of Tensorflow platform. The dataset was randomly split into training set (80%), validation set (10%), and testing set (10%). The network was trained with *Adam* optimizer (Kingma and Ba 2015), with a learning rate of 0.001, batch size of 20, and dropout of 0.5.

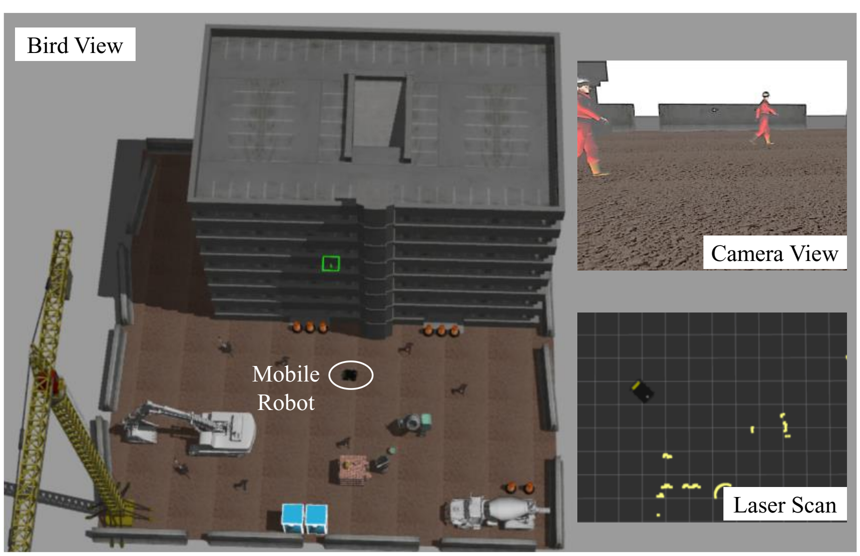

Figure 4: Overview of the robot simulation platform.

The second set of experiments was conducted in the robot simulation platform, where a husky robot (Clearpath Robotics 2013) was simulated at a construction site. The robot is equipped with LMS1xx 2D laser and camera sensors. The laser is used for Simultaneous Localization and Mapping (SLAM) to create a 2-D occupancy grid map. The occupancy map is then used for path planning. The onboard camera is used to capture the surrounding environment. Figure 4 shows the experiment setup. The platform is built on a laptop running Ubuntu 16.04 with Intel i7-4900MQ 2.8GHz CPU processor, NVIDIA Quadro K2100M, and 16G RAM. The distribution of ROS is Kinetic, and the version of Gazebo is 7.16.0.

4.2 Results

4.2.1 Results for trajectory prediction

The result of the proposed trajectory prediction method was compared with that obtained from two other LSTM-based models: (1) a standard LSTM model (Saleh et al. 2018) that predicts location one-step-ahead based on object positions and achieves multi-step prediction by running the model recursively; and (2) a seq2seq model with the same architecture as the proposed method but only considering entity movements without contextual information. Figure 5 illustrates two example results of trajectory prediction. The proposed method results in the predicted trajectory (blue line) that is closer to the ground truth (red line). The position-based model (yellow line) leads to a trajectory with a slightly larger discrepancy compared to the proposed method, whereas the position-based recursive model (green line) has the largest discrepancy from the ground truth.

Ground truth — Position (recursive) — Position (seq2seq) — Position + context (seq2seq)

Figure 5: Example results for trajectory prediction.

The performance is further evaluated quantitatively using two metrics, i.e., final displacement error (FDE) and average displacement error (ADE), which are most widely used to evaluate performance of trajectory prediction (Alahi et al. 2016; Xue et al. 2018). FDE measures the average distance between the final predicted location and the final actual location of all workers, while ADE measures the average distance between all locations along the predicted trajectories and the actual trajectories. Table 1 lists the quantitative results of trajectory prediction using three models. The recursive model leads to much larger FDE and ADE compared to seq2seq approaches due to the error accumulation when predicting trajectory over multiple time steps. The proposed context-aware seq2seq model achieves the smallest FDE among all models, despite a slightly larger ADE compared to the position-based approach. The possible reason is that by incorporating contextual information, especially the potential destination information, the model is trained to adapt more to the long-term goal, rather than accurately predicting each step.

Table 1: Trajectory prediction results of three models.

Model	FDE (pixel)	ADE (pixel)
1. Position (recursive)	28.32	15.41
2. Position (seq2seq)	9.00	**8.95**
3. Position +Context (seq2seq) (**proposed**)	**8.51**	9.00

4.2.2 Results for robot path planning

Table 2 shows the performance of the robot path planning method. The path planning method is demonstrated to be efficient given an average 0.201s planning time. The standard error of planning time is small, suggesting that planning time is stable across different simulated cases. The execution time is mainly dependent on the distance from start to the goal and obstacles between them. In addition, all the 15 simulated cases successfully generate paths without collision with construction workers and other obstacles.

Table 2: Performance of the robot path planning method.

Number of simulation cases	Planning time (second)		Execution time (second)		Number of cases without collision
	Average	Standard error	Average	Standard error	
15	0.201	0.004	35.147	11.025	15

Figure 6 shows representative examples to demonstrate robot path planning based on the predicted worker's trajectory. As indicated, the proposed global path is efficient, safe, and collision-free. Most importantly, the mobile robot can navigate to the goal without collision with construction workers. We also present two exemplary results without considering worker movement. As indicated in Figure 7, the global paths intersect with workers' potential trajectories, which may lead to the struck-by accident. Thus, it is of great importance to integrate worker trajectory prediction with robot path planning to effectively avoid human-robot collision on the jobsites.

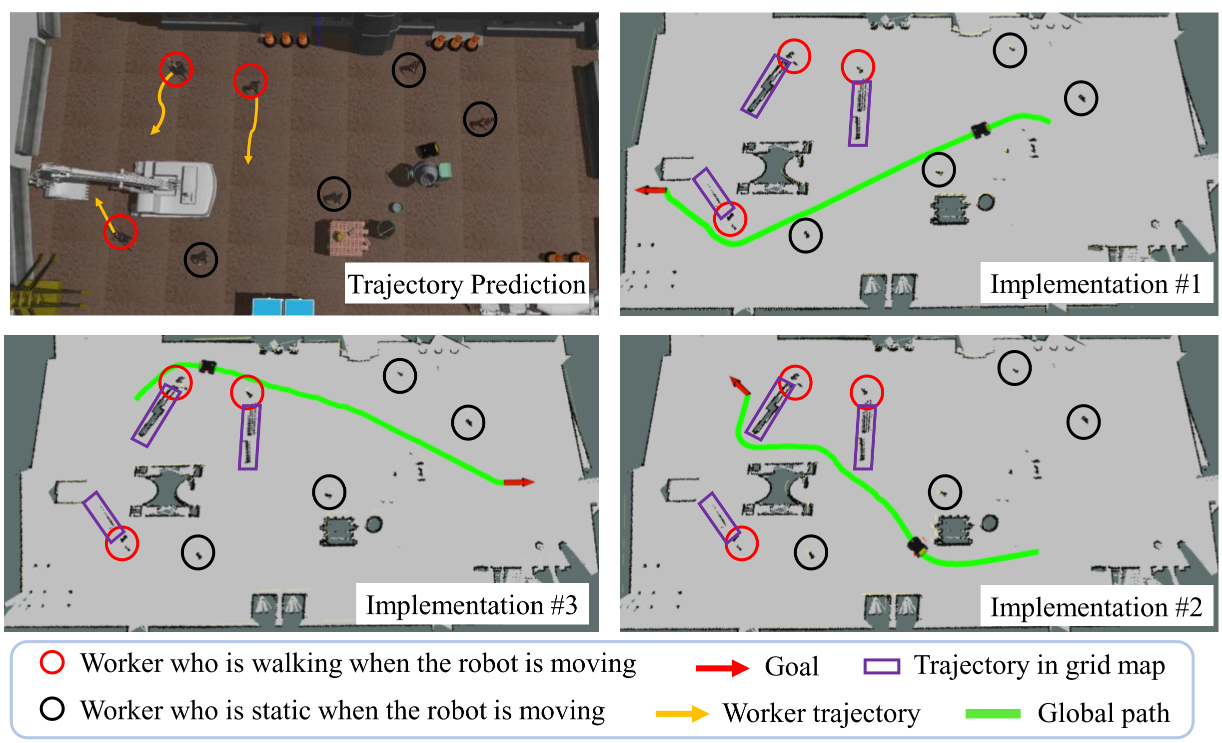

Figure 6: Examples of generated path considering worker movement.

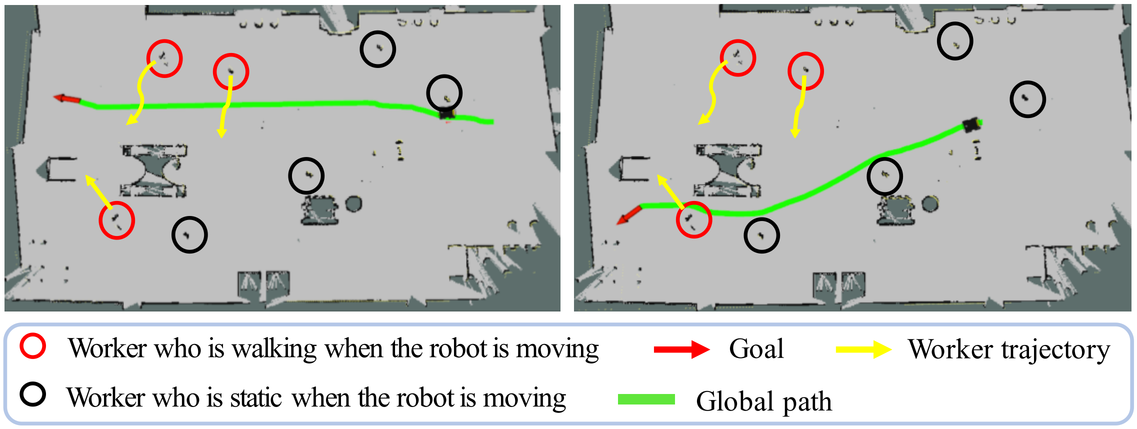

Figure 7: Examples of generated path without considering worker movement.

5 CONCLUSIONS

Autonomous construction robots have been deemed to augment and enhance efficiency as well as improve safety by reducing human errors. The overarching goal of this research is to develop a system that can navigate robots safely and efficiently in dynamic and unstructured construction sites with the existence of moving workers. To this end, a context-aware LSTM model is proposed for trajectory prediction on construction sites. A robot path planning algorithm that integrates workers' predict trajectories is designed to navigate robots on unstructured construction sites. Experiments were conducted using field video data and robot simulation platform. The results indicate that the proposed context-aware seq2seq model achieves the smallest final displacement error among the three investigated approaches. The efficiency of the robot planning method is manifested by the simulated experiment because the approach achieves a small planning time and generates paths without collision with workers and other obstacles. The value of the proposed method is highlighted by comparing to the state-of-the-art in collision-free path planning at construction sites. Different from the GPS-based planning method proposed in (Kim et al. 2003), our method is not affected by the quality of GPS signal. The proposed method also considers construction contextual information including entity interactions and involved activity information, which was ignored in previous studies (Chang et al. 2012; Kayhani et al. 2018). This study has the potential to complement current practice in construction safety. For instance, the proposed method can be integrated into construction proximity warning and alert system (Teizer et al. 2010) by providing predicted workers' trajectories. As such, the system can achieve more reliable and accurate alert information.

It should be noted that there remain several limitations that deserve further research efforts. First, while the robot simulation platform allows us to validate the proposed method, we necessarily miss out on the context and complexity in the real world. Our ongoing research is building the robot platform to collect data in real construction sites. Second, this study assumes a flat ground surface which may not be the case in real situations. Future study is needed to address robot path planning on the uneven ground surface. In this case, terrain traversability of the robot plays a critical role in finding an optimal path. In addition, algorithms should be developed to reconstruct an uneven environment for future path planning. Third, human trajectory was modeled as static obstacles for robots without considering the dynamic relationship between human and robots. In the future, it is indispensable to investigate more complex interactions to improve efficiency, fluency, and adaptiveness of human-robot cooperation. Finally, human trajectory prediction and robot path planning were validated in real experiments and the robot simulation platforms, respectively. Future research will evaluate the performance of the entire workflow by collaborating with ongoing construction projects.

ACKNOWLEDGMENTS

This research was funded by the National Science Foundation (NSF) via Grant 1850008. The authors gratefully acknowledge NSF's support. Any opinions, findings, conclusions, and recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of NSF or the University of Tennessee, Knoxville.

REFERENCES

Alahi, A., K. Goel, V. Ramanathan, A. Robicquet, L. Fei-Fei, and S. Savarese. 2016. "Social LSTM: Human Trajectory Prediction in Crowded Spaces". In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, June 27th-30th, Las Vegas, USA,961–971.

Ali, M. S. A. D., N. R. Babu, and K. Varghese. 2005. "Collision Free Path Planning of Cooperative Crane Manipulators Using Genetic Algorithm". *Journal of Computing in Civil Engineering* 19(2):182–193.

Atyabi, A., and D. M. W. Powers. 2013. "Review of Classical and Heuristic-Based Navigation and Path Planning Approaches". *International Journal of Advancements in Computing Technology* 5(14):1–14.

Bogue, R. 2018. "What Are the Prospects for Robots in the Construction Industry?" *Industrial Robot* 45(1):1–6.

Cai, J., Y. Zhang, and H. Cai. 2019. "Two-Step Long Short-Term Memory Method for Identifying Construction Activities Through Positional and Attentional Cues." *Automation in Construction* 106:102886.

Cai, J., Y. Zhang, L. Yang, H. Cai, and S. Li. 2020. "A Context-Augmented Deep Learning Approach for Worker Trajectory Prediction on Unstructured and Dynamic Construction Sites". *Advanced Engineering Informatics* Under Review.

Chang, Y. C., W. H. Hung, and S. C. Kang. 2012. "A Fast Path Planning Method for Single and Dual Crane Erections". *Automation in Construction* 22:468–480.

Clearpath Robotics. 2013. "Husky-Unmanned Ground Vehicle". Technical Specifications, Clearpath Robotics, Kitcener, Ontario, Canada.

Dijkstra, E. W. 1959. "A Note on Two Problems in Connexion with Graphs". *Numerische Mathematik* 1(1):269-271.

Dong, C., H. Li, X. Luo, L. Ding, J. Siebert, and H. Luo. 2018. "Proactive Struck-by Risk Detection with Movement Patterns and Randomness". *Automation in Construction* 91:246–255.

Fox, D., W. Burgard, and S. Thrun. 1997. "The Dynamic Window Approach to Collision Avoidance". *IEEE Robotics and Automation Magazine* 4(1):23–33.

Hart, P. E., N. J. Nilsson, and B. Raphael. 1968. "A Formal Basis for the Heuristic Determination of Minimum Cost Paths". *IEEE Transactions on Systems Science and Cybernetics* 4(2):100–107.

Hermes, C., A. Barth, C. Wöhler, and F. Kummert. 2009. "Object Motion Analysis and Prediction in Stereo Image Sequences". In *8. Oldenburger 3D-Tage*, Oldenburg, Germany.

Kayhani, N., H. Taghaddos, and S. BehzadiPour. 2018. "Construction Equipment Collision-Free Path Planning Using Robotic Approach". In *ISARC 2018 - 35th International Symposium on Automation and Robotics in Construction and International AEC/FM Hackathon: The Future of Building Things*, July 20th-25th, Berlin, Germany, 1-6.

Kim, D., M. Liu, S. Lee, and V. R. Kamat. 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,* May 21st-24th, Banff, Canada. 982–988.

Kim, S. K., J. S. Russell, and K. J. Koo. 2003. "Construction Robot Path-Planning for Earthwork Operations". *Journal of Computing in Civil Engineering* 17(2):97–104.

Kingma, D. P., and J. Ba. 2015. "Adam: A Method for Stochastic Optimization". In *3rd International Conference on Learning Representations*, May 7th-9th, San Diego, USA.

Kooij, J. F. P., F. Flohr, E. A. I. Pool, and D. M. Gavrila. 2019. "Context-Based Path Prediction for Targets with Switching Dynamics". *International Journal of Computer Vision* 127(3):239–262.

Lavalle, S. M. 1998. "Rapidly-Exploring Random Trees: A New Tool for Path Planning". Technical Report No. TR 98-11, Department of Computer Science, Iowa State University, Ames, Iowa .

Lee, T. 2007. "Loss Functions in Time Series Forecasting". *International Encyclopedia of the Social Sciences* 495-502.

Liu, T., P. Bahl, and I. Chlamtac. 1998. "Mobility Modeling, Location Tracking, and Trajectory Prediction in Wireless ATM Networks". *IEEE Journal on Selected Areas in Communications* 16(6):922–935.

Mac, T. T., C. Copot, D. T. Tran, and R. De Keyser. 2016. "Heuristic Approaches in Robot Path Planning: A Survey". *Robotics and Autonomous Systems* 86:13–28.

Manzo, J., F. Manzo, and R. Bruno. 2018. "The Potential Economic Consequences of a Highly Automated Construction Industry: What If Construction Becomes the Next Manufacturing". Midwest Economic Policy Institute.

Masehian, E., and D. Sedighizadeh. 2007. "Classic and Heuristic Approaches in Robot Motion Planning - a Chronological Review". *World Academy of Science, Engineering and Technology* 23(5):101–106.

Brossog, M., M. Bornschlegl, and J. Franke. 2015. "Reducing the Energy Consumption of Industrial Robots in Manufacturing Systems". *International Journal of Advanced Manufacturing Technology* 78(5–8):1315–1328.

Rashid, K. M., S. Datta, A. H. Behzadan, and R. Hasan. 2018. "Risk-Incorporated Trajectory Prediction to Prevent Contact Collisions on Construction Sites". *Journal of Construction Engineering and Project Management* 8(1):10–21.

Rudenko, A., L. Palmieri, and K. O. Arras. 2018. "Joint Long-Term Prediction of Human Motion Using a Planning-Based Social Force Approach". In *Proceedings - IEEE International Conference on Robotics and Automation*, May 20th-25th, Brisbane, Australia, 4571–4577.

Saleh, K., M. Hossny, and S. Nahavandi. 2018. "Intent Prediction of Pedestrians via Motion Trajectories Using Stacked Recurrent Neural Networks". *IEEE Transactions on Intelligent Vehicles* 3(4):414–424.

Soltani, A. R., H. Tawfik, J. Y. Goulermas, and T. Fernando. 2002. "Path Planning in Construction Sites: Performance Evaluation of the Dijkstra, A*, and GA Search Algorithms". *Advanced Engineering Informatics* 16(4):291–303.

Stentz, A. 1994. "Optimal and Efficient Path Planning for Partially-Known Environments". In *Proceedings - IEEE International Conference on Robotics and Automation*, May 8th-13th, San Diego, USA, 3310–3317.

Sutskever, I., O. Vinyals, and Q. V. Le. 2014. "Sequence to Sequence Learning with Neural Networks". *Advances in Neural Information Processing Systems* 3104–3112.

Tang, S., M. Golparvar-Fard, M. Naphade, and M. M. Gopalakrishna. 2019. "Video-Based Activity Forecasting for Construction Safety Monitoring Use Cases". In *Computing in Civil Engineering 2019: Smart Cities, Sustainability, and Resilience*, June 17th-19th, Atlanta, USA, 204–210.

Teizer, J., B. S. Allread, C. E. Fullerton, and J. Hinze. 2010. "Autonomous Pro-active Real-Time Construction Worker and Equipment Operator Proximity Safety Alert System". *Automation in Construction* 19(5):630–640.

The Robot Report Staff. 2019. SpotWalk Comes to Construction in HoloBuilder, Boston Dynamics Teamup. https://www.therobotreport.com/spotwalk-gathers-construction-data-holobuilder-boston-dynamics, accessed 14th April 2020.

Xue, H., D. Q. Huynh, and M. Reynolds. 2018. "SS-LSTM: A Hierarchical LSTM Model for Pedestrian Trajectory Prediction". In *Proceedings - 2018 IEEE Winter Conference on Applications of Computer Vision*, March 12th-15th, Lake Tahoe, USA, 1186–1194.

Hospital Construction. 2019. Hospital Series Weekly Overall Construction Time-Lapses. https://www.youtube.com/channel/UCEKwrM78pRv8WRcKvZNtE1w, accessed 14th March 2020.

Zhu, Z., M. W. Park, C. Koch, M. Soltani, A. Hammad, and K. Davari. 2016. "Predicting Movements of Onsite Workers and Mobile Equipment for Enhancing Construction Site Safety". *Automation in Construction* 68:95-101.

Ziebart, B. D., N. Ratliff, G. Gallagher, C. Mertz, K. Peterson, J. A. Bagnell, M. Hebert, A. K. Dey, and S. Srinivas. 2009. "Planning-Based Prediction for Pedestrians". In *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, October 11th-15th, St Louis, USA, 3931–3936.

AUTHOR BIOGRAPHIES

DA HU is a PhD student in the Department of Civil and Environmental Engineering at the University of Tennessee, Knoxville. He holds a master's degree in Civil Engineering from Texas Tech University and a master's degree in Disaster Prevention and Reduction Engineering and Protective Engineering from the University of Chinese Academy of Sciences. His research interests include automation in construction, construction robotics, and disaster response. His e-mail address is dhu5@vols.utk.edu.

JIANNAN CAI is an Assistant Professor in the Department of Construction Science at the University of Texas at San Antonio. She holds a Ph.D. degree in Civil Engineering from Purdue University and a M.S. degree in Civil Engineering from Tongji University. Her research interests include sensing, computer vision, and artificial intelligence in construction automation and robotics. Her e-mail address is jiannan.cai@utsa.edu.

YUQING HU is an Assistant Professor in the Department of Architecture Engineering at Pennsylvania State University. Her research interests lie in using Building Information Modeling (BIM) and graph-based artificial intelligence to improve design and construction automation. Specifically, her current research focuses on using these methods to multi-disciplinary design coordination. She graduated from Georgia Institute of Technology with a Ph.D. degree in Building Construction and a master's degree in computational science & Engineering. Her e−mail address is yfh5204@psu.edu.

SHUAI LI is an assistant professor in the Department of Civil and Environmental Engineering at the University of Tennessee, Knoxville. He graduated from Purdue University with a Ph.D. degree in Civil Engineering, a master's degree in industrial engineering, and a master's degree in economics. He conducts fundamental research in sensing, automation, robotics, and visualization, and applies the techniques in numerous applications, including smart construction, disaster response, and manufacturing. His e-mail address is sli48@utk.edu.