Automatic Crane-Related Workflow Control for Nuclear Plant Outages through Computer Vision and Simulation

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Abstract

Nuclear power plant (NPP) outages involve a large number of maintenance activities with a tight schedule and zero-tolerance for accidents. Outage projects thus need real-time control to ensure safety and productivity. During outages, crane lifting is critical for outage control and risk management. An effective outage control method should monitor detailed interactions between human and workspaces, and streamline the workflows of cranes to control both productivity and risks. Unfortunately, current approaches of outage control rely heavily on tedious and error-prone manual inspection that can hardly achieve detailed spatiotemporal monitoring.

This paper presents an automated outage control framework that enables detailed human behavior analysis, automatic comparison of as-planned and actual crane-related operations, and effective decision-making for crane-related workflow control. In this framework, a real-time human tracking algorithm uses 2D/3D imagery to automatically derive the status of workspaces (e.g., waiting, active). Then a change-analysis algorithm detects and diagnoses differences between as-is workflow information against as-planned schedules, and thus enables field managers to implement a close-loop outage control. Preliminary results indicate the potential of this integrated outage control in improving the safety, productivity, and quality of outages, as well as outage project planning.

Keywords

Nuclear power plant; Outages; Crane; Workflow control; Computer vision; Simulation

1 Introduction

In the United States, many nuclear power plants (NPPs) were built for more than 40 years [1] and they require regular maintenance. For example, the management company of Palo Verde Nuclear Power Plant needs to shut down each reactor every 18 months to refuel and repair degraded infrastructures. Such processes are called "outages" at NPPs. NPP refueling outages are challenging because they require tracking and coordinating thousands of activities in a short span of time, usually between twenty to thirty days. Moreover, any delays in the NPP outage processes will cause significant economic losses. If the Palo Verde Nuclear Power Plant is shut down for one more day because of a delay from an outage, the deficiency of power would lead to one to two million dollars' loss for the energy company. Therefore, to prepare for an NPP outage, an outage group in the Work Management department spends months on the outage planning, together with the occasionally long range plans that projects many years into the future. NPP outages require a significant supplemental workforce that consists of thousands of contract personnel, which increases the complexity of communication and information flows [2]. Other challenges, including scheduling, work group coordination, nuclear safety concerns arising from different system configurations, and resource allocation issues, can create delays and schedule overruns, driving up outage costs [3]. All these features of the NPP outage process appeal for an efficient and effective workflow control framework to reduce its cost, duration, labor, and accident rates.

With outage processes, crane-related tasks are critical for maintaining the safety and productivity of related workflows. Crane related tasks often involve lifts of over 30 tons, which are defined as "very heavy lifts" that can significantly increase the damages caused by crane-related accidents [1]. In addition, crane activities often require large moving spaces, increasing the difficulty of coordinating different labors, workspaces and tasks in spatial and temporal domains. Finally, a crane is usually a shared resource for multiple tasks involving different groups of workers, which creates a higher chance of encountering problems of communication, collaboration, and scheduling. Any accidents or delays related to crane are likely to propagate to relevant tasks, affecting the safety and productivity of the entire workflow. Therefore, crane-related tasks are critical for the NPP outage workflow control.

Crane-related safety and productivity are heavily discussed topics in the domain of construction engineering and management. For example, researchers tried to solve this problem by predicting and planning the moving path of the lifted object in order to prevent people from injury under its path [4,5]. Admittedly, previous studies are necessary but cannot handle the problems faced by the nuclear industry. People from both academy and industry still lack of an efficient and effective method to monitor and control human behavior in order to reduce crane-related errors and accidents caused by human factors, which is the major reason of crane-related accidents and near-misses in NPP. Such a deficiency is caused by two reasons. First, people from nuclear industry still lack a systematical understanding about how the features of NPP outage could influence crane-related anomalies and how such anomalies could influence the downstream tasks in NPP outage processes [1]. Any human error in crane-related construction workflows could cause delays that impact productivity and accident rates and such anomaly propagation effect will be amplified by extremely limited time, space, and critical facility resources (e.g. cranes) on the NPP outage jobsite. Second, NPP outages need an efficient and reliable data collection method for human behavior monitoring. In real-world NPP outages, the management team suffers from large amounts of manual data collection and analysis to monitor and maintain the safety and productivity of crane-related tasks and workflows [2]. As lengthy manual data collection and processing could seriously delay the information needed for timely decision-making, manual approaches for crane-related safety and productivity diagnosis cannot meet the requirements of efficient and effective workflow control in outages.

The contribution of this research address this gap through integration of computer-vision-based human behavior monitoring and simulation models that predict how anomalies in workflows escalate into delays and risks. A workflow control methodology that integrates real-time human behavior monitoring and decision making could reduce the labor-intensive work of maintaining the safety of crane-related tasks. The proposed framework consists of two parts. The task-duration anomaly propagation modeling will provide the decision-making methodology according to the as-planned workflow and the monitoring data. The computer-vision based human behavior monitoring algorithm will identify delays of tasks and the anomalies happening on the job site based on the as-planned workflow. This proposed methodology will help prevent the accidents in advance and quickly identify and diagnose the deviations between as-planned and as-is workflows for decision support.

2 Literature Review

Because of the huge size, mass and range of motion of cranes, any anomalies in crane-related activities could cause catastrophic consequences, such as injuries and fatalities. Beavers et al [6] determine the proximal causes and contributing physical factors of accidents by analyzing the Occupational Safety and Health Administration's (OSHA) case files during the years of 1997–2003. However, this approach only analyzed the direct causes of crane-related fatalities (e.g. falls, struck by load, and electrocution) instead of various indirect influential or casual factors (e.g. human misbehaviors, equipment quality issues, etc.). Such direct causal analysis cannot provide suggested adjustments about indirect factors for reducing the high fatality rates related to crane activities. In order to understand the causal factors of the accidents, the authors analyzed the newest accident cases of Fatality and Catastrophe Investigation Summaries from OSHA [7]. In addition, the authors determined the influential tree of an accident to see whether it has multiple indirect causal factors. The result of the influential tree analysis shows that 60% of the accidents have multiple indirect factors in their influential trees. These results indicate that on construction job sites, "domino effects" could enable small anomalies to trigger severe accidents [8]. In addition, human behavior is directly or indirectly related to more than 80% of the reported crane-related accidents in OSHA records.

Currently, few studies focus on the outage control of nuclear plants. Germain et al. [2] stated that the deficiency of communication and collaboration is due to large numbers of personnel and activities on outage job sites. That fact argues for the concept of "advanced outage control center (AOCC)," which is specifically designed to maximize the usefulness of communication and collaboration technologies for outage coordination and problem resolution. However, using the proposed AOCC cannot completely solve the problem of automatically and rapidly detecting the detailed deviation between as-is and as-planned workflows during outage, because detailed spatiotemporal data comparison and analysis is still manual in the current AOCC conceptual framework. Without efficient deviation detection between as-planned and actual workflows, diagnosing indirect impacts of propagative deviations is unrealistic. A report from NEUNG analyzed all accidents related to cranes in all nuclear plant in the U.S. from 1968 to 2002 [1]. According this report, the major reason that caused crane-related accidents in NPP is human behavior, which causes over 80 percent of the accidents. That report, which is specific to NPPs, corroborates the more general crane-related accident database of OSHA.

Researchers have developed many approaches to improve the safety and productivity of crane-related tasks. Tracking the position of crane loads enables nearby workers to keep away from zones in danger of load falls. Fang et al [5] used an inertial measurement unit (IMU) module for measuring load orientation and then predict the load sway trajectories. Yang et al. [9] demonstrated the use of a surveillance camera for measuring the jib angle and the trolley position of a tower crane during a work day. In construction projects, failing to acquire timely, detailed, accurate spatial information for decision-making can cause low project quality, low productivity, and accidents. Computer vision has drawn attention because it is useful for automated and continuous monitoring of construction sites. Seo et al [10] states that technical challenges exist for achieving efficient and effective safety and health monitoring for construction projects using computer vision techniques. These challenges include sufficient high-quality imagery data collection, automatic scene understanding, and activity recognition of equipment/workers. In the domain of human behavior modeling and analysis, Shappell and Wiegmann [11] stated that studies should focus more on human misbehaviors if accidents are to be further reduced, because human misbehavior occupies a significant part in accident causation. Garret et al [12] proposed a general human misbehavior framework originally developed and tested as a tool for investigating and analyzing the human causes of accidents. That research also emphasizes the importance of effective investigation in safety.

However, previous studies have not provided an unified framework for improving the safety and productivity of crane-related tasks considering human behavior and propagations of various errors. In busy and safety-sensitive NPP outages, such a framework is important for timely decision support. In outage processes, perpetuation of errors, delays and other propagative factors will be enlarged by the extremely limited time, space, labor, and availability of cranes and relevant resources. Any delays in an outage process may increase the worker's stress, which increases the misbehavior rate and causes accidents [13]. As a result, the workflow control system should be able to monitor crane-related human behaviors to discover the anomalies as early as possible, while limiting the propagation of anomalies according to the as-designed workflow and real-time monitoring data.

3 Task-duration Anomaly Propagation Model

In order to prevent possible anomalies from influencing the productivity of the entire workflow, researchers and people from industry have applied different methods involving training, planning, and inspection to prevent human misbehaviors at the front end [14] to stabilize the workflow. Such approaches bring a huge amount of manual work in the busy NPP outage projects and rely heavily on the experience of the management team, which is error-prone and inefficient. Therefore, it is very important to have a sensor-based workflow control system. This proposed computer-vision based workflow control system first automatically identifies all anomalies, which are defined as any differences between as-is and as-planned workflow, on the jobsite. Then the system will identify critical anomalies which influence more tasks or causing severer delays to help project managers adjust the schedule in order to limit the influence of anomalies in a controllable range. In nuclear power plant outages, cranes are always a key resource that influences the scheduling of multiple tasks. As a result, crane-related tasks will be the major focus of this workflow control system.

The first step of workflow control is to generate a mathematical model that describes how a task duration anomaly will influence the schedule of other tasks in order to identify these critical anomalies. A task-duration-anomaly propagation model describes how an anomaly in one task influences the starting time of other tasks. This model will show the critical tasks whose duration will possibly influence the productivity of the entire workflow, which provides a mathematical model of real-time decision making for scheduling and resource allocation. In this section, the authors identified three types of basic relationship types between tasks that repeatedly appear in outage projects: Linear, Co-prerequisite, and Resource sharing. A task-duration anomaly propagation model can help the project manager to understand the most influential tasks after an anomaly is discovered, thus optimizing decision-making.

3.1 Relationship Type 1: Chain

Figure 1 shows the structure of tasks that follow the "Chain" relationship. The authors define the duration of Task 1 as D_1, which follows the normal distribution

$N(T_1, \sigma_1^2)$ and so on. Therefore, the finish time of this workflow equals $D_1 + D_2 + D_3$ which still follows the normal distribution:

$$N(T_1 + T_2 + T_3, \sigma_1^2 + \sigma_2^2 + \sigma_3^2) \tag{1}$$

As a result, all tasks that have a chain relationship with each other can be combined into a new task when scheduling.

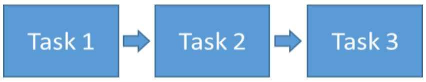

Figure 1. Structure of tasks that follow "Chain" relationship

3.2 Relationship Type 2: Co-prerequisite

Figure 2 shows a structure of tasks that follow the "Co-prerequisite" relationship. This is a very typical critical path problem. However, outage projects often have a very busy schedule. The float of the non-critical activities is usually very small. The authors define the duration of Task 1 as D_1, which follows the normal distribution $N(T_1, \sigma_1^2)$ and so on: $D_1{:}\,N(T_1, \sigma_1^2)$, $D_2{:}\,N(T_2, \sigma_2^2)$, $D_3{:}\,N(T_3, \sigma_3^2)$. The finish time of this workflow equals:

$$\begin{cases} D_1 + D_3{:}\ \mathrm{N}(T_1 + T_3, \sigma_1^2 + \sigma_3^2),\ \text{if } D_1 \geq D_2 & (2) \\ D_2 + D_3{:}\ \mathrm{N}(T_2 + T_3, \sigma_2^2 + \sigma_3^2),\ \text{if } D_1 < D_2 & (3) \end{cases}$$

In order to identify the probability of (2) happening, we have:

$$P(\,D_1 \geq D_2) = P(D_1 - D_2 \geq 0) \tag{4}$$

and $D_1 - D_2$ follows:

$$N(T_1 - T_2, \sigma_1^2 + \sigma_2^2) \tag{5}$$

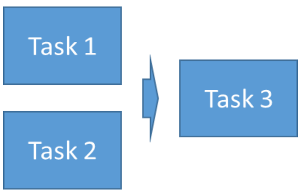

Figure 2. Structure of tasks that follow "Co-prerequisite" relationship

Equation (5) enables us to calculate the probability of changing of critical path. In outage projects, the floats (or slacks) of tasks not on the critical path are usually small. A slight delay of tasks that have a Co-prerequisite relationship with tasks on the critical path (most likely crane-related tasks) may cause the critical path to change and result in hardly predictable durations of the entire workflow.

3.3 Relationship Type 3: Resource Sharing

Figure 3 shows a structure of tasks that follows "Resource sharing" relationship. Tasks with sharing resources cannot be processed at the same time. The tasks with shared resources (Task 2A and Task 2B) follow the "first come, first serve" rule. Using similar signs to represent the duration of the tasks, the authors derived the finishing time of team A (finishing time of Task 3A) as:

$$\begin{cases} D_{1a} + D_{2a} + D_{3a}: \\ \mathrm{N}(T_{1a} + T_{2a} + T_{3a}, \sigma_{1a}^2 + \sigma_{2a}^2 + \sigma_{3a}^2), & (6) \\ \text{if } D_1 \leq D_2 \\ D_{1b} + D_{2b} + D_{2a} + D_{3a}: \\ \mathrm{N}(T_{1b} + T_{2b} + T_{2a} + T_{3a}, \sigma_{1b}^2 + \sigma_{2b}^2 + \sigma_{2a}^2 + \sigma_{3a}^2), & (7) \\ \text{if } D_1 > D_2 \end{cases}$$

Similarly, in order to identify the probability of having (6) happening, we have:

$$P(\,D_{1a} \leq D_{1b}) = P(D_{1a} - D_{1b} \leq 0) \tag{8}$$

and $D_{1a} - D_{1b}$ follows:

$$N(T_{1a} - T_{1b}, \sigma_{1a}^2 + \sigma_{1b}^2) \tag{9}$$

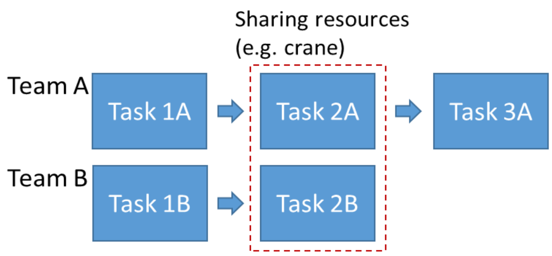

Figure 3. Structure of tasks that follow "Resource sharing" relationship

Resource sharing triggers uncertainties on the sequences of tasks, making the duration of the entire workflow unpredictable and causing the critical path to change. The proposed workflow control method will use simulation to understand the influence of the uncertainty of these "resource sharing" tasks and use computer vision technology to reduce their uncertainty in order to ensure the productivity of the entire workflow.

Table 1 shows the features of the proposed three types of relationships of tasks. In outage projects, tasks can have more complicated relationship types other than the three cases listed above. For example, two tasks can be executed at the same time but with a lower productivity (e.g. two tasks need material from the same tooling trailer). We will leave these more complicated relationship types for future researches.

Table 1. Features of different relationships between tasks

Relationship type	Changing critical path?	Changing task sequence?	Uncertainty bringing to the workflow
Chain	No	No	Small
Co-prerequisite	Yes	No	Medium
Resource sharing	Yes	Yes	Large

3.4 Simulation of the Task-Duration Anomaly Propagation Model

This research uses a simulation to show how different relation types of tasks influence the uncertainty of the duration of a workflow. Figure 4 shows the as-designed workflow of this simulation. First, the workers will be in the waiting area for completing the security check, which takes about 10 minutes. They have a 10% chance of failing the security check, causing a 15-minutes' security rework. After passing the security check, the team will work with a crane operator for about 30 minutes. On the other hand, another crane operation task on a different job site (defined as Site B) is also on the crane operator's schedule, and the crane operator will work on whichever site is ready first. As a result, when the crane operator is called for the box moving task, he or she needs to finish the task on Site B first if he already starts. This "first come, first serve" rule of the crane operator results in uncertainties in the workflow of Site A. The authors run the Monte Carlo simulation of the proposed workflow for 1,000 times, and Figure 5 shows the histogram of the workflow durations for this 1,000 simulations.

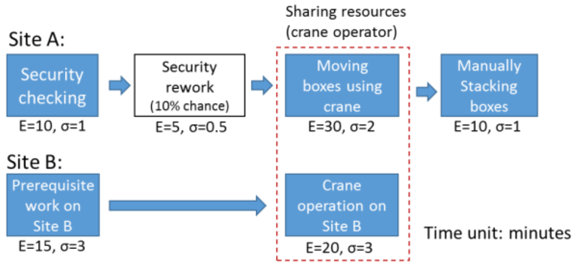

Figure 4. As-designed workflow of this indoor experiment

Ideally this workflow consists of tasks with "Chain" relationships between each other, which will finish in about 50 minutes and its standard deviation is 2.44 minutes. However, the simulation result shows that the average workflow duration is 56.0 minute with a standard deviation of 9.2 minutes and two peaks exist in the histogram. This result means that the "resource sharing" relationship between tasks and the possibility of rework can cause uncertainties to the duration of the entire workflow.

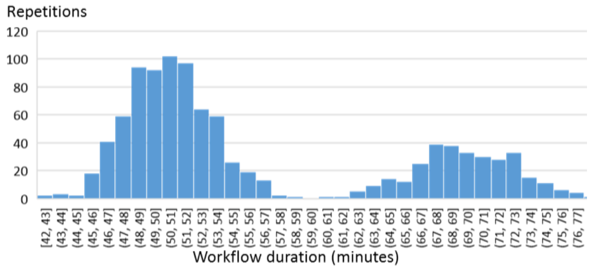

Figure 5. Histogram of the workflow duration

4 Computer-vision Based Real-time Outage Control

The previous section shows that the critical path method does not work well in outage projects because this method only works when the uncertainties of task durations is small. An effective outage control method should inspect the spatiotemporal details of human, workspace (including materials, equipment and environment), and all tasks related to cranes in order to reduce the uncertainties in the workflows. According to the causal factor analysis of OHSA report [7], human behavior is the most frequent cause of crane-related accidents. In outage projects, furthermore, human behavior become more complicated and unpredictable because of stress (nuclear safety), fatigue (working around the clock), and limited time and space (busy site and complicated environment). However, current approaches about outage control rely heavily on manual inspection and analysis, causing less-detailed or delayed job site information and inefficient diagnosis of deviations against the as-planned workflow. Such information deficiency brings difficulties to effective control of crane-related tasks. Furthermore, the systematic approach of human behavior monitoring and understanding in such a busy construction job site is not yet mature.

This method uses an algorithm that automatically detects real-time human activities in certain areas of a NPP outage job site, which can be compared against as-planned workflows in these areas for anomaly identification. This algorithm enables the real-time monitoring of human behavior in critical area of the jobsite, which helps identify the deviations between as-designed and as-is workflow while discovering misbehaviors as early as possible. This algorithm could reduce the uncertainty of the duration of the critical tasks in the workflow and thus expedite the decision-making by limiting the searching space of options.

This research will focus on monitoring human activity patterns in certain areas to reduce the uncertainties in the actual field workflows in a NPP outage project. A real-time and robust human tracking algorithm that uses 2D/3D imagery can automatically observe the critical areas that related to the tasks with co-prerequisite or resource sharing relationships. Then a deviation-detection algorithm will detect differences between as-is workflow information against as-planned workflows and human errors (e.g. queue jumping, chaos when distributing tools, idling around, etc.). Finally, a deviation assessment algorithm will diagnose the potential impacts of detected deviations according to the task-duration anomaly propagation model, thus enables a close-loop control of the workflow schedule. In this section, the authors will introduce two scenes of using computer vision techniques to reduce the uncertainties in various outage workflows.

4.1 Scene 1: Human Counting & Tracking

Outage management teams often struggle with understanding the real-time progress and transportation time of certain tasks. The human counting technique can identify each person, and then label all humans to different groups according to their visual features (e.g. hard hats with different colors) in the neighborhood of a crane, as shown in Figure 6. With this technique, the workflow control system will be able to estimate the transportation time of different groups of workers. Furthermore, human counting & tracking technique provides the possibility of identifying the collaboration status between teams (e.g. well collaborated, quarreling, having difficulties) by analyzing the trajectory of each individual worker, which can reduce the uncertainty caused by human behavior.

4.2 Scene 2: Waiting Line Monitoring

The crane is a critical resource that is always shared by multiple tasks. To predict the finishing time of tasks precisely, the workflow control system needs to monitor workers' activity at a relatively early stage of the workflow. Activities in nuclear power plant often involve strict clearance at its beginning, which leads to waiting lines at the checkpoints. A waiting-line monitoring technique thus enables the workflow control system to reduce the uncertainty of the duration of each task, shown in Figure 7. The waiting line monitoring technique will track each person in the waiting line area, acquiring the line-moving speed and whether people are jumping within a queue, which may indicate the level of experience and training of the team. Moreover, this technique will track the location of certain tools and equipment together with their users. With this information, the workflow control system will automatically identify possible anomalies in the workflow (e.g. shortage of tools, poor-trained team, and accidents), providing efficient indicators to estimate the task duration precisely.

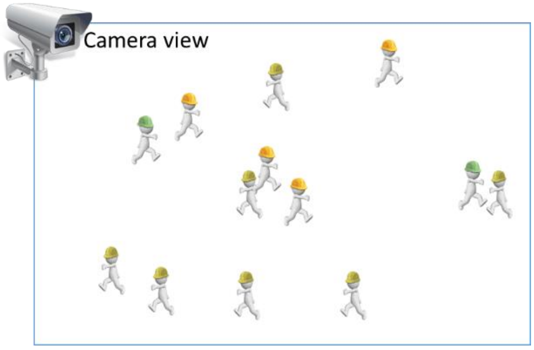

Figure 6. Scene of human counting & tracking

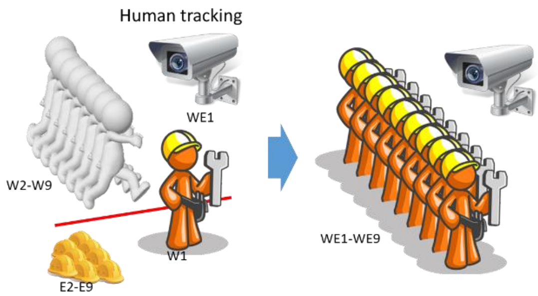

Figure 7. Scene of waiting line monitoring. W=Worker; E=Equipment; WE# = Worker with the No. # Equipment. Barcode or RFID can help identify the equipment.

Within the proposed framework, the 2D/3D imaging data of captured human behaviors of related personnel (e.g. video recording the job site activities related to the crane) will help the management team identify the pattern of anomalies that seems to commonly happen on the job site to trigger other accidents or delays. Also, a real-time and robust object tracking algorithm could use 2D/3D imagery to automatically derive the status of outage workspace, including as-built conditions of structures, materials and equipment, which will be helpful to support the workflow anomaly analyses. In addition, databases that record field activities (especially near-misses, activities that different from the plan, emergencies, etc) can restore the identified anomaly information and its propagation pattern instead of the raw 2D/3D field imageries, which saves data storage space while keeping the detailed jobsite activity information.

5 Experiment and Discussion

5.1 Experiment Setup

The authors designed an indoor experiment to observe how different types of task relationships influence the workflow duration and to test the as-is workflow capturing capability of the proposed workflow control system. This experiment involves three sites: one real site (Site B) in our lab and two virtual sites (Site A and Site C) in computer simulation. Participants will do activities mimicking different tasks in Site B; tasks in Site A and C as well as the transportations between sites will be simulated by people waiting outside the lab for a certain amount of time that is calculated by a simulation algorithm. Figure 8 shows the overall workflow in real and virtual sites. Each site will have the same workflow (shown in Table 2) and share three resources: crane, electricians, and mechanics.

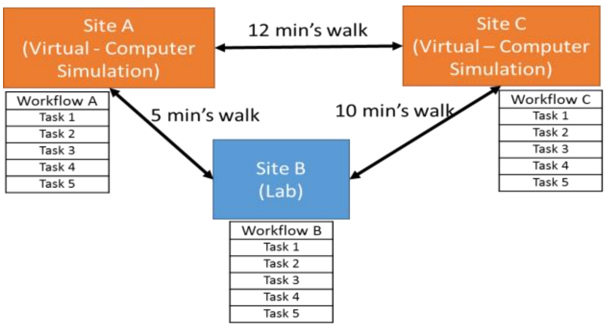

Figure 8. Overall workflow of the experiment

Table 2 Experiment workflow

No.	Task name	Resource
1	Remove the valve	Crane
2	De-term the motor operator	Electricians
3	Perform valve maintenance	Mechanics
4	Re-term the motor operator	Electricians
5	Re-install the valve	Crane

Figure 9 shows the layout of the experimental site (Site B) as well as the position of the sensors wherein light blue areas indicate the view of two Kinect V2 sensors. In site B, volunteers will walk slowly passing the Waiting line area mimicking the security check process and then move and stack some boxes in in the Working area. In this preliminary experiment, only one person will be in the view of the sensors at one time. This experiment uses both GigE Camera and Microsoft Kinect V2 as the sensors of collecting data (shown in Figure 10) for supporting computer vision and spatiotemporal analysis of the scene. Kinect sensors can easily track individual human and capture human action in a relatively short range (maximum 10 meters). On the other hand, GigE camera can monitor a large space with a fast data transfer rates up to 1000Mb/s. The combination of the advantages of these two types of sensors enables the precise tracking of human behavior in an indoor environment.

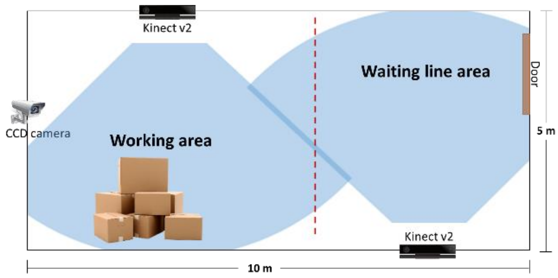

Figure 9. Layout of the experimental site

5.2 Experiment Results and Discussions

Currently, the proposed multi-visual sensor system can capture the human behaviors in the indoor environment. The system can also acquire the start/end time of each task by automatically counting the number of people in both working area and waiting line area in real-time. In the future, the authors plan to focus on estimating potential delays of future tasks according to the human behaviors of current tasks and predictive simulations by enabling multi-human tracking and human-behavior anomaly detection.

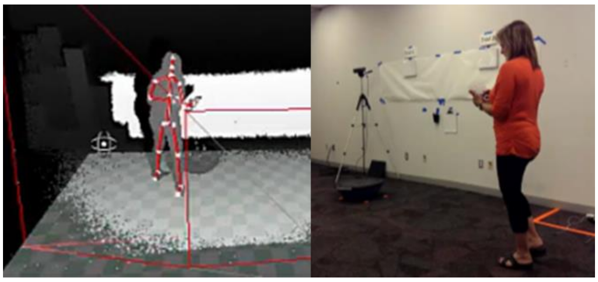

Figure 10. Collected Kinect 3D data (left) and video data (right)

In the indoor experiment, the authors observed that one communication mistake (the participant who represented crane did not inform other participants when it finished one of the critical tasks) delayed the overall workflow by 30%. This mistake influenced the starting time of 60% of the following tasks because many tasks are sharing the resource of crane. Due to the page limit, the complete analysis of the experiment will be in another publication. Overall, the results indicate that it is necessary to have a workflow diagnosis and control method to design the topology of the workflow that restrict the propagation of anomalies from one task to the whole workflow, and monitor and control the real-time status of workflows for proactive rescheduling and resource allocation in order to achieve effective and efficient NPP outage control.

6 Conclusion

Crane safety problems in a Nuclear Power Plant (NPP) outage are exasperbated due to the heavy lifts, busy construction site, and dangerous environment with nuclear facilities. Therefore, a reliable and efficient control framework that control human behavior and tasks related to the crane will potentially improve the safe, efficient proceeding of outage project in a nuclear power plant. This need relies on systematic theories and technologies of human error patterns, anomaly propagation patterns in the project, and efficient and effective inspection of the jobsite. This integrated outage control framework will not only improve the safety, productivity, and quality of current outage project, but also provide sufficient data for future outages to reduce excessively long planning stage of an outage project. In addition, the techniques demonstrated for improving crane safety and productivity may be transferable to other outage processes and bottlenecks to further improve overall outage performance.

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