MODELING OBJECT IDENTIFICATION AND TRACKING ERRORS ON IMAGE-BASED SAFETY ASSESSMENT OF EARTHMOVING OPERATIONS

Seokho Chi
Ph.D. Candidate, The University of Texas at Austin, Austin, TX, USA
shchi@mail.utexas.edu

Carlos H. Caldas
Associate Professor, The University of Texas at Austin, Austin, TX, USA
caldas@mail.utexas.edu

Abstract

Object identification and tracking have become critical for automated on-site construction safety assessment. The primary objective of this paper is to present the development of a testbed to analyze the impact of object identification and tracking errors caused by data collection devices and algorithms used for safety assessment. The testbed models workspaces for earthmoving operations and simulates safety-related violations, including speed limit violations, access violations to dangerous areas, and close proximity violations between heavy machinery. Three different cases were analyzed based on actual earthmoving operations conducted at a limestone quarry. Using the testbed, the impacts of device and algorithm errors were investigated for safety planning purposes.

KEYWORDS: object identification and tracking, construction safety, automated safety assessment, error impact analysis

INTRODUCTION

Safety is always first in construction projects. The United States Occupational Safety and Health Administration emphasizes that employers are responsible for providing workers with a safety working environment (Wilson and Koehn, 2000). To achieve a safe environment, effective on-site safety assessment is important. In general, site safety has mostly been monitored and assessed based on manual inspections; more specifically, worksite supervisors, such as project managers, superintendents, or safety managers investigate site hazards and report them to be either safe or unsafe using safety checklists. Although such efforts have contributed to improving construction safety, they have relied highly on the observer's competency in recognizing and measuring the acceptability or unacceptability of safety conditions (Ahmad and Gibb, 2004). In addition, such human observations are time-consuming, and it is almost impossible for observers to monitor site safety at all times; accidents are likely to arise suddenly. For these reasons, recent research studies have been conducted on automating the safety assessment process.

Studies on the image-based object identification and tracking of on-site objects have become more crucial since they facilitate automating site monitoring processes by providing dynamic information of construction resources and activities. Specifically for construction safety, the image-based object identification and tracking studies have employed the state-of-the-art technologies and customized methods and algorithms for real-time safety monitoring and assessment. For example, Chi et al. (2009) developed a methodology for object identification and tracking based on spatial modeling and image matching techniques. Using spatial data acquired by a high-frame-rate imaging camera, a work zone model was built, matched with objects from the database for identification, and tracked within an image sequence. Using the same device, Gonsalves and Teizer (2009) segmented construction workers from a video sequence and then modeled and tagged them to track their location. In addition, some researchers proposed the use of video cameras for monitoring and tracking objects. Abeid et al. (2003) developed a computer-aided monitoring system, PHOTO-NET II, for construction project management and site surveillance. Shih et al. (2006) monitored a remote renovation site using a set of panoramic cameras and recorded images and videos for tracking work progress and site resources. Teizer and Vela (2009) evaluated performances of different worker tracking algorithms using video cameras for surveillance purposes. Last, Navon and Kolton (2007) developed an AutoCAD-based automated model to monitor and control fall hazards. They identified safety hazards in terms of dangerous areas and activities and finally integrated them with the project's schedule for preventive actions.

Regardless of the benefits of these safety studies, safety planners still face challenges selecting applicable devices, methods, and algorithms for safety assessment. This is due to the fact that (1) construction operations and sites are unique and complex, (2) such devices, methods, and algorithms typically have measurement and processing errors and (3) the impact of the errors is different depending on workspaces. For these reasons, there is a need to develop methods to evaluate the impact of object identification and tracking errors caused by image-based devices and algorithms on the data collected and processed for safety assessment of specific construction operations.

The primary purpose of this paper is to develop an error impact analysis method to model object identification and tracking errors caused by image-based devices and algorithms and to analyze the impact of the errors for safety assessment of earthmoving and surface mining activities. As specific research activities, the previous study conducted by the authors identified data needs supporting automated safety assessment (Chi and Caldas, 2009) and investigated image-based devices and algorithms for acquiring the identified data including moving speed, access to dangerous areas, stopping distances and proximity between site objects. On top of the previous research, this paper determined safety rules using safety risk identification data, and finally developed a testbed to model workspaces and to evaluate how the object identification and tracking errors impacted the performance of safety decision making. Computer simulations with various earthmoving scenarios were conducted for method validation. Finally, conclusions and recommendations were derived from the research results.

The scope of this paper is limited to off-site planning based on error impact analysis for safety assessment. In other words, most existing studies discussed in the previous sections mainly focused on actual device and algorithm analysis and system development for real-time implementation of risk identification on sites. However, this research mainly focuses on construction safety planning. In addition, this study only considered earthmoving and surface mining activities and image-based devices and algorithms.

DATA NEEDS IDENTIFICATION FOR SAFETY ASSESSMENT

The research examined the possible causes of accidents for loading, hauling, and dumping operations and investigated potential safety risk factors contributing to accidents: excessive operation speed, dangerous access to prohibited areas, and inadequate clearance and limited visibility. These heavy-machinery-related accidents and their risk factors were reviewed from the Mine Safety and Health Administration's and the National Institute for Occupation Safety and Health's fatality investigation reports and operation safety handbooks (NIOSH, 2007; MSHA, 2009). For each of the risk factors, best practices in terms of safety regulations identified spatial data needs to support automated safety assessment. The data needs included moving speed, access to dangerous areas, stopping distances, and proximity to other on-site objects including workers and heavy machinery.

DEVICES AND ALGORITHMS FOR DATA ACQUISITION

Once the research identified spatial data needs for automated safety assessment, it was necessary to consider how to collect spatial data and transform the acquired raw data into the data needed for safety assessment. The research investigated and customized image-based object identification and tracking approaches for construction applications since they would support informative safety decision making for unique and complex construction operations. More specifically, "object tracking" was necessary because an object's proximity and moving speed were able to be estimated using 3D information of object positions. "Object identification" was also required since safety rules were generally applied differently to different object types. The research evaluated image-based data collection devices such as LADARs, Flash LADARs, video cameras, and stereo vision cameras and explained the benefits of the stereo vision camera and how the stereo camera and the algorithms detected on-site moving objects, tracked their motion trajectory and finally classified object types by using object database and classifiers.

SAFETY RULES FOR SAFETY DECISION MAKING

Once the object identification and tracking acquired the identified data needs, safety rules using the collected data were determined for actual safety decision making. From the previous mentioned three data needs, violation types to be monitored for safety assessment were identified. They contained speed limit violations, access violations to dangerous areas, and a close proximity violations between objects. This section will provide in-depth explanation on how determined safety rules are able to detect such violations.

Safety Rules to Detect Speed limit and Dangerous Access Violations

The safety rule for speed limit violation detection was designed as "a speed limit violation occurs when moving speed of the tracked object exceeds its speed limit." This straightforward rule keeps monitoring the movement of on-site workers and heavy equipment and monitors violations. Similarly, the safety rule for dangerous access violation detection was designed as "a dangerous access violation occurs when the tracked object enters pre-determined prohibited areas." The safety rule first marks dangerous or strategic areas and then monitors objects' proximity to the areas. In earthmoving and surface mining activities, the dangerous areas include specified hazard areas, areas near highwalls, trenches, holes, cracked ground, road edges for haulage trucks, dumping edges (berms) for dump trucks and unstable material piles. Besides the dangerous areas, a strategic area needs to be considered for more effective safety assessment. It contains a material stockpile in which an access is authorized only for a loader performing material scooping and a loading area in which close proximity is allowed when a loader approaches a truck for material loading.

Safety Rules to Detect Close Proximity Violations

In order to design a safety rule for close proximity violation detection, industrial standards for automobile crash avoidance system were reviewed. Many automobile manufacturers have designed on-board monitoring systems to help predict collision accidents, making it possible to reduce collision damage or take preventive action to avoid a collision (Toyota Motor Europe, 2008; Bogenrieder et al., 2009; Mobileye Technologies Limited, 2009). As operation principles, the system first monitors vehicle speed and steering angle, and detects the position, distance, and speed of any obstacle in front of the vehicle. The system then estimates a collision state with the vehicle or pedestrian ahead, taking into account the time to collision and the time to stop, which can be calculated by considering the inter-vehicular distance, the relative traveling speed, the motion vectors, and the braking system's capability.

The rules used in the academic studies by Riaz et al. (2006) and Oloufa et al. (2003) followed similar standards as the automobile industry's standards. They considered motion vectors and the stopping distance for close proximity detection. This safety rule was applied to this research. This rule first estimates an approaching status by analyzing the motion vector. The rule predicts the post distance after 0.2 seconds between vehicles using their motion vectors and then compares this distance with the current proximity. If this distance is smaller than the proximity, we can say both vehicles are approaching each other. Second, the stopping distance determines the size of safety margin surrounding heavy equipment (Chi and Caldas, 2009). More specifically, the faster heavy equipment move, the larger safety margins are assigned. By considering all of these information, the safety rule for proximity violation detection was designated as "a close proximity violation occurs when proximity between objects are smaller than their stopping distances."

AN ERROR IMPACT ANALYSIS METHOD

Using the determined safety rules, a prototype simulation testbed was developed. The primary purpose of the testbed is to assist safety planners in understanding workspaces and to assess errors related to the use of different technologies for safety planning decision making. The testbed first models virtual workspaces for earthmoving and surface mining activities and then simulates operations and related safety violations, such as speed limit violations, access violations to dangerous areas, and close proximity violations between heavy machinery. The testbed also models different object identification and tracking errors caused by image-based algorithms and devices as well as safety rules to detect safety violations. This testbed investigates the impact of errors on the performance of safety decision making. This section will discuss the structure, the elements, and the functions of the testbed.

Testbed Structure

The overview of the testbed structure is illustrated in Figure 1. Using spatial information of actual sites, a user can input a site map, relevant safety features such as an access-prohibited area or a safe material-loading area, heavy equipment types involved, trajectory information of moving equipment, strategic camera positions, speed limits, and gross operating weights of the equipment into the testbed for safety violation detection. The testbed applies different object identification and tracking errors and then executes a simulation several times for each error rate. Different error rates (e.g.: 0, 2, 4, 6, 8, 10, 12, 14, 16, 18, 20, 25, and 30%) are used for sensitivity analyses of both object tracking and identification accuracies. To apply different error rates to the original data, a random number generator is used. The simulation runs a user-specified number of times for each error rate, for analyzing the impact of either tracking or identification accuracy. The testbed then outputs summary images and movie files. The testbed also summarizes safety-related violations using safety rules identified and analyzes performance.

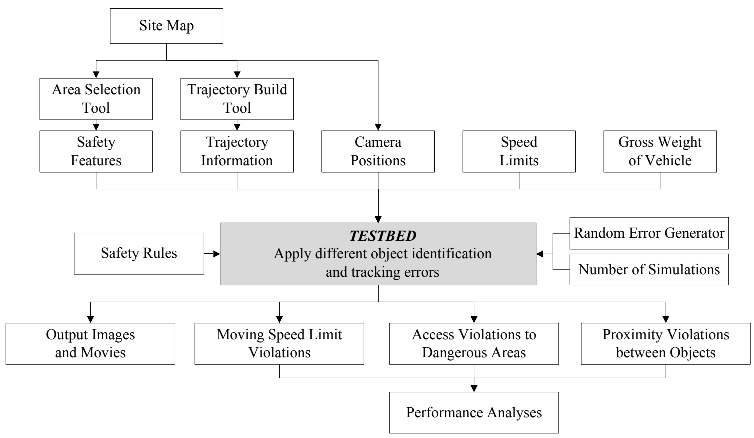


Figure 1: Testbed Structure

Data Input

A user can first select a JPEG-format site map and then use two software tools: an area selection tool and a trajectory build tool. The area selection tool was designed to determine a dangerous access area, a discriminated access area such as a material stockpile, or a safe material-loading area. This tool first assists a user to plot a desired area using a computer mouse and input an area name, and the tool then generates a text file representing map specifications. The users can also determine strategic camera positions.

The trajectory build tool was designed to simulate the trajectories of heavy machinery. A user first enters the name of heavy equipment tracked. The users then plot each vehicle's moving trajectory on the map and the tool generates a text file with x and y values of the plotted trajectory in meters. In other words, whenever the user plots one pixel of the map, the pixel's row and column values are transformed to the global x and y values (meters from the top left corner) based on the scale of the map. The center point of an object's height, the z value, is predetermined based on the equipment type. Here, the x, y, and z values represent volume centroid of the equipment in meters.

In addition, there are three more input variables. One is the speed limit of the site, which is used for monitoring speed limit violations. The others are gross operating weights of heavy equipment and site surface types, which determine a stopping distance for monitoring a close proximity violation.

Internal Processing

Once safety-related area information and heavy machinery movement information construct simulation scenarios, the testbed runs a random error generator to modify original trajectory and classification information of heavy machinery with different tracking and identification errors. Again, the user can plot several sequential points to construct the trajectory of the heavy machinery involved. Each plotted point includes three different types of information: a heavy machinery type, the distance information of the point from the camera position, and the time information when the machinery locates at the point. As detailed explanation, a random tracking error generator first transforms the global x, y, and z values to the local coordinate using the designated camera position and the coordinate conversion matrix. The error generator then applies zero to 30% different tracking error rates to the local x, y, and z values and the revised values by the error are finally transformed back to the global frame. A random identification error generator similarly applies different identification error rates to heavy machinery information and modifies the original classification of the machinery.

The testbed also applies previously determined safety rules on the revised trajectory and classification information to detect safety-related violations including speed limit, dangerous access, and proximity violations. The testbed, however, was flexibly designed to adapt and adjust different safety rules.

Last, the testbed considers a different time tolerance for safety violation detection. The testbed applies nine different time intervals from zero seconds to five seconds (0, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 4.0, and 5.0 seconds) and evaluates how the number of false alarms decreases with different time tolerance. More specifically, the zero-second time interval means frame-by-frame analysis. In order words, the testbed detects safety violations frame by frame. However, the five-second interval detects a violation if the violation has been continuously monitored during five seconds. Thus, such consideration would be expected to decrease the number of false alarms and increase the testbed efficiency by filtering noise out for practical testbed utilization.

Testbed Output

The testbed basically outputs the final trajectory image (Figure 2(a)) affected by different data errors (Figure 2(b)) and a movie file showing actual operations, movements of heavy machinery, and safety violations. The testbed also creates temperature-based frequency information of the tracked trajectory (Figure 2(c)). In Figure 2(c), a trajectory of heavy machinery was colored from blue to red based on visiting frequency. A highly-visited area such as a main haulage road and a loading area became close to red and a lowly-visited area became close to blue. This information helps a user identify congested (high density) areas and free spaces for safety planning.

The testbed then estimates safety-related violations based on safety rules. The testbed counts the number of original speed limit, dangerous access, and close proximity violations with zero identification and tracking errors. Using these numbers, the testbed counts the number of false alarms and the number of missed original violations due to object identification and tracking errors. By considering the number of vehicles that appeared in the images and the number of encounters between vehicles on images, the testbed calculates the probability of false violation occurrence versus object identification and tracking errors.

(a) (b) (c)

Figure 2: Testbed Outputs: (a) original trajectory of heavy machinery, (b) trajectory with 10% tracking error, (c) temperature-based frequency information of the trajectory

Theoretically, the worse an object's tracking accuracy is, the more speed violations are expected to occur. Object identification accuracy would increase the speed violations only when different speed limits are assigned for different equipment types. Second, when tracking errors become more prevalent, heavy machinery tends to break away from its original trajectory more; that is to say, if a large size of a dangerous area is designated near the original trajectory, the number of dangerous access violations is expected to increase. Object identification would affect the monitoring results only when different access authorities are assigned to different object types. For examples, a material stockpile is able to be allowed only for a loader to access, but not for a truck. Third, while the tracking accuracy is getting worse, the vehicle's speed tends to increase and the stopping distance becomes larger. Thus, more proximity violations are expected. The object identification accuracy would affect proximity violations as well. If an actual loader is mistakenly identified as a heavy truck, the gross weight increases and the stopping distance increases as a result.

Last, using the derived number of safety violations, the testbed finally estimates violation detection accuracy, false alarm rates, and missing detection rates of the testbed. With the number of simulated actual violations, if the testbed detects them as violations, then it is called a *true positive* (TP). However, if the testbed misses them, then it is called a *false negative* (FN), which represents missed violation detections. Similarly, if the testbed correctly rejects non-violated status, then it is called a *true negative* (TN). However, if the testbed detects them as violations, then it is called a *false positive* (FP), which represents false alarms. The violation detection accuracy, the false alarm rate, and the missing detection rate can be calculated by considering (1) TP and TN, (2) FP, and (3) FN, respectively.

TESTING AND VALIDATION

For testbed performance validation, various cases with different object identification and tracking accuracies were considered and the results were statistically analyzed. Three earthmoving cases were constructed based on the ground truth that was actually monitored from the M. E. Ruby, Jr., limestone quarry located in Cedar Park, Texas, where 1.5 million tons of materials are produced every year. The testbed codes were written using the C++ programming language in Microsoft Visual C++ 6.0. Intel Open Source Computer Vision Library (OpenCV) was employed for image and video processing.

The first scenario was constructed to represent a loading operation (Figure 3(a)). Seven trucks and one loader were involved in the operation. Dangerous access areas were predetermined near highwalls and unstable ground. A material pile and a safety loading area near the stockpile were also located. Three cameras were positioned for monitoring. The second scenario was built to represent another loading operation with seven trucks and two loaders involved (Figure 3(b)). Dangerous access areas near the material crusher and unstable ground, four material piles, a loading area, and six cameras were located. Six cameras were positioned for monitoring. The third scenario was constructed to represent a hauling operation with fourteen trucks involved (Figure 3(c)). Dangerous access areas were assigned near road edges, highwalls, and unstable ground. Six cameras were positioned for monitoring.

(a) (b) (c)

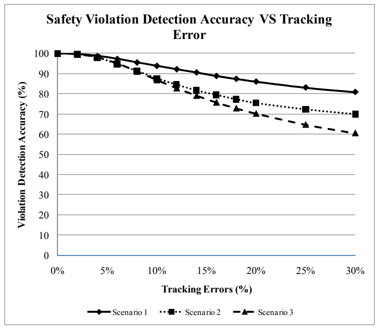
Figure 3: Three different scenarios: (a) Scenario 1, (b) Scenario 2, (c) Scenario 3

Simulation Results

Each scenario ran simulations 100 times to derive an analysis of the sensitivity of the testbed performance to different tracking error rates, ranging from 0% to 30%. In order to estimate accuracy, false alarm rates, and missing detection rates, each scenario originally had simulated violations. For statistical analysis, mean (%) and standard deviation (%) with 95% confidence interval for safety violation detection accuracy were discussed. Figure 4(a) illustrates how tracking errors impacted the performance of safety violation detection. The simulation results indicated that the violation detection accuracy was decreased by increasing tracking errors with the short range of standard deviations (Figure 4(b)).

Table 1 explains how these results can be utilized for actual device and algorithm evaluation. Let us imagine a safety planner set 90% accuracy as acceptable tolerance and evaluated several combinations of devices (A, B, and C) and algorithms (1 and 2) with different tracking errors. As shown in the table, the safety planner can determine both device A and B are acceptable with algorithm 1 for the site. However, the safety planner still needs to consider other factors such as familiarity, cost, and easiness to select one from two device candidates.

In addition to the results against tracking errors, the testbed evaluated the violation detection performance against identification errors. The simulation results showed that, however, the detection accuracy was not that affected by the identification errors. Regardless of different identification errors, the accuracy was higher than 99.5%. That was because the identification error did not change the original trajectory of heavy machinery, so no false speed limit violation occurred and just few false access and proximity violations were generated. However, the number of false access violations increased proportionally to the number of loader accesses to material stockpiles for material scooping and similarly the number of false proximity violations was increased by the number of close loader approaches to a truck for material loading. These numbers would help safety planners plan acceptable tolerance for safety assessment and false alarm generation.



Tracking Error	0-10%	10-20%	20-30%
Scenario	Average S.D.		
1	0.21	0.94	2.04
2	0.28	1.17	1.42
3	0.22	0.43	0.51

(a) (b)

Figure 4: Results versus Tracking Errors: (a) Violation Detection Accuracy, (b) Standard Deviations

Table 1: Utilization Example of the Simulation Results

Device	Algorithm	Tracking Error	Violation Detection Accuracy (%)		
			Scenario 1	Scenario 2	Scenario 3
A	1	6%	97.3	94.8	95.0
B	1	8%	95.5	91.4	91.0
C	1	10%	93.8	87.7	86.8
A	2	12%	92.2	84.5	82.8
B	2	14%	90.6	81.6	79.1

CONCLUSIONS

In summary, a testbed was developed and computer simulations with three earthmoving scenarios validated its performance for the error impact analyses. The safety rules detecting speed limit, dangerous access, and close proximity violations were first determined. The testbed then modeled several earthmoving operation scenarios, modeled different object identification and tracking errors, applied the previously determined safety rules for safety decision making and finally evaluated the impact of different object identification and tracking errors on the safety analyses. The paper also presented utilization examples of the testbed with the analyzed result of violation detection accuracy. The results of this research would be used for improving site safety assessment and planning by assisting safety planners to understand workspaces and to evaluate errors related to the use of different technologies for safety assessment.

REFERENCES

Abeid, J., Allouche, E., Arditi, D., and Hayman, M. (2003) PHOTO-NET II: a computer-based monitoring system applied to project management. Automation in Construction, 12(5), 603-616.

Ahmad, K. and Gibb, A. (2004) Towards effective safety performance measurement – evaluation of existing techniques and proposals for the future, construction Management Systems. Spon Press, London, UK.

Bogenrieder, R., Fehring, M., and Bachmann, R. (2009) Pre-Safe in rear-end collision situations. Daimler AG.

Chi, S. and Caldas, C. H. (2009) Development of an automated safety assessment framework for construction activities. Proceedings of the 26th International Symposium on Automation and Robotics in Construction (ISARC), Austin, TX, 38-46.

Chi, S., Caldas, C.H., and Kim, D.Y. (2009) A methodology for object identification and tracking in construction based on spatial modeling and image matching techniques. Computer-Aided Civil and Infrastructure Engineering, 24(3), 199-211.

Gonsalves, R. and Teizer, J. (2009) Human motion analysis using 3D range imaging technology. Proceedings of the 26th International Symposium on Automation and Robotics in Construction (ISARC), Austin, TX.

Mobileye Technologies Limited (2009) Mobileye advance warning system. Mobileye Technologies Limited, Nicosia, Cyprus.

MSHA (Mine Safety and Health Administration). (2009) Fatalgrams and fatal investigation reports. U.S. Department of Labor, Washington, DC.

Navon, R. and Kolton, O. (2007) Algorithms for automated monitoring and control of fall hazards. Journal of Computing in Civil Engineering, 21(1), 21-28.

NIOSH (National Institute for Occupational Safety and Health). (2007) Traumatic occupational injuries: construction fatality investigation reports. U.S. Department of Health and Human Services, Washington, DC.

Oloufa, A. A., Ikeda, M., and Oda, H. (2003) Situational awareness of construction equipment using GPS, wireless and web technologies. Automation in Construction, 12(6), 737-748.

Riaz, Z., Edwards, D.J., and Thorpe, A. (2006) SightSafety: a hybrid information and communication technology system for reducing vehicle/pedestrian collisions. Automation in Construction, 15(6), 719-728.

Shih, N., Lai, J., and Tsai, Y. (2006) The application of a panorama image database management systems (PIDMS) for information integration of construction sites. Journal of Information Technology in Construction, 11, 641-654.

Teizer, J. and Vela, P.A. (2009) Personnel tracking on construction sites using video cameras. Advanced Engineering Informatics, 23, 452-462.

Toyota Motor Europe (2008) Toyota and safety. Corporate Affairs, Toyota Motor Europe, Belgium.

Wilson, J.M. and Koehn, E.E. (2000) Safety management: problems encountered and recommended solutions. Journal of Construction Engineering and Management, 126(1), 77-79.