COGITO

CONSTRUCTION PHASE
DIGITAL TWIN MODEL

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D4.4 – Proactive Real-time Risk Monitoring and Detection Methods v2

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Executive Summary

The COGITO Deliverable D4.4 "Proactive Real-time Risk Monitoring and Detection Methods v2" aims at documenting the state-of-the-art regarding the existing methods for enhancing safety in construction, focusing primarily on areas relevant in the context of COGITO. This report includes: (a) the need for right-time safety in the construction phase and its state-of-the-art, (b) the definition of a close call and the proposed close call reporting process, (c) the sensor-based methods for close call data collection and risk monitoring and detection, (d) the methods for intelligent close call data analysis and reporting, and (e) the tools for accident prediction in regards to heavy construction equipment and pedestrian workers in the realistic, complex, and dynamic construction environments. This deliverable also documents the current version of the developed Proactive Real-Time Risk Monitoring and Detection application called ProActiveSafety. In addition, it reports on the iteration of the development activities within the COGITO Task T4.2 "Proactive Real-time Risk Monitoring and Detection".

In summary, due to the evolving workspace typically found at construction sites, hazards can emerge dynamically. Visibility-related fatalities constitute more than half of the fatal occupational accidents in construction, caused by workers being in a blind zone of heavy equipment or not being seen due to obstructions. To promote safety, research has been done on (a) enhancing the existing manual close call reporting process and (b) developing close call data gathering and analysis, and proactive warning systems to notify of dangers and to alert pedestrian workers or operators when immediate attention or action is required to prevent an accident. The proactive warning systems often rely on sensors to detect the distance between moving heavy machinery and pedestrian workers or obstacles. Several types of sensor-based methods for risk monitoring and detection exist and are analysed in depth in this report. For instance, camera-based, ultrasonic or radio systems are some of those. Three categories of input data were found to be used for trajectory data gathering in the construction literature: vision-based data, raw location tracking data, and 3-dimensional point cloud data from drone sensors. Close call data gathering and analysis, and furthermore, trajectory prediction in construction often refers to post- or run-time data processing, respectively. While post-processing close call data is very suitable for safety officers interested in infrequent safety status updates, run-time data processing focuses on the short-term prediction of a moving resource's future paths (e.g., worker, equipment), i.e., within 1 to 10 seconds ahead for accident avoidance.

The Proactive Real-time Risk Monitoring and Detection application, called ProActiveSafety, consists of four modules, namely (i) the data analysis module, (ii) the trajectory prediction module, (iii) the hazard zones checking module and (iv) the user interface. ProActiveSafety enables the Health and Safety (H&S) digital twin to predict hazardous situations (e.g., through the generation of risk heat maps or probability density calculations) based on state-of-the-art machine learning techniques on up-to-date near-real-time data queried from the digital twin platform. To this end, sample location tracking data have been utilised to train a type of artificial Recurrent Neural Network (RNN) called LSTM network which performs short-term proactive monitoring of hazards affecting moving workers and equipment in the dynamic construction environment. The future development will focus on the risk analysis module and will integrate construction semantic information (e.g., construction site layout plans) and hazard zones checking to further enhance the safety analysis.

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List of Acronyms

Term	Description
AR	Augmented Reality
BIM	Building Information Modelling
CAN	Controller Area Network
CMS	Camera-Mounted System
COGITO	Construction Phase diGItal Twin mOdel
DCC	Digital Command Centre
DigiTAR	Digital Twin visualisation with Augmented Reality
DTP	Digital Twin Platform
EKF	Extended Kalman Filter
FOV	Field of View
GNSS	Global Navigation Satellite System
HMM	Hidden Markov Models
H&S	Health and Safety
KF	Kalman Filter
LaDAR	Laser Detection and Ranging
LiDAR	Light Detection and Ranging
LSTM	Long Short-Term Memory
MDN	Mixture Density Network
ODbL	Open Database License
PPE	Personal Protective Equipment
QGIS	Free open-source Geographic Information System
RaDAR	Radio Detection and Ranging
RNN	Recurrent Neural Networks
RTK	Real-time Kinematic
RTLS	Real Time Location Sensing
OSM	OpenStreetMaps
SbS	Sensor-based System
SFM	Social Force Model
S-GAN	Social Generative Adversarial Network
STS	Sociotechnical Systems
ToF	Time-of-Flight
TTC	Time to Collision
UKF	Unscented Kalman Filter
WOEA	Work Order Execution Assistance

1 Introduction

Many occupational safety and health administrations worldwide pursue a "zero-accident" vision to protect workers' life, health and well-being ([1] [2] [3]). According to laws in most industrialised countries, a safe workplace must be provided before an employee can start working [4]. As injury and fatality rates rise or decline by economic activity, however, well-articulated standards and processes related to the construction safety, health and well-being [5] alone may not adequately prevent dangerous working conditions. Many of these have proven inadequate upon execution in the field ([6] [7] [8]) or are challenging to adapt to the ongoing digitalisation efforts across all industries. For example, contact collision incidents between pedestrian workers and heavy construction equipment still occur in large numbers [9]. For this reason, even industry leaders observe that further reduction of accident numbers is very hard to achieve [10].

During construction operations, consequences of different severity can result from incidents: low, medium, or high [11]. Respective examples are minor collateral property damage, bodily injury or fatality. While the occurrence of these highly depends on human judgement, one of the contributing and repeating factors is pedestrian workers being too close to the equipment without being detected in time. Therefore, from an equipment operator's point of view, limited or no visibility causes disturbance of workflow, increases the risk of accidents and stresses the affected persons negatively. Current best-practice techniques rely on always-on passive measures such as back-up beepers on machines and personal protective equipment (PPE) worn by the construction personnel. Wearing a hard hat and a reflective safety vest [12] for example, is required by law to improve visibility in hazardous proximity incidents that occur every day between workers and heavy construction equipment. However, such passive measures by themselves, unfortunately, are incapable of recognizing a hazard and do not warn personnel actively.

An alternative approach to tackle this problem is by educating the workforce and thus, effectively reducing the possibility of an accident. It requires identifying, registering and reviewing incidents that might lead to an accident or to so-called close-calls. A close-call (i.e., a near-miss) is a subtle event in the chain leading to a potential accident that remains unrecognized but should be treated like an accident [13]. The required investigation and feedback to such incidents has always been a reactive measure so far. Although one may find the root cause that led to the event and prevent it from happening again, preventive or (better) predictive measures should be used to proactively plan for and maintain a safe working environment in the first place [14]. In short, to further improve construction safety performance, it is necessary to understand the underlying causes of accidents in much greater detail [15] [16].

1.1 Scope and objectives of the deliverable

This deliverable presents a survey of the existing methods for enhancing safety in construction through proactive risk monitoring and detection. The deliverable also reports on the work that carried out within WP4 towards designing, developing and delivering a prototype version of the Proactive Real-time Risk Monitoring and Detection service which enables the H&S digital twin to predict hazardous situations.

1.2 Relation to other tasks and deliverables

This deliverable is based on the conceptual architecture defined in deliverables D2.4 *Cogito System Architecture v1* and D2.5 *Cogito System Architecture v2*. The Proactive Real-Time Risk Monitoring and Detection application called ProActiveSafety receives data tracking the location of the construction resources (i.e., pedestrian workers and heavy machinery/equipment) from the Digital Twin Platform (DTP) and more specifically from the IoT Data Pre-processing module described in detail in deliverables D3.4 *IoT Data Pre-processing Module v1* and D3.5 *IoT Data Pre-processing Module v2*.

ProActiveSafety is responsible for communicating additional safety hazards to SafeConAI (D4.2) to enhance the safety analysis as well as for proactively issuing warnings through the Work Order Execution Assistance (WOEA) service (D4.6). The identified health and safety hazards will be visualised both off-site and on-site. The Digital Command Centre (DCC) is COGITO's off-site data visualisation solution developed within T7.3 *Data Transformation for 3D BIM Rendering* and T7.4 *3D Mesh Data Quality and Consistency Checker and 3D Data Transformation Testing*. The on-site data visualisation will be offered by the Digital Twin visualisation with Augmented Reality (DigiTAR) tool using Augmented Reality (AR) head mounted displays, and it is developed within T5.4 *User Interface for Construction* Safety. Finally, the health and safety hazards will be utilised by the VirtualSafety application (described in deliverable D4.8) to create realistic training scenarios to improve safety culture and increase awareness of potential hazards in construction.

1.3 Structure of the deliverable

The deliverable is structured as follows; Section 2 presents the state-of the-art on methods for enhancing safety in construction and discusses the factors affecting the safe operation of construction equipment. Section 3 underlines the urge of right-time safety and a close call reporting system. Section 4 presents the available sensor-based methods for risk monitoring and detection, providing a comparison on a selection of technical characteristics of proximity sensing devices critical for the implementation in construction. Section 5 describes the process of computing proximity events from location tracking data as well as the evaluation of their level of seriousness, whereas Section 6 presents the Proactive Real-Time Risk Monitoring and Detection application conceptually. Finally, Section 0 concludes this report and describes the future developments.

1.4 Updates to the first version of proactive real-time risk monitoring and detection methods

Deliverable D4.3 demonstrated the first version of the *Proactive Real-time Risk Monitoring and Detection Methods.* Since the submission of the first version, the authors have improved existing segments of the work and re-worked the concept of the application. Furthermore, this version of the report defines the workflow and processing of data in detail. This version comprises the following additional parts:

- Definition of right-time safety, see Chapter 3
- Introduction to the existing methods of close call processing and reporting (see Section 3.5)
- Description of novel approaches for detecting, processing, analysing and reporting close calls (see Section 3.6)
- Brief description of Real-time Kinematic (RTK) Golbal Navigation Satellite Sysetm (GNSS) technology (see Section 4.8)
- Close call data analysis (see Chapter 4), including a description to
    - Protective envelopes
    - Close call detection
    - Definition for hazard criteria and weights
    - Four experiments utilising pre-existing data to verify the usability of the close call data analysis
- More detailed description of the data analysis module of the ProActiveSafety application (See Chapter 6).

The 'risk analyser module' was removed and will be part of the graphical user interface (see deliverable D4.6 Personalized Alerts, Prediction and Feedback Tools).

2 Existing methods for enhancing safety in construction

2.1 Hazard prevention

During the design of construction sites, a variety of means exist [17] to prevent pedestrian workers from getting in close contact with equipment in operation; much can be utilised long before the construction actually begins. As always, prevention is the most effective method to avoid accidents [18]. Therefore, a good practice in occupational construction safety is to follow a hierarchy of protective measures; these include, but are not limited to (a) the identification of possible hazards in the operating area of the construction equipment, (b) the implementation of appropriate protective measures and (c) the documentation of such measures. Following the "S-T-O-P" principle (based on [19]), these have priority:

- Substitution: Substitute the dangerous equipment with a safer alternative.
- Technical measures: Apply technical measures to minimize the exposure of personnel in blind zones. For example, improve vision using a camera-mounted system (CMS). Check if/what other alert/sensor systems are valuable and/or necessary.
- Organisational measures: Use organisational measures to decrease the number of personnel exposed to nearby equipment. For example: define and mark hazardous work areas; establish rules of conduct such as toolbox meetings before the work starts; regulate entry, use signallers, security guards; separate vehicle from pedestrian worker paths using barriers; observe and enforce order.
- Personal measures: Protective measures applied to personnel, such as wearing personal protective equipment (PPE), e.g., high-visibility warning vests, as a barrier to exposure. While research concludes that in some cases low visibility issues are resolved using reflective vests worn by the workers, other research claims that few technologies exist that pro-actively aid pedestrian workers or equipment operators in dangerous proximity incidents [20, 21].

In brief, as research has shown, a risk assessment should start early in a project [22]; ideally, it should start before the selection and procurement of construction equipment [23]. The requirements and criteria for planning safe construction site layout plans must be specified. Research has already shown the benefits of the latter's digitalisation, for example, through the use of Building Information Modelling (BIM) and virtual reality [14], [24, 25] methods. Such digital methods consider regulatory and operational requirements while still involving employees' safety knowledge and experience. More recently, the integration of sensors in BIM-based safety management applications appeared [26].

2.2 Factors affecting safe equipment operation and accident reporting

Construction sites, contrary to work environments in the maritime [27, 28, 29, 30, 31], airline [32], agricultural or manufacturing [15], [33] sectors, perform activities in a defined but continuously evolving work space. This means safety issues can emerge dynamically and require attention at the right-time [12]. Right-time is defined as acting upon an event

While there are several conditions adversarial to the creation of a safe working environment, equipment operator blind zones are among the most significant factors; such zones are a frequent cause of visibility-related fatal accidents. Several techniques exist to precisely quantify these accidents [34, 35]. Before equipment manufacturers can sell new machines, they must verify that a sufficient field of vision is provided (e.g., according to ISO 5006 for earth-moving machinery) [36]. Although several approaches have been investigated to mitigate blind zones (e.g., software-based identification of visibility issues - from 3D design, enhanced field-of-view through the use of mirrors, camera-monitor systems and/or work lights that enhance lighting conditions on working sites), numerous visibility issues remain [34].

Blind spots can be split into static and dynamic; static blind spots can be created by the equipment components themselves, while dynamic blind spots originate from the movement of the operator's field of view (FOV) [34] and/or objects outside the equipment cabin. The latter requires the operator to exercise a greater level of vigilance and to conduct repeated vicinity checks to identify pedestrian workers and other significant obstructions. Further research [37] suggests a need to conduct inspections in areas that may appear unconventional to the operator, including underneath the equipment and anywhere in the vicinity of the task performance area. This also involves the operators checking areas previously known to be clear of personnel as they may have been re-occupied before the operators return to the same area.

Workers being in an equipment's blind zone or "not seen because of obstructions" were mentioned in 56% of all visibility-related fatalities in construction [23]. Researchers concluded that equipment that deviates from its usual paths of operation increases the likelihood of accidents [38]. Other research suggests that decreasing vigilance is a result of workers being engaged in specific tasks while ignoring distracting noises [23]. When a truck or piece of machinery is reversing (in about 75% of all equipment-related accidents), a worker can be easily distracted by focusing on the assigned work task alone. Workers are probably more vigilant at the beginning of a project; at that time, they pay more attention to alarm signals. Alarms can, nevertheless, quickly become routine to the workers and over time, the noise is processed more as an annoyance that tends to be ignored.

Illumination factors are another vital aspect of visibility; however, they are frequently not recognized in accident descriptions [16]. Therefore, they also play a minor role in research. When an accident occurs, the typical response is to attribute the cause to the most apparent actor. For example, a worker in a blind zone has a risk of being struck and killed by a moving vehicle. Conventional industry procedure is to classify this incident as a "struck-by" fatality and the assumption from this occurrence is that equipment is dangerous. While this may be a "struck-by" accident, closer examination of the root cause may reveal that vision impairment was the primary factor and the equipment, because of its proximity, size and weight, was a secondary factor. Research showed that lighting was the primary contributing factor in about 7% of all visibility-related cases [23]. Overall, standards and guidelines in reporting accident and fatality events can be improved to conduct more thorough root cause analyses.

2.3 Choice and impact of alarm types

According to investigations of visibility-related accident reports [23], in 87% of the cases, operators would have benefited from some use of technology for automated notification or intervention (e.g., obstacle detection, warning/alerting, and/or avoidance). So far, however, few machines use advanced technologies for monitoring their surroundings. To improve the awareness of operators and pedestrian workers, suitable alarms consisting of various warning and alert types must be carefully studied. Warnings generally notify of danger; alerts require immediate attention or action to prevent an accident. The predominant warning/alert signals for any technology are [20]:

- *Acoustic*: Alarms range from a "hiss", a composition of broadband/directional sounds also called "white" noise, or a "beep" i.e., a high pitch/omnidirectional alarm. They come from speakers installed on the equipment and are e.g., always activated when the equipment is reversing. Beepers sharpen the pedestrian workers' attention with an audible signal. Especially beepers issue quite some noise nuisance [39, 40] (leading to annoyance and stress of employees/residents and ultimately to rejection).
- *Visual*: Multiple ways exist to display a warning or alert on a monitor in the equipment cabin or more recently on built-in displays installed on structural components of an equipment cabin [41].
- *Vibration*: An alarm will vibrate on a body part. Unless intelligent personnel protective equipment (PPE) is developed, vibration is only recommended in moderate climates when workers wear thin clothing.

It is worth noting that warnings/alert signals generally turn off automatically once the person leaves the danger zone; this may decrease the risk for desensitizing operators. Some (older) systems previously allowed operators to manually configure alarms (e.g., turning them on/off), which is generally not advisable. The surrounding work environment and hearing thresholds are significant for the human perception of a produced sound signal in a construction area. Some pedestrian workers may even wear ear-muffs, protecting them from noise generated by another machine (e.g., a powered hand tool). When used as a warning tone, acoustic signals must be configured to adjust the volume according to the ambient noise levels (or enable smart/connected ear-muffs).

2.4 Intelligent intervention and functional safety

Digitalisation of construction equipment adds value by making machines more intelligent and increasing the automation of business and work processes. Regarding the construction safety, the concept of using automated technology to detect and mitigate hazards is relatively new as it requires "new forms of cooperation" between workers/operators and machines. As an example, even if clear visibility is guaranteed and active warning systems ensure better attention, many other tasks remain for the operator to handle; depending on their skills they might require assistance in driving or manoeuvring. Examples are intelligent obstacle avoidance, machine performance optimisation and handling nuisance alerts. These and other automation tasks can be solved with a combination of robust sensor hardware and intelligent software. For example, 3D mapping and visualisation technologies play a crucial role in evaluating data that is directly communicated from the machine to a central monitoring system. Whereas (visual) sensor systems work independently of each other, e.g., automatic detection of pedestrian workers and/or objects in danger zones, the generation of alerts requires intelligent data processing and visualisation [42].

Intelligent intervention thus recognizes the interaction between humans and technology in workplaces as part of sociotechnical systems (STS). The data acquired simultaneously from, e.g., a camera, an ultrasonic sensor and a Light Detection and Ranging (LiDAR) system are evaluated simultaneously. This superposition of the sensor signals increases reliability in detecting and recognising hazardous risks across a multitude of possible surrounding terrain scenarios (which are common in construction). The measurement result then triggers a predefined system intervention: When a danger is detected, the behaviour of a system is actively controlled to protect the detected workers and/or operators and bring the system back to a safe state, for example, via autonomous braking or an evasive manoeuvre [43].

3 Need for right-time safety and a close call reporting process

3.1 Time dimension in safety and health performance measurement

Effective monitoring and control of construction safety and health in modern projects requires sufficient planning and management in order to succeed. Various measures such as lagging indicators, leading indicators and safety climate have improved safety [44]. These traditional approaches of measuring safety performance still rely on manual means and subjective measures (e.g., surveys or manual counts), which are often costly, infrequent or slow to conduct, and error prone [45]. In addition, the availability and usefulness of indicator data diminishes over a short period of time due to the quick progress on construction sites [45].

Edirisinghe [46] introduced a good definition on leading indicator lifespans: "the time period the indicator remains useful relative to a potential incident". They pointed out that time-delays between indicator data collection, result reporting, and responsive action can undermine any possible advantages of having such information available. According to the same study physical hazard indicators have the shortest lifespan and – due to the dynamic nature of the work environment – should be collected immediately, if necessary, in real-time, to derive safety performance evaluations. Perception and management leading indicators – their terms are all introduced later in this report– are typically collected on a regular basis over time. While in-depth information about the root cause of accidents or incidents is important to prevent similar ones from happening again, the time dimension in analysing the causality of accidents and incidents is vital, but is very often overlooked in research studies and practical world applications [46]. Dyreborg [47] therefore argues that the "time-window" to understand the "cause-and-effects relationships" [48] is rather important.

Although automation in safety and health performance measurement processes is one solution [49] [50], to date, there exists no formalised approach for right-time or real-time automated safety and health monitoring, data analysis, information reporting, knowledge generation, and/or visualisation in the construction industry.

3.2 Formalisation of a right-time pro-active construction safety and health system architecture

Limited elements of critical hardware and software technology exist to design of a complete right-time pro-active safety and health system architecture. This has yet to be realised due to the:

1. impracticality of contemporary technology (i.e., amount of required installation and maintenance of sensors for data acquisition),
2. inefficiency or unreliability of existing data processing algorithms (data analysis),
3. lack of realistic methods for realising a safety feedback system architecture (reporting and alerting), and
4. absence of proven safety management actions (safety culture).

Thus, efforts are warranted into the identification and resolution of critical needs in right-time data acquisition, data processing, and reporting in complex and data noisy environments. Implementation of right-time pro-active safety and health research requires addressing several open research questions:

- What traditional safety information from accident causation models and safety indicators is useful for a right-time or real-time construction safety and health process?
- What type of data gathering sensors, processing techniques, and data visualisation environments can provide efficient, effective, reliable, fast, and accurate safety information in a highly dynamic, unstructured, and/or cluttered environment?
- Even if such fast and accurate sensor, information, and visualisation technologies are available, how can the proposed framework (ultimately targeting safety applications), handle large amounts of data, reduce measurement errors, in what data file format and what existing open software interfaces and perform all of that at the right time, eventually in real-time or near real-time?
- How are the potential construction hazards recognized early, preferably at the planning stage, and how can previously unrecorded safety data be gathered to assist safer construction design?

- What safety information provides the most relevant feedback to the project stakeholders and how can it be communicated to workers so they utilise it in their transition from skill-based to knowledge-based decision makers and how can organisations transform safety management actions?

To address these challenges, we propose to use right-time data collection and processing techniques and immersive visualisation environments as a catalyst for the conversation of safety and health information.

3.3 Linking accident causation models and safety indicators

The main concept behind the accident triangle of Heinrich [19] is that severe accidents can be prevented if one takes care of the more frequent unsafe acts first. Bellamy [51] noted that the investigation of accidents can help preventing ones of the same type. As [46] argues, however, both studies did not consider the time dimension in analysing causations. They note "it is essential to consider the time dimension in causality analysis in order to undertake an evaluation of the time-sensitivity of the different types of indicators".

According to the literature review, including [14] [17] and a recent study conducted by [46], the following definitions are provided to explain the context of data types in the developed framework:

- **Right-time construction safety and health is defined as "the (latest) point in time when knowledge could be utilized to prevent an injury or collateral loss."** Right-time in real-world applications might frequently be real-time, for example, when a worker-on-foot requires real-time situational awareness and instant reaction time to avoid being struck by a piece of equipment traversing in too close proximity to the work area. Less frequent in the context of pro-active safety and health means, for example, the support of project safety and health design and planning or deciding upon a company's long-term strategy for safety engineering and management (e.g., implementing the vision and mission of safety climate and culture, satisfying client requirements and relationships).
- Physical accident/incident precursor indicators: "Evaluation of the characteristics of the physical work environment." These include (pre-) work site conditions (e.g., weather, illumination, road conditions, and availability and condition of tools and materials), the presence and state of resources (e.g., static, moving, or interacting workers, equipment, and materials), work crew and equipment interfaces, and risk exposures and management approach.
- Management leading indicators: "Counting safety management activities" (e.g., frequency and number of inspections, safety walks or checks by contractor's and client's safety representative, training sessions, hazard reports, and the time it takes to address issues).
- Perceptions or situational awareness leading indicators: "Periodic measurement of worker's and management's perception of safety climate" (e.g., surveys measuring effectiveness of safety and health program, level of quality to commitment to safety culture).
- Safety levels related to events: "Measurement of accidents (e.g., injury or fatality), minor incidents (e.g., first aid treatment or small collateral damage), near-misses (e.g., unsafe act or event almost leading to accident/incident), and situational or personal issues (e.g., state of communication, supervision, and worker health and fatigue, behavioural factors of humans)".

It is important to understand the time sensitivity associated with the leading safety indicators. Some might even be dismissed if the time lag between data capture and analysis is too significant. According to [44] a great emphasis is on selecting the appropriate frequency of useful data capture and reporting. These indicator data types are further discussed in the next sections where remote sensing, processing, and reporting techniques – as introduced earlier in the background review – play a vital role in capturing safety precursor indicators at the right-time.

3.4 Organisational approach for right-time safety

Figure 1 depicts the complex time-dependent nature of safety performance indicator data that become available to different levels within an organisation through the use of manual and/or automated recording methods. As construction stakeholders require different pieces of safety information at different time intervals, technology may assist in this task. Construction safety planning is important, but less time-critical, since it typically occurs months or weeks (in other words ‘at the right-time’) in advance of the start of construction.

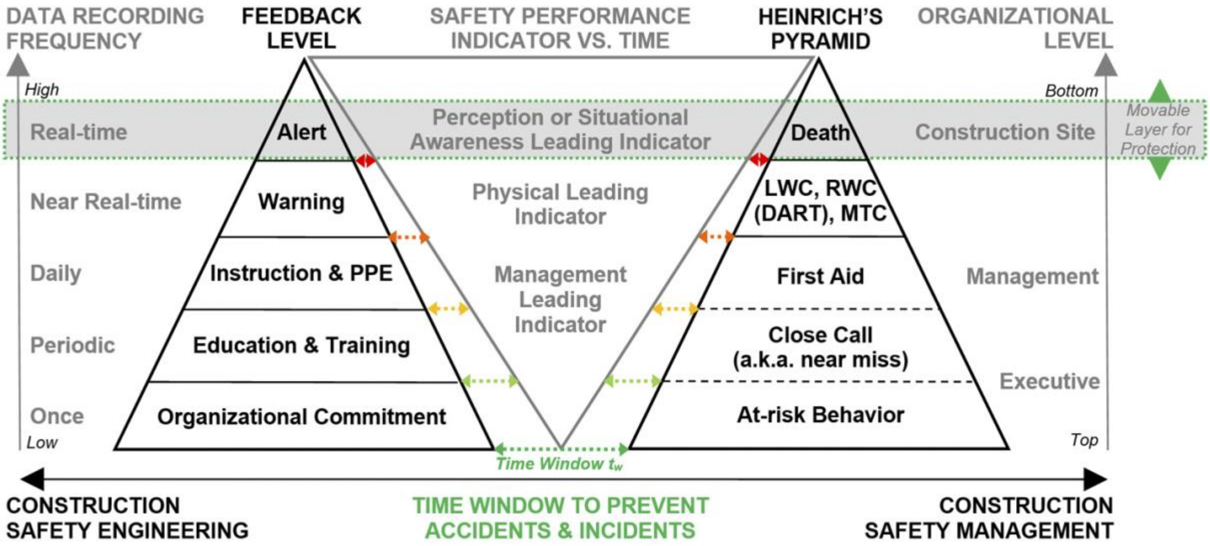


Figure 1: Right-time construction safety and health framework of ‘movable layers for protection’ addresses the critical time window for accident prevention and response [12]

Perception and management indicator measurement frequencies vary accordingly from weeks to months depending on the committed resources. Although these indicators identify gaps (also referred to as holes in the Swiss Cheese Model [12]) in an existing safety program, they have a limited ability to detect any potential hazards in near real-time. Data from these indicators require execution of appropriate actions once holes are detected. Once the severity of the hazard intensifies, injury, illness, or death may become more likely.

On-site real-time hazard monitoring is vital to detect physical hazard indicators. Real-time warning and alert feedback are required. As [46] noted, a good strategy is to use real-time captured leading indicators as a hazard precursor and execute appropriate actions immediately once holes are detected or intensify. A “movable layer for protection” – shown in an example as a layered barrier in Figure 1 – prevents a fatality using – at the latest – real-time data recorded on a construction site once the perception or situational awareness of site personnel fails.

The time window to prevent accidents accordingly narrows the worse the consequence becomes. For example, a “warning” to construction site management might be issued in “near real-time” to change poorly laid out road site conditions (one of the physical leading indicators) based on automated or manual equipment speed recordings. Another example to prevent accidents and incidents even earlier would be periodic training, i.e., educating the workforce about the significance of close-calls (e.g., struck-by equipment) or at-risk behaviour (e.g., knowingly performing unsafe acts) more than once.

3.5 Existing close call reporting, analysis, and feedback process

Several research efforts in construction describe a close call as an event that almost resulted in an accident. However, there is no research that provides a scientific definition of the exact characteristics of a close call [52]. In the context of this report, we define a close call as a proximity event between a human (pedestrian worker) and a known hazard (equipment), leading to a potential endangerment of the human. Therefore, close calls should be recorded and followed-up with a close call reporting program. Such programs, in an ideal case, measure safety performance and reduce the probability of accidents. However, the success of close call reporting crucially depends on the participation of persons to report near-misses, which can lead to inconsistent or false results [53]. Due to the often, complex contractual organisation of projects, construction companies often face difficulties in implementing effective close call reporting and analysis programs.

Using only manual approaches to gather information about close calls is impractical as the latter can be subtle and frequent events; the event's assessment might also vary depending on the observer. Since human-machine interactions are one of the more serious problems in the construction industry [54], This work specifically focuses on the continuous logging of the involved resources' position in a close call for a more detailed investigation, e.g., in the case of human-equipment and human-hazardous material incidents. It proposes a change to the traditional close call reporting and follow-up process (see Figure 2).

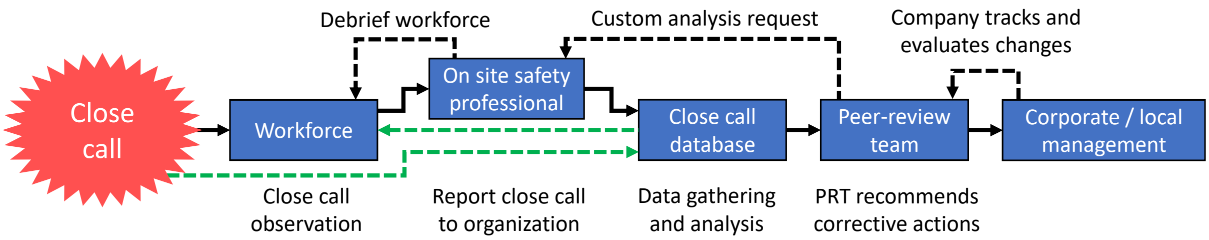


Figure 2: Close call reporting, analysis, and personalised feedback process [14]

Close calls, as introduced earlier, are typically reported when a human witnesses or participates in an event which compromises or threatens to compromise the health or safety of a person or the environment. If necessary, a person may at first try to prevent an accident or a further incident. The person then notifies their supervisor or safety coordinator directly on-site or using a close call reporting application on a mobile device (i.e., usin a smartphone or tablet if permitted on-site). Some organisations offer close-call reporting through a neutral third-party service to remove sensitive information. At least some general information about the event is shared once the case reaches the corresponding safety professional within an organisation. Afterwards, a problem-solving peer-review team consisting of workforce (trained in operational skills), safety professionals (trained in root-cause analysis), and management (trained in continuous-process improvement) will try to raise the awareness regarding the seriousness of the case. Various means exist to learn more about the risks and how to mitigate them, for example, calling for dedicated close call review meetings, department safety meetings, one-on-ones with workforce or supervisors, or involving a neutral third party. The team finally recommends corrective actions while protecting employees from blame [55]. By reaching this point, well-working close call reporting processes in practice should have ensured timely feedback to the person(s) who reported the incident in the first place.

3.6 Digital close call detection, reporting, analysis, and feedback process

To underpin the proposed approach takes advantage of the previously reviewed sensor-based systems in conjunction with a cloud-based close call data management system. The following paragraphs accompanying Figure 3 explain the existing practice and proposed approach in-depth.

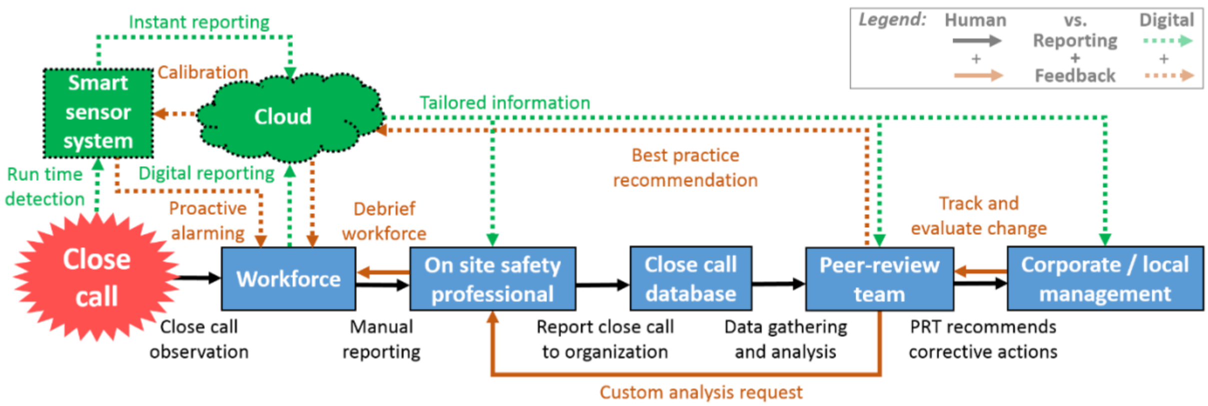


Figure 3: Close call reporting and feedback processes: (a) the legacy process is illustrated using solid arrows and boxes; and (b) the proposed process is represented using dashed arrows and boxes (NB: the proposed process augments but does not replace the existing close call reporting process shown in Figure 2) [17]

Any workforce member (i.e., a pedestrian worker or a person handling equipment) can be involved in a close call incident. This could happen, e.g., when the worker and the machine interact in close proximity to each other.

As per *current close call reporting practice* (shown with solid lines and shapes in blue colour in Figure 3), any observer would report such events manually. They would then be registered to a close call database by the on-site safety professionals. A peer-review team would analyse the close call database periodically and inform the corporate or local management about potential practices changes to prevent a similar close call from happening again. The local management would finally propagate the feedback to the workforce via the peer-review team and the on-site safety professionals. The process so far involves several stakeholders. Many are likely operating at different locations and/or not timely available. Feedback to or debriefing the workforce is relatively slow or non-existent. Unfortunately, new close calls or even accidents can occur in the meantime.

In addition to the human efforts reporting close calls and following-up, digital means are to be applied (shown with dashed lines and shapes in green colour in Figure 3). The *proposed approach* incorporates a cloud-based system utilising digital reporting and sensor information to register and manage close calls respectively either by (a) a personal observation that is digitally reported (e.g., only if the work environment permits using an application of a smartphone or tablet), or (b) a specialized *Smart Sensor System* (SSS).

Such a decentralized (edge computing) unit based on sensor inputs (run time detection) analyses hazardous incidents and instantaneously notifies the workforce. While the individual signals from the sensors are fused, reported, and reacted upon later, the SSS - most importantly - provides an assistive warning signal (pro-active alarming feedback) instantly sent to the workforce individuals (not requiring any cloud processing). This helps prevent potential accidents from happening; based on such run-time analysis performed in the SSS, the workforce is proactively alarmed about potential close call incidents before they turn into an accident.

The automatically recorded close call information is sent to the cloud where on-site safety professionals, the peer-review team and the corporate/local management have access and can concurrently review at any time. The cloud connects all stakeholders to the relevant information. It also connects the system components, e.g., the computation units, to the data. It is, therefore, an entity that ties together the system. The information on the cloud should be tailored to the individual stakeholder's interests to make sure that it is sufficiently informative and is not drown by the otherwise insignificant details.

Based on the information available on the cloud, debriefing of the workforce happens as soon as possible. This may include updates on the latest close-call incidents to learn from and possibly avoid similar incidents. Additionally, future machine learning techniques will assist in identifying recurring or new patterns in close call reports. Then close call reports can include – aside from the general observations such as the location, observer, participants involved in the close call, timestamp, severity, cause, and measure – newly available details such as equipment trajectory and velocity.

Based on the latest available information, there a two-way calibration could be conducted; the SSS data, along with a labelled close call incident could be uploaded for:

- Long term prediction, analysis, and information gathering,
- Parameter optimisation, and
- Data access from stakeholders.

The updated parameters should assist the SSS to improve its analysis capabilities. Over time and with large amounts of data in the future, a system like the proposed one shall be capable of generating far more accurate predictions than humans ever would.

4 Sensor-based methods for risk monitoring and detection

While safety education and training offer an additional way to increase awareness or change the behaviour, close proximity incidents between pedestrian workers and equipment will eventually require right-time proactive measures. As explained in [12], few solutions solve this problem for good. Up to now, construction equipment operators rely on their own judgement to detect close-by hazards. Consequently, operators often ignore alarms due to desensitisation or due to background noise [34, 39].

As illustrated in Figure 4, based on their principle of operation, the various existing Sensor-based Systems (SbS) can be categorised in:

- Camera-monitor systems,
- Ultrasonic systems,
- RaDAR systems,
- Radio systems,
- 3D camera sensors (incl. infrared),
- 3D time-of-flight sensor and
- LiDAR/LaDAR systems.
- RTK GNNS location tracking

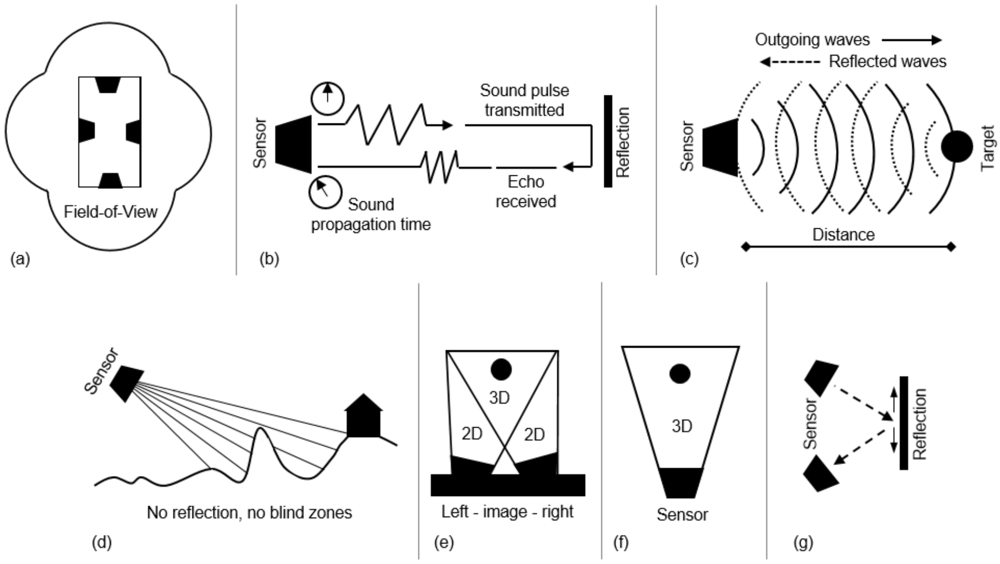


Figure 4 – Operating principles of Sensor-based Systems (SbS): (a) camera-monitor, (b) ultrasonic, (c) radar, (d) radio, € 3D camera, (f) 3D-TOF camera, and (g) LiDAR/LaDAR systems [17]

4.1 Camera-monitor-systems (CMS)

Camera-Monitor-Systems are auxiliary devices providing short-term, short-range visual aid to equipment operators e.g., during manoeuvring. Most CMS offer a flexible camera configuration to adapt to machine-specific designs/requirements (e.g., regarding the number of cable-connected cameras and their view angles, the need for little to no calibration or maintenance, the integration of pre-programmed monitors). Systems providing wireless signal transmission of video data over longer distances already exist (e.g., allowing the connection of cameras to monitors from remote mounting points), then, however, battery-powered cameras requiring charging on a daily basis become necessary. CMS typically use weather- and environment-resistant system components (e.g., IP 66K) and industrial connectors (e.g., M12).

CMS have three predominant operating principles:

- *Single-view* using a rear-, side-, or front-camera view only. It is specifically designed for equipment that reverses often or operates in carry-mode with front attachments (e.g., trucks, loaders, or forklifts [15], [33]).
- *Surround-view* using four standard cameras which provide a panoramic view in the equipment cabin's mounted monitor (Figure 4a).
- *Bird-view* generates digital images using ultra wide-angle cameras (e.g., mounted at the front, sides, and rear), which are further processed by video stitching and combined into a single 360° video image stream.

One of the main applications utilising CMS is equipment involved in earthwork. While certain equipment operations were found to be more dangerous in reverse, some equipment experienced higher accident rates when traveling forward [23]. These cases were recognised explicitly in excavator operations [56]. This can be attributed to the dynamic blind spots created by the moving extensions of the equipment. Since excavators require constant adjustment of the bucket height, the increased likelihood of a broken line-of-sight to a potential victim remains a significant concern. A potential solution to this problem can be the so-called 'smart cameras' with Pan-Tilt-Zoom functionality [57]. Smart cameras combine image sensors with processing units that perform the imagery analysis, control and decision-making on the device.

Likewise, commercially-available operator alert systems based on computer vision technology can detect operator's fatigue and distraction, therefore assisting the latter to maintain the level of attention necessary for long work hours and monotonous tasks; in this case, however, additional (vision or other) sensorial systems are required for detecting hazards in the equipment's vicinity [58]. Finally, making use of potentially integrated networking capabilities, not only the operators can be notified, but also the information can be transmitted to supervisors and central components such as a cloud environment for later data processing.

4.2 Ultrasonic systems

Ultrasonic waves measure the distance to a nearby object (from 0.1 to 3 meters, some even up to 9 meters) by calculating the time difference between sending and receiving a sound pulse with a frequency greater than 20 kHz (Figure 4b). Ultrasonic systems often appear on the rear, the sides or the front of the equipment; they can detect multiple objects at the same time, however, without the ability to distinguish them. A single/generic alert will be triggered regardless of the number of objects in close proximity to the equipment, e.g., a single object would be shown on the screen or a single sound would be triggered by the proximity buzzer in the equipment cabin. As soon as one object leaves the danger zone, any continuing alert will signify the presence of other remaining hazards. The application of ultrasonic systems is widely applied in automotive vehicles; some of its benefits and limitations in construction applications (e.g., unloading of delivery trucks or manoeuvring of forklifts) are:

- it accurately detects a vast number of obstacle types, independent of colour, surface, or environmental conditions;
- it is insensitive to dirt, dust, moisture, and potentially fog (system-dependent).
- it offers a multi-level, auditory proximity warning system and the possibility of (semi-) automated stopping of the equipment.
- it creates nuisance as all objects within the range of the sensor signal cause acoustic (potentially false) alerts, affecting the willingness to respond.

4.3 Radar systems

A Radio Detection and Ranging (RaDAR) sensor detects fixed and moving obstacles with the help of electromagnetic impulses. The operator can measure the distance between the equipment and the worker/object on a screen in the equipment cabin. Electromagnetic waves transmitted by the RaDAR (i.e., the primary signal) are reflected on the object's surface and are then received back as a secondary signal. The measured time between the transmission and the reception is used to determine the distance to the object (Figure 4c). Even in the harshest environments with the most inadequate visibility conditions, radar systems can detect people and objects reliably over a large range (typically up to 20 m) and at speeds of up to 20 km/h. Their high resistance to dirt, mud, dust, heavy rain, fog, darkness, smoke, humidity, heat, cold (optionally equipped with heated sensors), ultraviolet rays and vibration ensures reliable operation. Warning systems with radar sensors notify the operator with a brief time delay (50 milliseconds) from the time of object detection using an acoustic and/or optical signal (typically in a sequence of increasing speed). Furthermore, Controller Area Network (CAN) bus-capable radar systems provide an interface for proactive vehicle intervention. In construction applications, radar systems offering multi-level proximity alerting are often coupled with CMS. The detection range is divided into several zones which helps prevent accidents by alerting the operators about to manoeuvre and reverse equipment. However, rough terrain can lead to frequent, unnecessary false alarms. In order to avoid false alarms, radar systems can be combined with 3D terrain mapping or object recognition with a (rear-view) camera.

4.4 Radio systems

In addition to the operating principles of the systems mentioned above, proactive systems can issue alarms from equipment to pedestrian workers. Radio systems (Figure 4d) using electromagnetic fields detect pedestrian workers in close proximity to the equipment. Systems using radio frequency signals can also interact between vehicles, i.e. provide “vehicle-to-vehicle” communication, sending nearby equipment operators acoustic or visual alerts when approaching one another. They can instantly warn the machine operator and those at risk (e.g., pedestrian worker/s) in real-time; these systems effectively allow vehicle speeds of up to 25km/h [59]. Radio systems have been successfully used in the underground mining industry [60], [61], with implementations in construction applications being investigated [32, 58].

At least one radio transmitter mounted on the equipment emits a signal that an active transponder (i.e., a personal tag) returns; multiple transmitters would permit detecting the actual location of a personal tag. Radio signals have no blind spots, can penetrate through objects e.g., reinforced concrete, allowing the detection of persons behind obstacles (NB: some materials are susceptible or resistant to electromagnetic fields). While the personal tag issues an alert if a predefined distance criterion has been met, the operator receives a warning as well. All involved entities can react promptly: machines come to a stop or leave a danger zone; pedestrian workers’s level of awareness is raised in order to pay attention to the danger caused by equipment being too close. It should be noted, nonetheless, that existing data from radio systems, if logged at all, still require data fusion with a Global Navigation Satellite System (GNSS) to produce meaningful close-call positioning data.

4.5 3D camera sensors

3D camera sensors (Figure 4e) provide simultaneous capture of 2D images from at least two cameras. Data is processed into a single 3D image capturing the spatial component of the information. They can warn the operator in critical incidents, e.g., in case surrounding personnel or objects are in extremely close proximity, using acoustic and optical signals. In addition, the incident is visualised live in the cabin’s display monitor, as a CMS does, so the operator can remain focused on the main work task. A 3D camera sensor is superior to a CMS as it provides imagery with depth information (up to 60 m). It allows for more reliable distance measurement and object identification but still has similar disadvantages to a CMS. Some of these can be solved, e.g., integrating an infrared (IR) camera provides powerful illumination in poor ambient light conditions.

3D camera technology, e.g., stereo video cameras, although widely used for the observation of the environment in robotics and automotive assistance systems for private or commercial vehicles, are less common for construction equipment [62], [63], [64] [65] [66]. They are, however, one of the critical components in developing autonomous equipment. Efficient data processing enables fast object recognition from imagery data. Short-term data can also be recorded and used in performing an analysis of the root cause that contributed to accidents.

4.6 3D time-of-flight sensors

A Time-of-Flight (ToF) sensor (Figure 4f) captures a 3D point cloud of the work environment in real-time and processes the range data directly without the support of an external computer [67] offering customisable detection zones. ToF sensors send out an infrared light signal which is reflected by an object; for each pixel, the distance between the camera and the measuring object is calculated from the different light phase shifts. Thousands of pixels are captured in a single shot, thereby delivering a detailed three-dimensional distance image; continuous images deliver video imagery with range depths. A limitation is that very reflective targets (e.g., fluorescent material on a safety vest) hardly return a useful signal - the overstimulation of the sensor does not allow for accurate range estimation. 3D ToF sensors have robust IP67 housings.

4.7 Lidar systems

LiDAR or LaDAR (Light or Laser Detection and Ranging) (Figure 4g), a method for optical distance measurement, provides accurate results using a pulsed laser beam which is reflected by the target [17]. The reflected beam is detectable under all light conditions and can be used even in complete darkness. Once received by a detector, the time between transmission and reception of the reflected beam is measured, from which the distance is calculated. In contrast to a continuous wave laser, a pulsed laser has a higher power density (thus have an extended measurement range). The LiDAR technology is designed to be eye-safe (laser class 1) and typically operate in fixed positions, e.g., fixed laser curtains (2D laser scanners) with a customisable opening angle or wide measurement zones. Given the high resolution on obtained object profiles, LiDAR systems can be directly used for worker or object detection and identification. A large number of parameters can be directly processed and visualised by means of a software interface. The system, however, is to some degree susceptible when used in very rough terrain, heavy dust and precipitation (which are likely to occur in outdoor construction environments).

4.8 RTK GNSS location tracking

RTK (Real-Time Kinematic) technology aims to improve the accuracy of conventional GNSS systems; Figure 5 indicates the concept of RTK. It consists of a base module and rover modules. The base module is stationary. Its precise location is computed by independent surveying methods. Both, the rovers and the base station compute their GNSS location by connecting to GNSS satellites. By comparing the GNSS location of the base station to its precise location, the base station transmits the deviation to the rovers. The freely moving rovers use this difference in algorithms to compute an inch-accurate location.

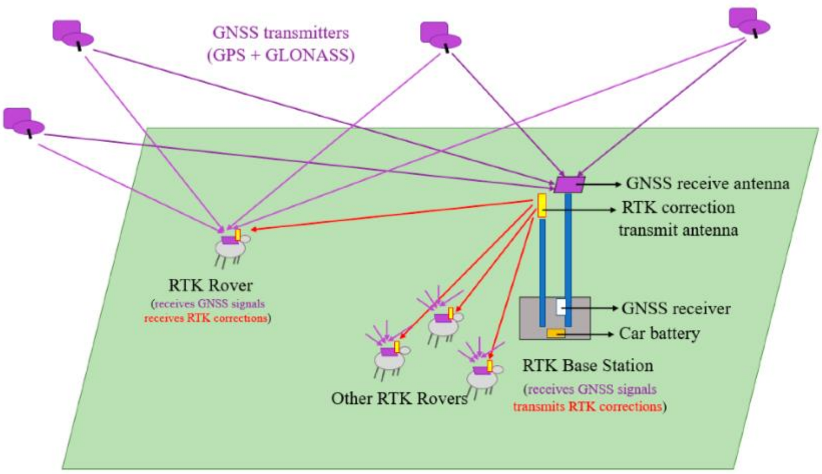


Figure 5: RTK improves GNSS location tracking (Source: RSRG).

4.9 Comparing sensor technologies

Table 1 summarises the characteristics of the aforementioned sensor systems. Noteworthy to mention are the characteristics such as: the signal, line-of-sight, range, false alarm frequency as well as the sensitivity to environmental and human factors: two-way-alarm, proactive alarm and nuisance alarm frequency. The qualitative values of the characteristics marked with an asterisk were determined based on the findings in literature. For example, CMS scores 'medium' because the false alarm rate is higher (its operator could easily ignore a display screen) compared to a radio system (which can autonomously slow down the equipment).

Radio systems, however, have higher initial investment and require continuous maintenance. Careful assessment of these characteristics should always be applied to each individual use case.

4.10 Advocating for sensor system fusion

Unfortunately, there is no single sensor system that could alone be used for current proximity sensing because each one comes with benefits (e.g., identification, a visual extension of danger zones) and limitations (e.g., range, functional security measures). This work advocates for sensor data fusion because location data is often missing in close call data recording. This is very much aligned to the progression of autonomous vehicles in the automotive industry, where RaDAR and LiDAR systems complement each other’s weaknesses or GNSS data provides location data. Research in construction also adopts similar strategies [68].

4.11 Applying proactive and passive measures

Warnings/alerts by sensors can be issued in *passive* and *active modes. Passive* because a sensor may provide no additional information than the raw data. A bird’s view CMS, for example, provides a video stream on a small screen at the front of the equipment cabin. A standalone CMS still requires the operator to recognize and react to hazards. *Active* when a hazard has already been detected and pre-processed for the human (e.g., the event of an object with too close distance) and an alarm signal is given automatically. A radio system, as explained in the previous section, can do this. Either way, the prompt reaction upon approaching the danger is required, but only possible for an operator in charge of the equipment. Sounding a horn, applying the equipment brake, or starting an obstacle avoidance manoeuvre are common ways. A pedestrian worker with low awareness will not have a ‘second chance’ with the passive approach and will be hit (unless the operator reacts first).

4.12 Demanding data reasoning and feedback

Active sensors detect, react, and warn about hazards yet they lack, as discussed in the literature [69], [70], “realistic modeling and visualisation of risk in safety management”. Teizer et al. [14] have shown from a practical perspective why knowledgeable personnel in charge of construction safety rarely can measure or evaluate site-specific safety data. Some obvious reasons are lack of available time because they often manage multiple projects at the same time. Other more technical reasons are that sensors create large data sets and software for meaningful data reasoning and feedback hardly exists. Except for the radio systems, few of the sensor systems listed in Table 1are able to generate and/or report close call data.

Table 1: Comparison of selected characteristics of proximity sensing devices (common technical specifications according to manufacturers; * represent findings in the literature and own research) [17].

Sensor system	CMS	Ultrasonic	Radar	Radio systems		3D camera	3D-TOF	Lidar	RTK GNSS
				Magnetic field	UHF				
Signal line-of-sight required	Yes	Yes	Yes	No	Yes/No	Yes	Yes	Yes	Yes
Maximum range [m]	5-100	3	8-17	18	>20	60	10	2-100	<20
Multi-level alarm zones	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A
Adjustable range	No	No	Yes	Yes	Yes	No	No	No	N/A
Adjustable angle	Yes	No	Yes	No	No	Yes	Yes	Yes	N/A
Predominant use	Surround	Rear	Forward/Side	Surround	Surround	Forward	Forward	Curtain	Tracking/ Geofencing
Proactive alarm	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A
Two-way alarm (vehicle-to-person and vehicle-to-vehicle)	No	No	No	Yes	Yes	No	No	No	N/A
False alarm frequency*	Medium	Medium	Medium	Low	Low	Medium	Medium	Medium	N/A
Sensitivity to environment*	High	Low	Medium	Low	Low	Medium	High	Medium	Medium
Nuisance alarm frequency*	Medium	High	High	Medium	Medium	Medium	Medium	Medium	N/A
Installation, operation, and maintenance*	Low	Low	Low	Medium to High	Medium to High	Medium	Medium	Medium	N/A
Object detection/recognition	No/No	Yes/No	Yes/No	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	No
Data logging	Limited	No	No	Yes	Yes	Limited	Limited	No	Yes
Functional safety*	High	High	High	Medium/High	Medium/High	High	High	High	High
Industrial security*	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	High
Overall investment (incl. cost, installation, maintenance)*	Low	Low	Low to Medium	Medium to High	Medium to High	Medium	High	High	High

5 Close call data analysis

The proposed close call reporting, analysis and personalised feedback process takes advantage of remote sensing and information modelling to automatically record the circumstances that lead to close calls. By attaching an RTLS tracking device on every *resource* (pedestrian workers, equipment and material that was a-priori declared hazardous), their available trajectory data will be analysed along with the corresponding information in BIM (e.g., hazard paces) to locate/geo-reference close calls (step 1 in Figure 6) and enable the inference of further valuable information that led to the close call (step 2). Once analysed, the data generated provide an elevated level of detail not previously available (step 3). This way, measurement and evaluation of close calls during the actual construction phase becomes an active leading indicator which can result in a quicker (perhaps immediate) improvement of the safety performance [71]. The statistical analysis currently ends on assessing the close calls of a particular work environment (simulated or actual construction site), but a future research vision is to extend the close call data analysis to the levels of an organisation or industry (step 4). This would lead to benchmarking close call metrics for many construction sites or an entire industry. Once such data becomes available, peer-to-peer pressure to outperform competitors may lead to further reduction of the number of close calls, ultimately leading to higher safety performance of the industry. The corresponding workflow for fusing all data types and data post processing generates descriptive analytics on each close call event.

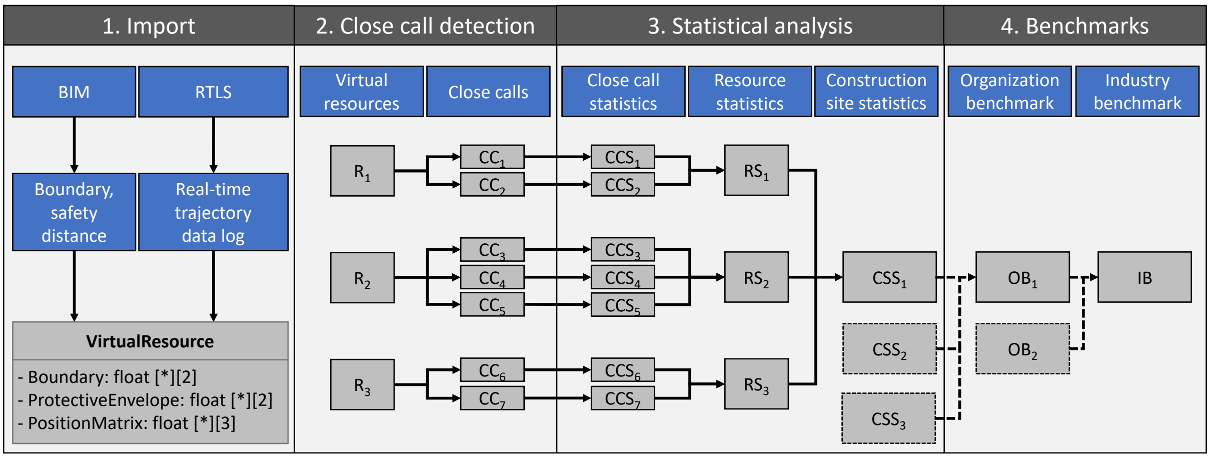


Figure 6: Proposed workflow for the data processing algorithm (dashed lines are part of a future predictive close call data benchmarking)

The *proposed methods* in this workflow are explained next in more detail. It is followed by a detailed investigation into the theoretical verification of the proposed methods using first a *simulated data set in a fictional construction setting* and thereafter (after ensuring the methods work successfully) several *realistic data sets for experimental validation on live construction sites*. As a note, the initial selection of simulated over realistic data permitted the verification of the proposed method under ideal (repeatable) conditions. In the simulated setting, a fictional building information model and trajectory information was assumed for the artificial pedestrian workers' and equipment travel paths.

5.1 Construction resource data

Construction resources are physical objects and spaces that are required to finish a construction process. In this research, the term *construction resource* refers to (a) the pedestrian workforce, (b) construction equipment, and (c) objects or structures of temporal or final state. The number of any of these resources in the scene under investigation can be one or many. They can also be static or dynamic in nature. Pedestrian workers as well as equipment are moving frequently, while temporary objects, such as scaffolds or hazardous materials like gas bottles, are mostly static and stay in one position. Other examples of static or as-built structures which can be hazardous are unprotected edges in elevator shafts or leading edges in high-rises.

As needed later in the *experimental field validation*, actual geometric data of the as-built conditions of the work environment were recorded using terrestrial laser scanners and unmanned aerial vehicles (UAV) [72]. The point cloud information was georeferenced and imported as simplified boundary objects in building information models [73]. The resource trajectory data in the outdoor work environments was recorded using remote sensing technology.

Construction resource data is defined as a term to summarise *boundary data* from building information modelling and *trajectory data* from trajectory logging files. Microsoft EXCEL-files served as the initial medium to transfer this information, since construction personnel is familiar with this software package. The data for each resource is contained in a separate file.

Ultra-wideband (UWB) [74] and Global Navigation Satellite System (GNSS) [14] offered two suitable options to record the trajectory data in real-time. It was important to consider that deployment of any of RTLS in the field highly depends on the work environment that is under proposed investigation. Business and technological factors, such as return on investment (ROI), signal propagation, size of measurement errors, hardware form factors, power consumption, ease of installation and maintenance, and many more factors must be and were considered as well [74]. However, they are not the main focus of this study.

5.2 Protective envelopes and boundary data representing resources

To automatically detect and analyse close call events between *resources*, additional descriptive information for each individual resource involved in a *close call event* is necessary. For example, its precise position and boundary information define a *protective envelope*. For the sake of simplicity, all data presented in this study are kept to two-dimensions (2D, plan view). As a result, the protective envelopes come in shapes of circles or polygons (Figure 7). The number of involved resources as well their parameters, i.e., the size of the protective envelope called the *safety distance*, are set in advance based on the previous research findings as in [74]. Trajectory information and building information model complement this chosen approach.

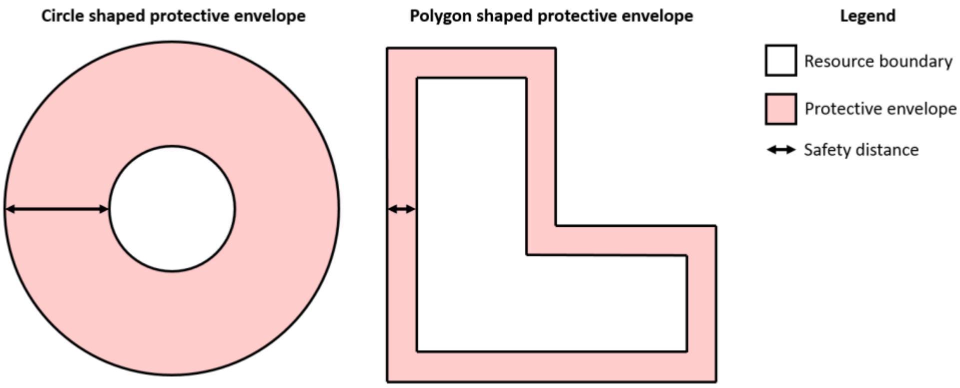


Figure 7: Examples of two protective envelopes (plan view)

Boundary data represents a simplified version of the true shape of a resource/element in 2D space, typically derived from a building information model. While a straight wall object, for example, is represented as a rectangle of the same length and width in 2D, workforce and equipment are more simplified. The width of the shoulder of an adult is approximately 0.6 m [74]. The value is rounded up to 1 m, which leads to representing the shape of a pedestrian worker as a circle. Much slower speeds than equipment, for example, and rapid changes in direction suits this representation of a worker well. In contrast, in most application scenarios the simplified shape of a piece of equipment is a bounding box. A bounding box [75] encompasses all of its inner attachments. More complex objects are represented as a freeform using polygons. As explained earlier, boundary data contains a *safety distance* which extends the object boundary and creates a *protective envelope*.

5.3 Protective envelopes

Unless specified otherwise by a user upfront, every resource boundary is surrounded by its own protective envelope (see Figure 7). While the protective envelope is used to detect close call events between resources, the size of its safety distance and its shape are based on the following assumptions:

- *Pedestrian workforce*: A circle with a radius of 1.5 m is selected. This value is based on the average distance a human walks in one second, reacts and comes to a complete stop [74].
- *Construction equipment:* A protective envelope for equipment must be wisely chosen considering several of its operating parameters. These include but are not limited to: operating speed, angle of operation and articulation. Even external factors such as ground conditions might be included when calculating a machine's breaking distance. While [76] has shown that multiple hazard zones for equipment are advisable to avoid a hit, generally a fixed value decided by a user is added around the equipment's known bounding box.
- *Temporary object:* The size of a protective envelope for temporary objects (e.g., safe storage of gas bottle) is determined according to rules and regulations set by governments and local authorities [35]. The resulting shape is a resized version of the existing boundary.
- *As-built structure:* Many structures once erected remain on site and might also require protection. Guardrails, for example, preventing workforce or equipment from falling to lower levels typically have protective envelopes associated to them. Their safe installation is also regulated by official regulations or company best practices [77].

5.4 Trajectory data

Trajectory or position logging devices frequently store a resource's relative position and the current time, namely timestamps, inside a log-file [14, 78]. The logging frequency and additional logging information such as the battery status both depend on the type of device. In this research, a frequency of one event per second (1 Hz) is assumed to simplify the following calculations. When a log file is imported, its information is trimmed to a uniform trajectory matrix,

$$T(R) = \begin{pmatrix} x_{start} & y_{start} & t_{start} \\ x_{start+1} & y_{start+1} & t_{start+1} \\ \vdots & \vdots & \vdots \\ x_{end-1} & y_{end-1} & t_{end-1} \\ x_{end} & y_{end} & t_{end} \end{pmatrix} \tag{1}$$

where t_{start}, t_{end} refer to the first and last logged timestamps and *x* and *y* to the location of the device. This matrix is referred to as *trajectory data*. To help with further definitions, a function which returns the position of *resource R* for a specific *timestamp t* is defined as:

$$P(R,t) = \begin{cases} (x_t, y_t)\ , & \text{if } t \in \{t_{start}, t_{start+1}, \dots, t_{end}\};\ x_t, y_t, t, t_{start}, t_{end} \in T(R) \\ & \text{undefined, otherwise} \end{cases} \tag{2}$$

5.5 Close call event

Currently, there exists no common definition for close calls [52, 79]. A *close call*, as defined in this document, refers to a close-proximity event between one or several pedestrian workers and a hazard, leading to an endangerment of the workers. In other terms, a close call between two resources A and B is defined as an overlap of their protective envelopes at positions $P(A,t)$ and $P(B,t)$. When using trajectory data, there are two possible approaches towards categorizing close call events: (a) to categorize every proximity event as a separate close call or (b) to combine consecutive occurring proximity events to a single close call. The latter is the more sensible choice and is the one used throughout this work.

5.6 Close call event buffering

For each close-proximity event, a proximity event buffer is created to store information for later processing. This information includes a timestamp [yy:dd:hh:mm:ss], position [m], velocity [m/s], and orientation [°]. Information on the distance [m] and facing direction [°] towards the other resource is also stored. In the example shown in Figure 8, a piece of equipment has been traversing too close to a gas bottle.

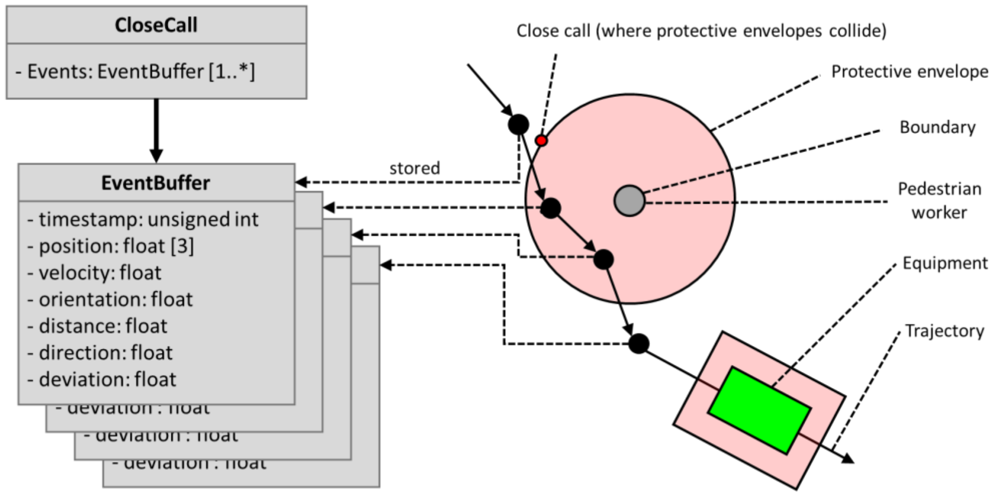


Figure 8: Visualised close call and the creation of a close call event buffer for each tracked resource

5.7 Close call analysis

For two resources A and B, a close call detection algorithm (1) analyses their trajectories and (2) checks for each *timestamp* $t \in T(A), T(B)$ if their protective envelopes overlap. If an overlap is found, a new close call gets created and a proximity event buffer is assigned to it. Every consecutive proximity creates a new event buffer which is added to the same close call. If no further overlap is detected, the close call is completed and the next proximity will create a new close call. Inside a completed close call, three event buffers will be marked for later processing:

- *Entry event:* First assigned event buffer.
- *Exit event:* Last assigned event buffer.
- *Closest event:* Event buffer where the distance between both resources is the smallest.

Additionally, the buffer events from the entry event to the closest distance event are summarised to the *entry path* and likewise the events from the closest distance event to the exit event are summarised to the *exit path*. As the trajectory data only consists of coordinates and timestamps, *velocity*, *facing direction*, *distance*, and *orientation* must be calculated separately.

5.7.1 Velocity

The close call algorithm has to compute a distinct velocity for each event buffer using only the resources' position data. As the trajectory logging frequency is assumed to be 1 Hz, the *velocity* v of a resource for *timestamp* t_i is numerically equal to the 2D-Euclidean distance between $P(A, t_{i-1})$ and $P(A, t_i)$,

$$v(A, t_i) = \begin{cases} 0, t_i = t_{\text{start}} \\ Euclid\big(P(A, t_{i-1}), P(A,\ t_i)\big), t_{start} < t_i \leq t_{end} \\ undefined\ ,\ otherwise \end{cases} \tag{3}$$

5.7.2 Facing direction

The *direction d* towards which workers or vehicles are facing at a timestamp t_i is expressed as a normalised 2D-vector on the *x*-*y*-plane. Similar to the calculations for velocity, this vector can also be computed using two position vectors. To be consistent, the direction will be calculated using $P(A, t_i)$ and $P(A, t_{i-1})$. Let *norm* be a function that returns the normalised version of a vector. Then the facing direction of a dynamic resource at *timestamp* t_i is defined as

$$d(A, t_i) = \begin{cases} \|P(A, t_i) - P(A, t_{i-1})\|, \ t_{\text{start}} < t \leq t_{\text{end}} \\ d(A, t_{start+1})), \ t = t_{\text{start}} \\ undefined, \ else \end{cases} \tag{4}$$

5.7.3 Distance

For a *timestamp* t_i the distance between two resources is defined as the closest distance between their boundaries (see Figure 9). The vector spanning this distance is described as the *boundary distance vector.* As these calculations are based on simple geometric operations, they are not discussed in greater detail.

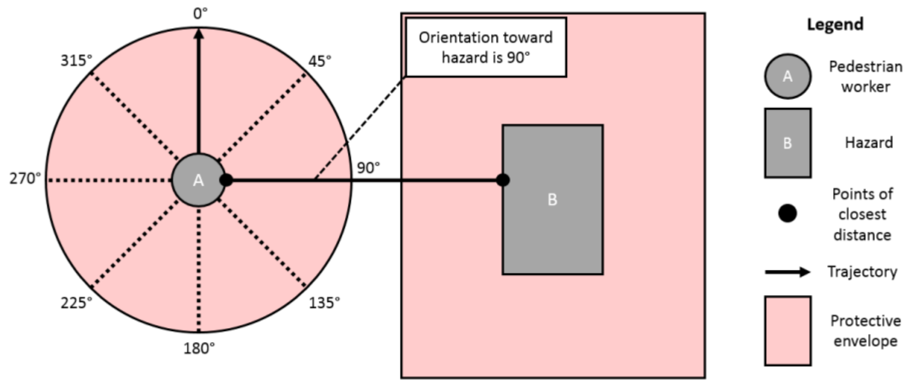


Figure 9: Orientation

5.7.4 Orientation

The orientation value for an event buffer quantifies the position of the hazard relative to the facing direction of the resource. For this purpose, the resources' *facing direction vector* as well as the *boundary distance vector* will be utilised to compute an angle from 0° to 360°. The angle expresses by how many degrees a worker has to turn to the right to face the hazard directly (see Figure 9).

5.8 Algorithm for automated close call data processing

5.8.1 Trajectory analysis

After storing all proximity event buffers, the close call analysis algorithm post-processes each close call to extract additional information that is later used in data or statistical analysis:

- *Duration:* The duration of the close call event in seconds. Under the assumption that the logging frequency equals 1 Hz, the number of event buffers is equal to the duration.
- *Entry duration:* The time interval between entry event and closest event (including the closest event).
- *Exit duration:* Duration between closest event and exit event (excluding the closest event)
- *Hazard weights:* Values which indicate the severity of a close call. This includes a separate weight for the orientation, velocity, distance, deviation, and duration.

Additionally, the *deviation* from an optimal direct path (see Figure 10) is calculated. This direct path is assumed to be a path that leads directly from the entry position over the closest position to the exit position.

It is calculated using the same number of steps as the real trajectory. The direct path positions are calculated by using a linear spacing algorithm between the entry position and closest position and between the closest position and exit position, respectively. In the following, the ratio between length of real path and length of direct path is described as the deviation of the close call. This value indicates how much the worker or vehicle has strayed from the shortest optimal path during the close call event.

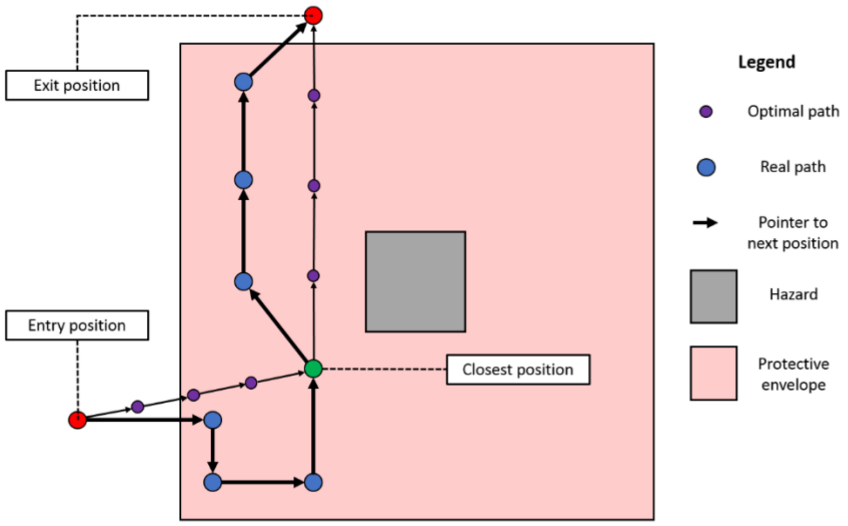


Figure 10: Real path and direct path

5.8.2 Radar plot

For each close call a radar plot is computed showing the weight values for velocity, duration, deviation, distance, and orientation. These weights, as explained next, visualise the severity of the different aspects that contributed to the close call event. The higher the value points in the radar plot, the more the aspect contributed to the endangerment of the resource. Velocity and length during the close call event (see Figure 11 give a user a brief overview of a resource's safety performance. As suggested by [14] personalised feedback or other change (i.e., selection of other equipment or type, modification to site layout plans) can be issued and future performance monitored until the issue is resolved.

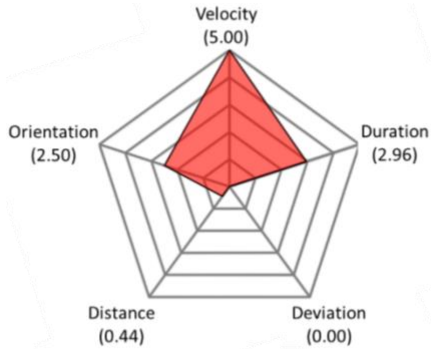


Figure 11: Radar plot indicating factors leading to close calls

5.8.3 Hazard weights

The following introduces the formulas to calculate the weights (velocity, duration, deviation, distance, and orientation) (Figure 12). While the original values for the weights can be based on historical data records, they may be adjusted over time or with the experience of close calls. $Weight_{\max}$ refers to a maximum weight.

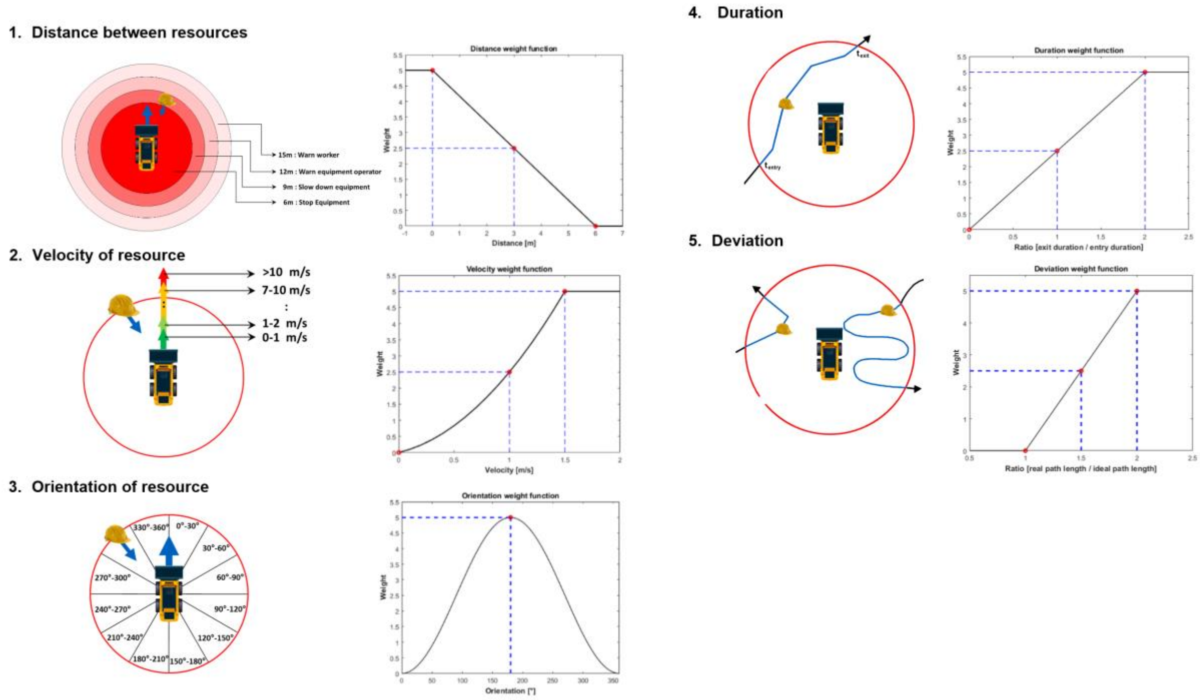


Figure 12: Description and graph for the different hazard weights: Distance, Velocity, Orientation, Duration and Deviation

5.8.3.1 Velocity weight

The velocity weight for a close call is calculated using the velocity weight function (Figure 12), with the average velocity of the close call as an input. In addition to $W_{\max}$ the course of this function depends on the parameter $v_{\max}$ which represents the maximum velocity a vehicle or pedestrian worker is allowed to have. The ISO standard 5006:2017 [36] points out that there is no common definition for safe velocities to operate construction equipment. The speed limits on construction sites depend on numerous factors like the type of equipment or the ground surface conditions [80]. In the following sections, $Vel_{\max}$ is assumed to be 1 m/s (or 3.6 km/h).

It is assumed that a velocity of 0 is always the safest and therefore the weight is set to 0 for all parameters of $W_{\max}$ and $v_{\max}$. Furthermore, moving with a velocity equal to the speed limit $v_{\max}$ is weighted with $\frac{W_{\max}}{2}$. Since the risk of severe injuries increases exponentially, the weight function also increases exponentially as a function of velocity. Moving with a speed of 150% of the allowable speed limit (or even faster) is rated with $W_{\max}$. In brief, these conditions lead to three specific points,

- $P_0 = (0, 0)$,
- $P_1 = \left(v_{\max}, \frac{W_{\max}}{2}\right)$,
- $P_2 = (1.5\, v_{\max}, W_{\max})$

on the velocity weight function which is of the form $f(x) = ax^2 + bx + c$ for $x \in [0, 1.5\, v_{max}]$. Inserting these points into this function creates a linear system of equations which can be written as a matrix equation

$$\begin{pmatrix} 1 & 0 & 0 \\ 1 & Vel_{\max} & Vel_{\max}^2 \\ 1 & (1.5\, Vel_{\max}) & (1.5\, Vel_{\max})^2 \end{pmatrix} \begin{pmatrix} c \\ b \\ a \end{pmatrix} = \begin{pmatrix} 0 \\ 0.5\, Weight_{\max} \\ Weight_{\max} \end{pmatrix} \tag{5}$$

and solved using the MATLAB matrix division operation.

5.8.3.2 Duration weight

The *duration weight Du* could be determined using the duration of the close call alone. However, this might lead to a correlation between the size of a hazard envelope and the duration weight, as the risk of being longer inside a hazard increase with its size. Given that one of the research aims is to quantify aspects that help analyse pedestrian workers' behavior, it is more sensible to examine the ratio between entry duration and exit duration. This value could indicate if the worker noticed the hazard or if the worker took action accordingly to leave the dangerous area soon after sensing it. Combined with other values, for example the exit velocity, one can draw more conclusions about the incident.

The weight function (Figure 12) is composed of a linear function for ratios from 0 to $R_{\max}$ and a constant function with a value of $W_{\max}$ for all ratios above $R_{\max}$. In the event of the entry duration being equal to the exit duration, the weight function returns half of $W_{\max}$.

Figure 12 displays the duration weight function for $R_{\max} = 2$ so that it returns $W_{\max}$ once the entry duration is at least half as long as the exit duration. Let the ratio for the duration weight function be defined as

$$R = \frac{exitDuration}{entryDuration} \tag{6}$$

Then the weight function for duration is defined as

$$Du(R) = \begin{cases} \frac{W_{\max} \quad R}{R_{\max}}, \ 0 \le R \le R_{\max} \\ W_{\max}, R \ge R_{\max} \end{cases} \tag{7}$$

5.8.3.3 Deviation weight

The ratio between the length of a real path and a shortest path (Figure 12) is described as the *deviation De* of a close call event. Since the ideal path of a close call event leads directly through three positions of the real path (namely: entry, closest, and exist points), the real path length is always greater than or equal than the ideal path length. Therefore, the ratio between these values is 1, if both lengths are equal. In this case the worker walked the ideal path and the deviation weight is set to 0. A$Weight_{\max}$ is assigned if the actual walked path is twice as long as the ideal path length. Let $Path_r$ be the real path length and $Path_s$ be the shortest path length. Then the deviation weight function can be defined as

$$De(Path_r, Path_s) = \begin{cases} \left(\frac{Path_r}{Path_s} - 1\right) W_{\max} \ ; 1 \le \left(\frac{Path_r}{Path_s}\right) \le 2 \\ W_{\max} \ ; \ Path_r \ge 2Path_s \\ undefined \ ; \ Path_r < Path_s \end{cases} \tag{8}$$

5.8.3.4 Distance weight

For the computation of the *distance weight Di* of a close call event, the resources' individual safe distances as well as the closest distances are required. There are three major cases to distinguish for the distance between two resources (see Figure 13):

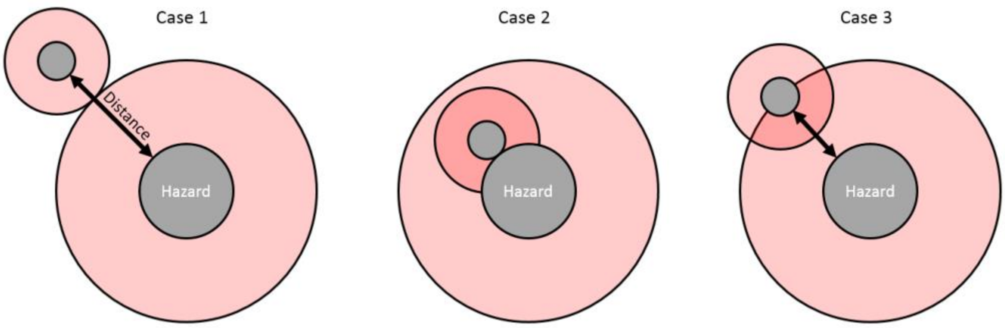


Figure 13: Three cases for the distance between two resources

- Case 1: The distance is equal to the sum of both safe distances or greater. This is assumed to be the best case and a weight of 0 is assigned.

- Case 2: The distance is equal or smaller than 0 (which is the case if the resource models overlap). This would be the worst case and is evaluated with $Weight_{\max}$.
- Case 3: The distance lies between the two cases mentioned above. In this case the assigned weight is between 0 and $W_{\max}$.

Let D_A and D_B be the assigned safe distances for resource A and resource B with $D_A \leq D_B$, let d be the input distance and D_{sum} be the sum of D_A and D_B. The distance weight function is partially defined as a linear function for distances between 0 and D_{sum}, composed with a constant function of $W_{\max}$ for all distances that are smaller than 0 and another constant function of 0 for all distances greater than D_{sum}. The slope of the linear function is equal to $-\frac{W_{\max}}{D_{sum}}$. In summary, the weight function can be written as

$$Di(d, D_{sum}) = \begin{cases} W_{\max} \; ; \; d \leq 0 \\ -\frac{W_{\max}}{D_{sum}} \; d + W_{\max} \; ; 0 < d < D_{sum} \\ 0 \; ; \; d \geq \; D_{sum} \end{cases} \tag{9}$$

As an example, Figure 12 displays the distance weight function for safe distances of $D_A = \; 1$ m and $D_B = 5$ m, where the value for d ranges from -1 to 7 m.

5.8.3.5 Orientation weight

Computed orientations, as shown earlier, range from 0 to 360 degrees. Using the average orientation over all buffer events is not feasible as potential left-side and right-side orientations would cancel each other out (average of 90° and 270° is 180°). Therefore, the *orientation weight* W_{orient} depends on three values:

- O_{entry}: Orientation at entry event buffer.
- O_{exit}: Orientation at exit event buffer.
- $O_{closest}$: Orientation at closest position event buffer.

Separate orientation weight values for each of these three values are calculated. Evaluating the orientation is then a matter of perspective. Weighting hazards appearing from the front (around 0°) can help to find inattentive workers, while hazard behind a worker can pose a dangerous threat even to very cautious workers. Therefore, unless other methods are used to track whether a human has recognized a hazard or not, the evaluation of orientation may depend on a users' personal preference. In the presented scenario, hazards appearing from behind will be evaluated as more dangerous.

The resulting function is based on a sine function, which is translated upwards on the y-axis by 1, then translated vertically to the left on the x-axis by $\frac{3\pi}{2}$, then stretched horizontally by a factor of $\frac{180}{\pi}$ and then stretched vertically by a factor of $\frac{Weight_{max}}{2}$. To make sure that the absolute orientation weight is not greater than $Weight_{\max}$ the weights for closest orientation, entry orientation and exit orientation are averaged. If the function for a single orientation weight is

$$w(o) = \left(\sin\left(\frac{o\,\pi}{180} + \frac{3\pi}{4}\right) + 1\right) \frac{W_{\max}}{2}, \tag{10}$$

then the overall weight is averaged as

$$W_{orient}\left(O_{entry}, O_{exit}, O_{closest}\right) = \frac{w(O_{closest}) + w(O_{entry}) + w(O_{exit})}{3}. \tag{11}$$

There is also the possibility to rate both hazards from behind and from the front with high weights. However, this would cause the values to lose their informative value since the weight would be the same for incautious workers which do not recognize a hazard as well as for workers which could not see the hazard from behind. In brief, a user may configure the tool based on their personal preferences.

5.9 Verification of method

The following sections apply the previously defined criteria to four different experiments. These experiments aim to strengthen the selection of indicators for close call events. The first experiment uses an artificially generated data set, while experiment 2,3 and 4 base on location data from real construction resources.

5.9.1 Experiment 1: Artificially created dataset

As mentioned earlier, a first test of the developed method occurred in a simulated construction scenario. Close calls among few resources were artificially generated. The close calls were analysed and details for each resource were discovered, for example: the course of close calls, individual resource- and hazard-statistics, a heatmap as well as comprehensive construction site safety statistics. All generated information is displayed on a layered Graphical User Interface (GUI) (implemented in MATLAB®) which permits a user to assess the newly generated construction safety information from multiple view points and levels of detail. The GUI was designed based on industry expert input in a way allowing to find intuitive answers to typical safety-performance-related questions:

- What are the areas where close calls occur frequently?
- What workers or pieces of equipment are involved in a close call and are there any particular differences in the safety performance among them?
- How does a worker react on entering a hazard zone, when might the worker recognize to be at risk, and how will the worker react upon detecting it?
- What ways exist to leverage the newly generated information for continuous safety performance improvement, e.g., in safety education and training?

The artificially generated data set (called scenario) is based on known trajectories (straight lines) where the ground truth is known and evidence available is used to verify the close call analysis algorithm. This scenario included five workers that traverse a construction site in a continuous manner, facing two temporary static hazards and one dynamic vehicle. Each worker simulates a behaviour which addresses one of the different hazard weights. To raise the orientation weight value for a worker, for example, the vehicle creates a close call in a workers' blind space. All trajectories are straight lines. This permits simplicity in the verification process of the algorithm. A heatmap displayed in the GUI further allows the evaluator to spot the close calls.

Some more specifics to the scenario: one pedestrian worker (A) traversed the site at a speed of 2 m/s (at a maximum allowable speed limit of 1 m/s). A second pedestrian worker (B) was a too short distance towards the hazards (301 and 302). A third pedestrian worker (C) simulated a behaviour which should result in a high deviation weight. The duration weight was tested by pedestrian worker (D). Pedestrian worker (E) was confronted with a traversing vehicle (F) to verify the orientation weight function. The heatmap functionality was verified by comparing the trajectories with the hazard locations on the map (see Figure 14).

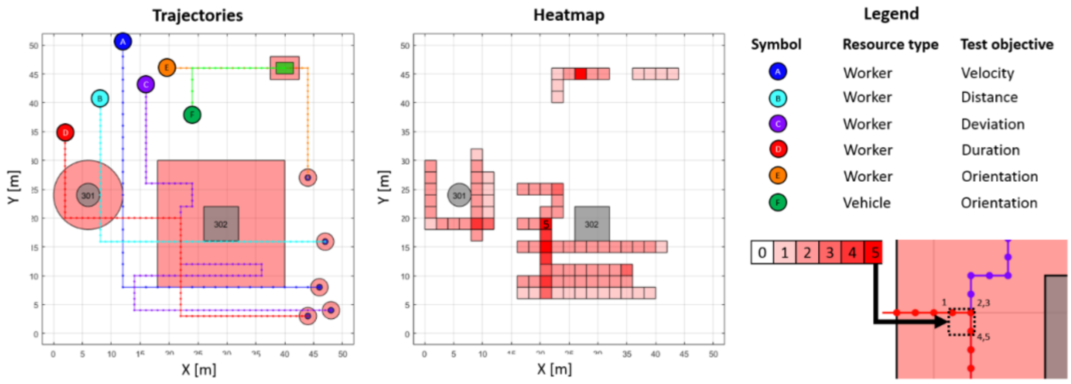
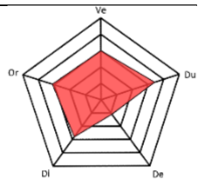


Figure 14: Verification of close call analysis algorithm using an artificial construction scenario

The weight radar plots for all resources are displayed in Table 2. Resources A, B and D showed expected results that verify the functionality of the velocity, distance, and duration weights. In contrast to the other resources, C shows two raised weights for deviation and duration. As the deviation value quantifies the straying of the worker from an ideal path and the duration value increases with a longer exit duration, a raised deviation weight might tend to be accompanied by a raised duration weight. In contrary, the radar plot of resource D shows a sole raised duration weight. Therefore, a mutual correlation between these values can be excluded. Resource E shows two raised weight values as well. This can be explained as: (a) vehicle and pedestrian worker do not have a large safety distance and (b) the vehicle stopped right behind the worker with a distance of close to zero meters. In theory, each one of the recorded close call events should be followed up. However, a user in a realistic scenario may need to set preferences on the more severe close calls. According to the initial findings in a simulated test environment, weight values of approximately 4 or higher would require such much more detailed follow-ups.

Table 2: Weight radar plots and values for every resource and average team performance

Category	**Resource**					**Team**
	A	B	C	D	E	
Radar Plot						
Velocity	**5,00**	2,50	2,50	2,50	2,50	3,00
Duration	2,96	3,42	**5,00**	**5,00**	0,78	3,43
Deviation	0,00	0,00	**5,00**	0,51	0,00	1,10
Distance	0,44	**4,93**	2,50	1,84	**4,26**	2,79
Orientation	2,50	2,50	3,26	2,86	**4,46**	3,12

5.9.2 Experiment 2: Building construction site

A dataset was gathered on a real building construction site where several pedestrian workers were present at an elevated work level. A restricted workspace was located inside the work area. Although the protective guardrails around the leading edges met the required safety standards, the present supervisor estimated it as insufficient (asking his and subcontracted personnel "to stay away from the edges"). One of his particular concerns was the arrival of a new subcontractor. Their new work crew for tying rebar yet had to familiarize themselves with the work environment (including work at height). Therefore, the close call analysis algorithm aimed at analysing the trajectories of three of the subcontracted workers for potential close calls near the leading edge and/or unauthorized entry into the restricted work space.

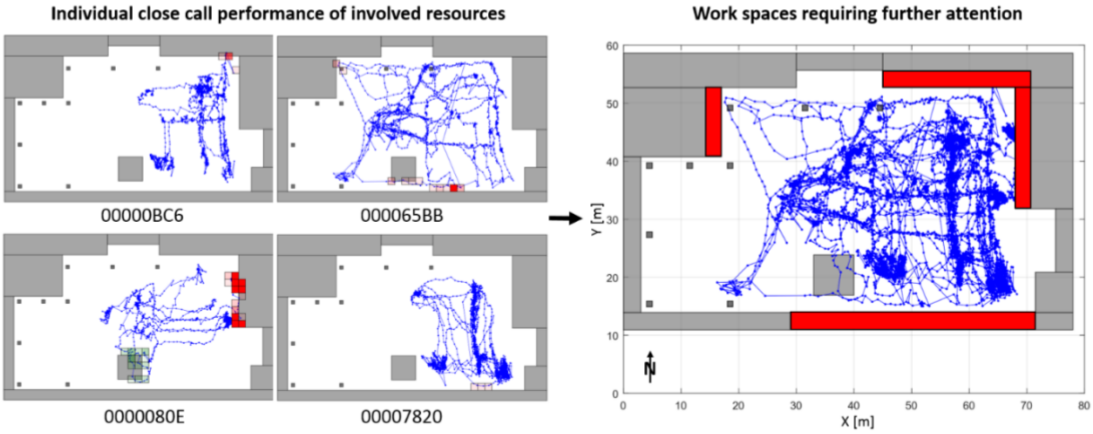
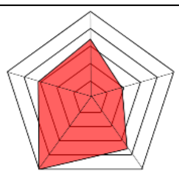
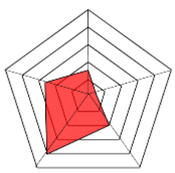
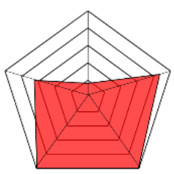
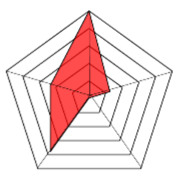
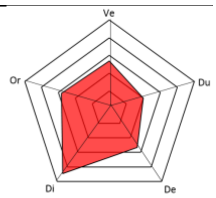


Figure 15: Heatmaps identify close calls in a BIM-based site layout (extracted for each resource and construction sites from GUI levels 2 and 1, respectively in the order of appearance from left to right)

As shown in Figure 15 (see the grey areas in plan view) the restricted space and the leading edges were modelled as individual objects using BIM. UWB served as the sensing technology for recording the trajectories of the personnel. UWB allowed to allocate a specific ID to every worker. The information in Figure 15 displays the individual trajectories (in blue colour) and, by applying the developed close call algorithm, the resulting heatmap (in a range of red colours) for every worker. The images indicate several close calls, mostly towards the southern and eastern sides of the work environment. Interestingly to note are the green tiles, also visualised in Figure 15. They indicate that a person (tag ID: 0000080E) entered the material storage area. Since it was the material manager there was no real violation. Worker 000065BB once passed by the restricted work space. As shown, the use of sensing technology, data analysis, and visualisation offers also the option of positive feedback.

The analysis of several of the generated hazard weight radar plots for the pedestrian workers give further insights into the observed close calls. Table 3 displays the individual workers' hazard weight radar plots and the team's performance. The worker with the ID: 00000BC6 shows higher hazard weights than most other workers. Although the data visualisation indicates only two other close calls nearby, they must have been serious close calls (medium speeds, but very close to the leading edges).

Table 3: Weight radar plots and values for every resource and average team performance

Category	**Resource**				**Team**
Tag ID	00000BC6	000065BB	0000080E	00007820	
Radar Plot					
Velocity (Ve)	3.40	1.52	0.83	**5.00**	2.69
Duration (Du)	1.90	0.47	**4.36**	1.25	2.00
Deviation (De)	3.57	2.01	**4.98**	0.00	2.64
Distance (Di)	**5.00**	**4.07**	**4.98**	3.78	**4.46**
Orientation (Or)	3.13	2.62	3.23	2.34	2.83

Additional insights can be retrieved from reviewing the team's close call performance. Figure 16 displays the number of close calls by each worker over the weights. Trend lines are also shown. Worker ID 00007820 had one and worker ID 000080E had 17 close calls. While the one worker (00007820) traversed close

(Di=3.78, note: lowest distance to the hazard of all workers) to a leading edge at high velocity (Ve=5, note: highest of all workers) on a straight trajectory (De=0, note: lowest of all workers), the other worker (0000080E) had numerous more close calls, most of which happened at low velocities and for extended periods of time. Confronting the workers with the data in an exit interview, answers for such behaviour were sought: one worker responded with "[I] have been on the direct path to a work station" and the other worker replied "[I was] constantly aware of the danger of tying rebar in a confined area near the leading edge".

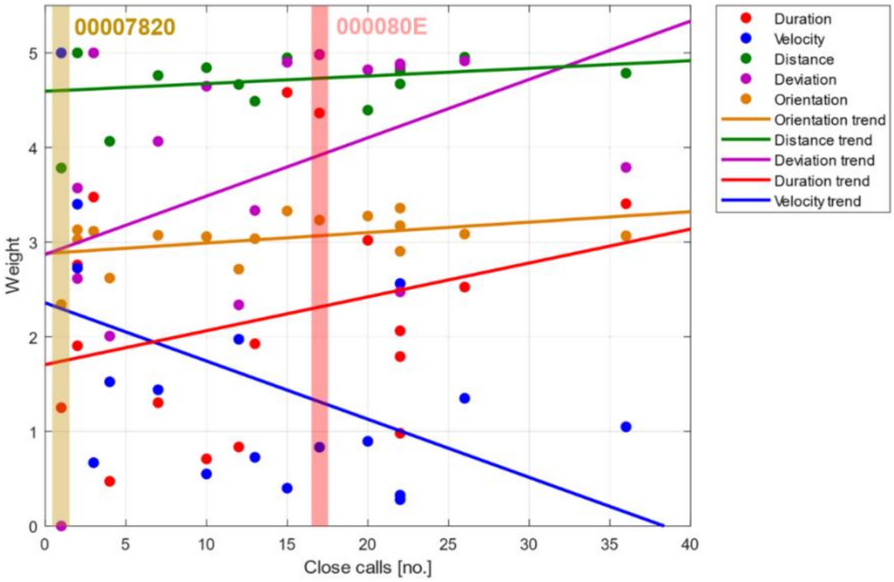


Figure 16: Close call performance by work team member

Further investigation can be taken by looking at a box plot. A future research objective will be to investigate outliers in more detail (Figure 17). The analysis of the experimental data indicates that a too close distance of pedestrian workers to a hazard is a major concern. While worker ID 00007820 had only one close call, he clearly traversed at very high speed. This might ask further questions: What pedestrian velocities are permitted and at what point in time should control measures come into effect? As practiced by industry leaders, in such a case when workers are observed running on construction sites, the worker would be instructed first, then pulled temporarily from work and provided with additional instructions before being able to return to work. Repetitive poor performance, though, may put a worker's employment at risk.

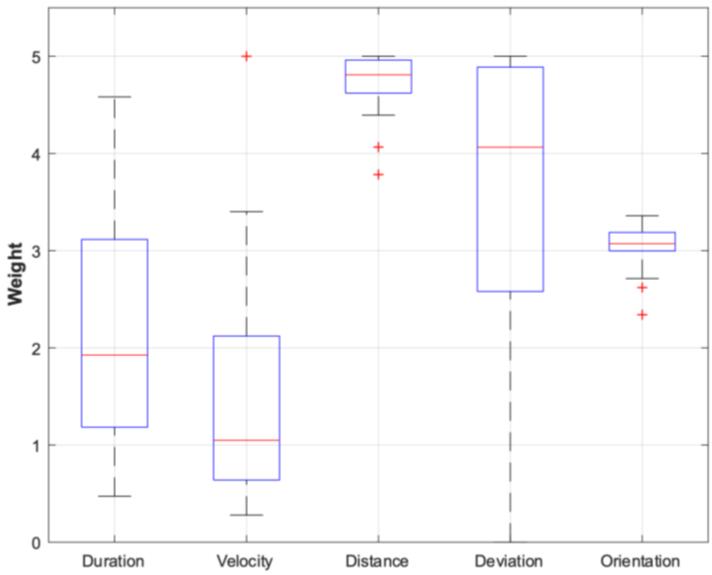


Figure 17: Box plots with 95% confidence intervals: close call criteria by weight

Since most workers fear such strict retaliation, programs can be developed that heighten workers' morale. As a consequence, the responsible safety personnel on site could be advised to inspect the leading edges that are marked in red in Figure 15. Showing an illustration like Figure 15 (object locations with close calls are highlighted in red) could even be shown to the workforce in Job Hazard Analysis (JHA) or toolbox talks ahead of every task execution. While providing active feedback with realistic data from the same construction site has the potential to strengthen workers' risk awareness quickly, future research has yet to validate this assumption.

5.9.3 Experiment 3: Infrastructure construction site

A second realistic trial of the close call analysis algorithm utilised data from a large infrastructure construction site. In a confined work space (an excavated pit) 4 pedestrian workers, 1 tractor, and 1 mobile crane operated conjointly. While the original data analysis was performed by Cheng et al. [31], the objective of this evaluation was to find close calls between the pedestrian workers and the moving construction equipment (or parts of it, for example its attached load). The potential hazard of a pedestrian worker being pinned by the rotating body of the mobile crane was not analysed, because its outriggers were safely guarded. Similar to the first experiment, the results show the individual trajectories, heatmaps (see Figure 18 and hazard weight radar plots (see Figure 19).

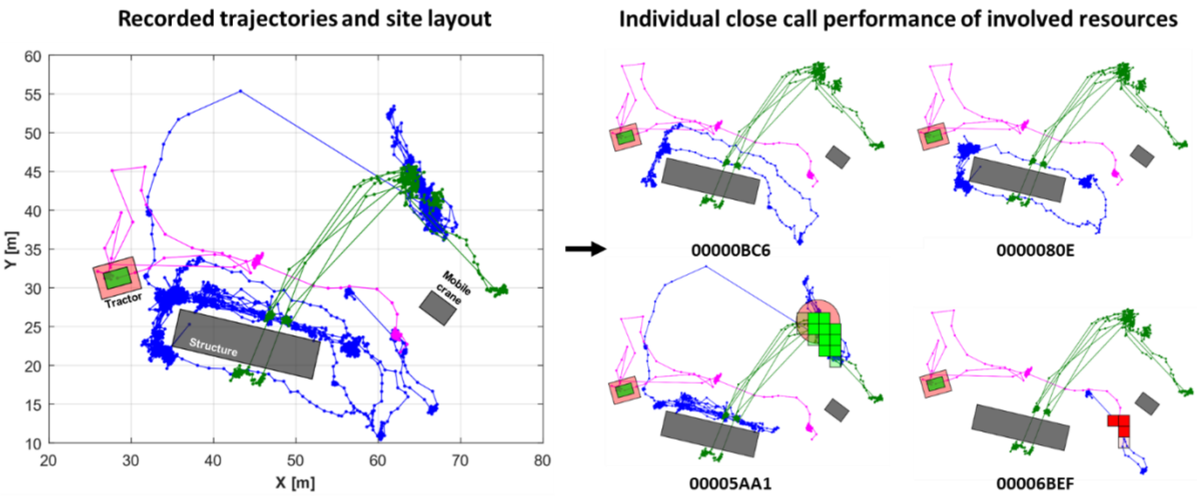


Figure 18: Close call heatmap visualisation (note: structures are grey, equipment movement are pink and green, and trajectories to pedestrian workers are blue)

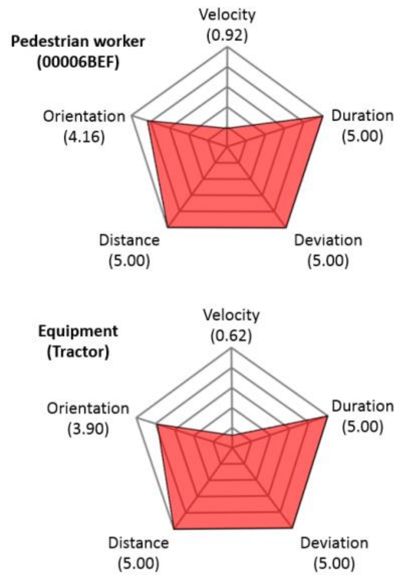


Figure 19: Hazard weight radar plots

The pedestrian workers (different from the first experiment) with ID: 00000BC6 and ID: 0000080E were not involved in a close call. Worker with ID: 00005AA1 came several times very close to or under the swinging loads performed by the mobile crane. As [81] [82] already noted on the same data set, the worker was authorized to work near the operating crane (detach or attach loads to the crane hock). Therefore, the tiles are marked green.

The trajectory of the pedestrian worker with ID: 00006BEF, however, collided with the path of the tractor that delivered material into the pit. The tractor's and the pedestrian worker's hazard weight radar plots (Figure 19) show nearly matching values for 5 of the observed values. Although these close calls were discovered, they were not severe as both resources moved with very low velocities (≤ 1 m/s). One could argue that the pedestrian worker operated as a temporary flagman, guiding the vehicle into a confined space inside the excavated pit.

5.9.4 Experiment 4: Integrate geometry from BIM model

The last experiment integrates the hazardous zones from a BIM-model. As the model is geo-referenced, the trajectory recorded using GNSS can be merged with the hazardous zones. Figure 20 represents the experiment. The geo-referenced BIM-model contains two hazardous zones: A platform (301) and an open-cut trench (302). Transforming their geo-location into the internal coordinates, we can display both the model and the trajectory data. In this experiment, two pedestrian workers (102 and 102) and two vehicles (201 and 202) were tracked.

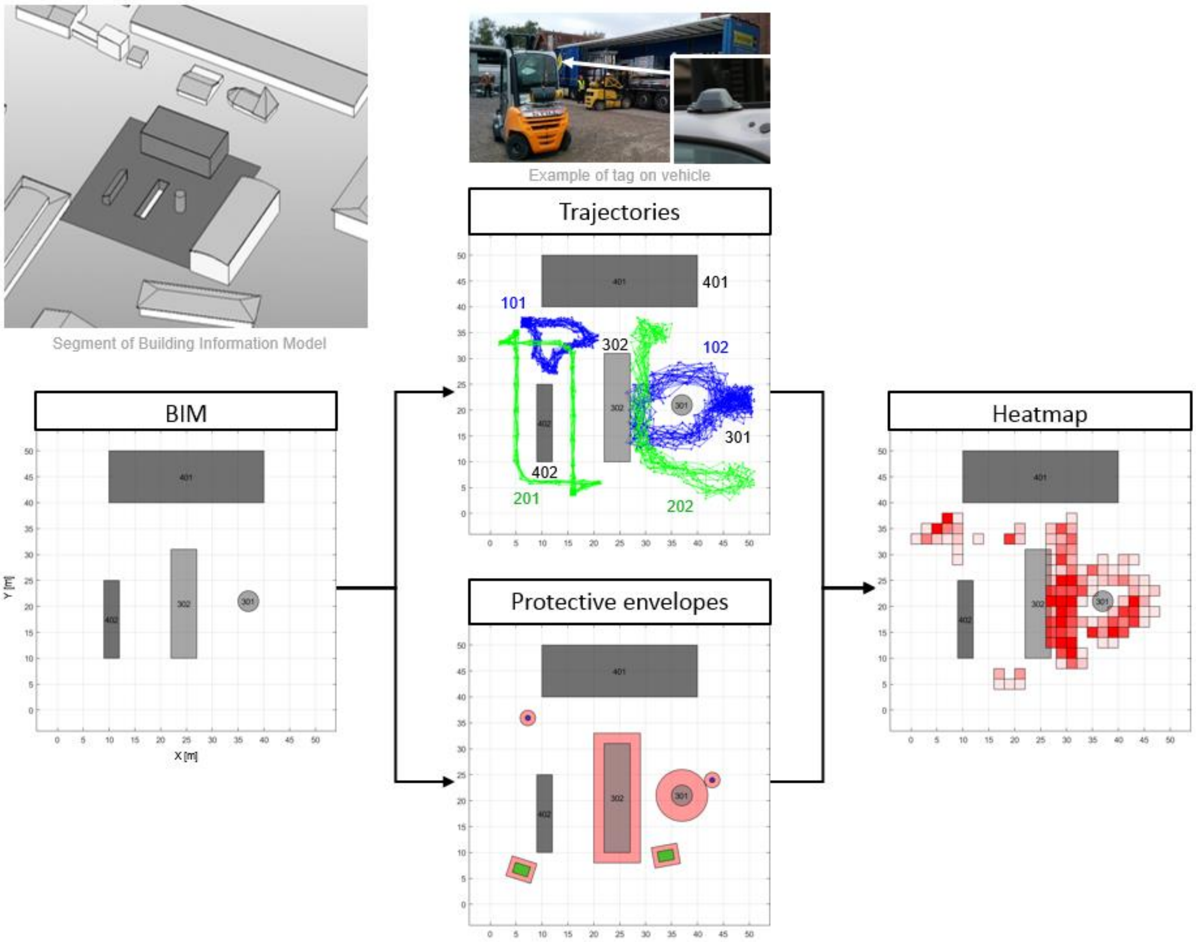


Figure 20: BIM integration of hazard zones along with trajectory information generate heatmap visualizations

5.10 Reporting and feedback cards

The data generated in this research might be used to give safety professionals the required facts to take corrective actions that protect the human workforce. While multi-lingual manual reporting cards for close calls may still exist in the future, they have–as outlined before–shortcomings in practice (e.g., incentives, collection, and feedback cycle). A successful transformation to digital recording and feedback is possible and yet has to be investigated in the future in much more detail. A conceptual digital feedback card would, for example, need to be tested for simplicity and acceptance by the workforce (Figure 21). While intrinsically safe mobile devices are required for industrial construction applications, recording and analysis via Internet-of-Things solutions like [83] exist to reduce the time needed in the feedback cycle. The foreman would then have new information in toolbox meetings available for use in safety awareness training.

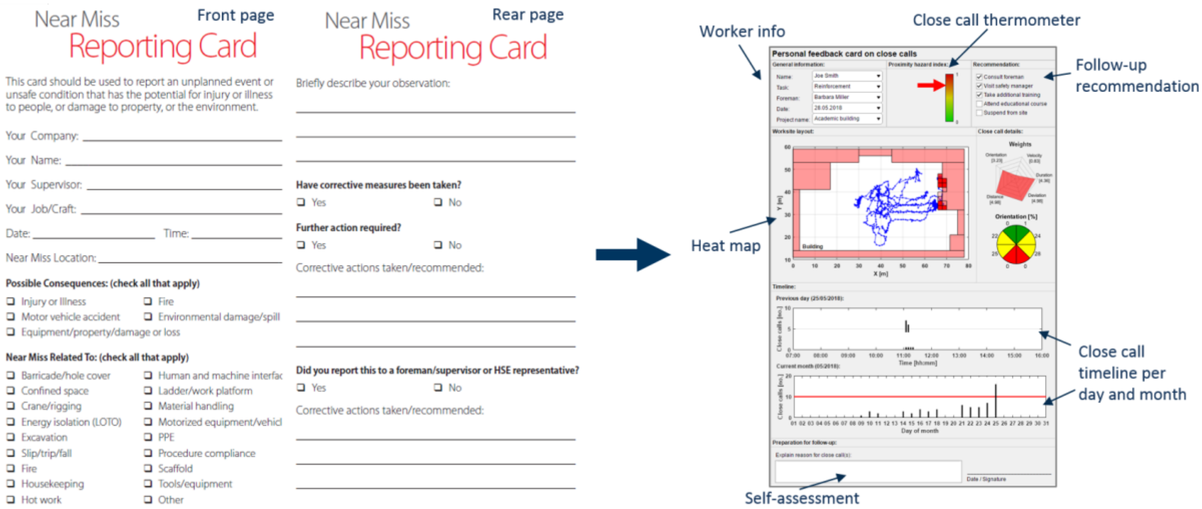


Figure 21: Conceptual transformation of manual close call reporting into digital reporting and feedback cards

6 Proactive real-time risk monitoring and detection

Aligned with the COGITO System Architecture, the Proactive Real-time Risk Monitoring and Detection component, called ProActiveSafety, enables the H&S digital twin to predict hazardous situations (e.g., through risk heat map generation, probability density calculations), based on state-of-the-art machine learning techniques on up-to-date data queried from the DTP. To this end, sample location tracking data have been utilised to continuously train a type of artificial Recurrent Neural Networks (RNN) called LSTM network to perform short-term proactive monitoring of hazards of moving workers and equipment in the dynamic construction environment.

Figure 22 illustrates the ProActiveSafety components and their dependencies to other modules and services. The application communicates with the DTP to retrieve location tracking data as well as hazard zones. The location tracking data is provided to the DTP by the IoT Data Pre-processing module (see deliverable D3.6 for an elaborate description of the module) while the hazard zones are geospatial elements computed by SafeConAI that are further pushed to the DTP (further information can be found in deliverable D4.2). ProActiveSafety processes the input data in its four components, namely (i) the data analysis module, (ii) the trajectory prediction module, (iii) the hazard zones checking module and (iv) the UI for visualising safety information. ProActiveSafety is responsible for the proactive issuing of warnings through the Work Order Execution Assistance (WOEA) service; moreover, additional safety hazards are communicated to the SafeConAI to enhance the safety analysis. The additional safety hazards are identified through a close-call events analysis performed in the ProActiveSafety application. The following sections describe the concepts behind ProActiveSafety's operation while deliverable D4.6 demonstrates how the application is technically integrated with the DTP.

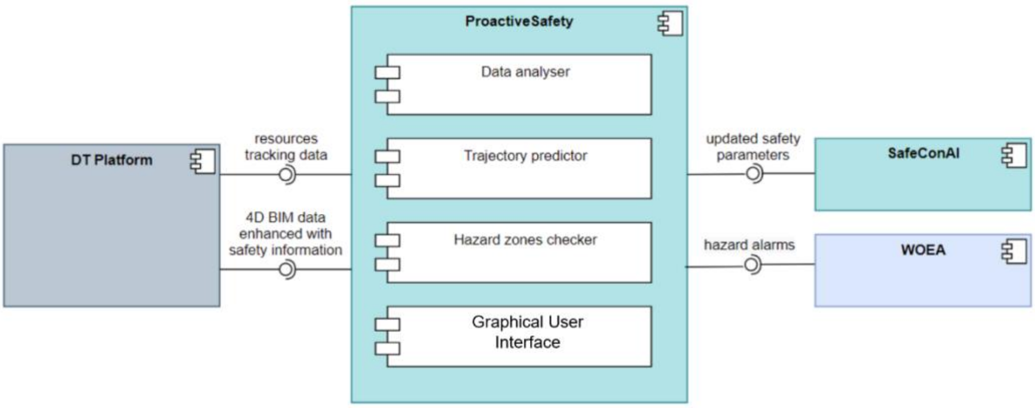


Figure 22: ProActiveSafety component diagram as defined in deliverables D2.4 and D2.5

6.1 GNSS location tracking technology as part of the DTP

In this section, the use of RTK GNSS technologies as a Real-time Location Sensing (RTLS) backend is discussed; such a system was employed to obtain the sample datasets used throughout the training of the algorithms presented. It should be noted, nevertheless, that during its normal operation, ProActiveSafety extracts location data from the DTP; the IoT Data Pre-processing module is in turn responsible for gathering, processing and conveying the location data from the physical tracking devices to the DTP.

GNSS is infrastructure-less technology and thus suitable for complex and dynamic environments such as construction sites. In the following, a prototype system is used to acquire high-accuracy timestamped location datasets for the various construction resources (i.e., pedestrian workers and moving equipment). The system utilises smartphone devices equipped with dual-frequency GNSS sensors that outperform the older embedded GNSS technologies in terms of positioning accuracy [84]. In addition, the experimental setup supports the installation of Real-Time Kinematic (RTK) equipment to further increase its accuracy. The RTK equipment consists of an integrated RTK antenna mounted on a safety helmet, RTK base stations and RTK receivers mounted on the smartphone devices.

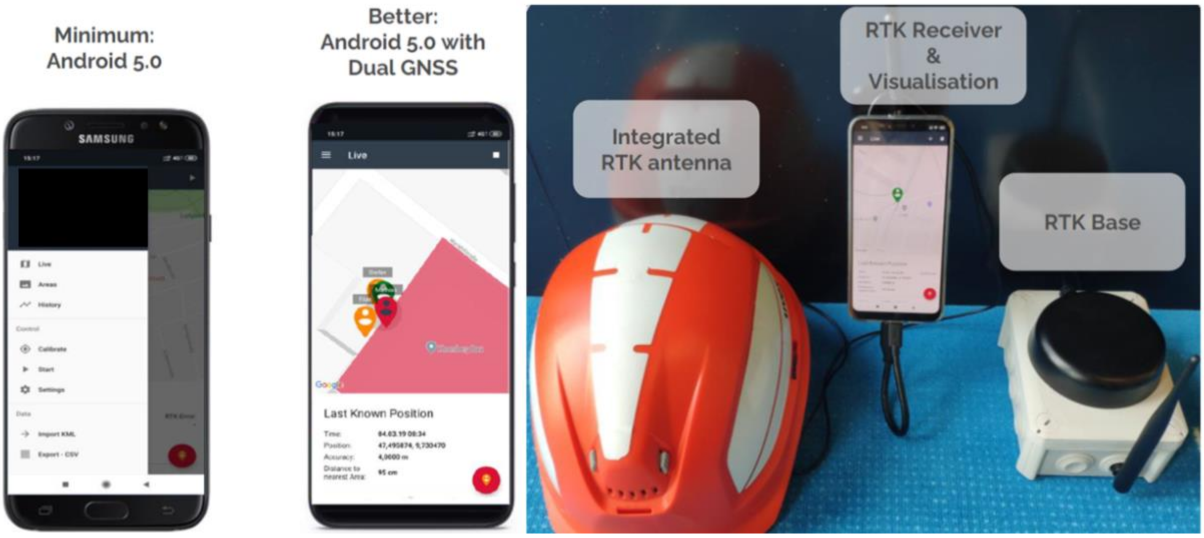


**Figure 23: Prototype system for on-site location tracking.
Smartphone app (left) and RTK setup (right) for enhanced accuracy,
including an integrated RTK antenna, RTK receiver and RTK base station [75]**

Figure 23 shows the RTK tracking device. It receives the correction from a server (NTrip: Networked Transport of RTCM via Internet Protocol) instead of a base station. Thus, there is no need to survey a base station. However, this requires full network coverage. The device can display location data and superimposes a cadastral layer. This specific tracking tag uses a free and open-source Geographic Information System (called QGIS).

Figure 24: Smartphone with external RTK antenna (left), map with superimposed cadastral layer (middle) and backside of the tracking tag (right)

The GNSS RTK system aims to provide precise real-time location data for the workers and heavy machinery/equipment at a construction site. Since this information creates a view of the locations of workers and equipment, errors are avoided and accidents are prevented; the latter is possible thanks to the simplified communication and automatic logging which relieves workplace coordination needs.

In Table 4 an example location data capture is provided showcasing the different attributes available from the system.

Table 4: Tracking data

	Stream 1	Stream 1	Stream 1
time	1,6595E+12	1,6595E+12	1,6595E+12
timeNMS	1659467391	1659467390	1659467389
latitude	47.49387717	47.49387733	47.49387767
longitude	9.95362067	9.95362067	9.95362083
accuracy	0.00000000	0.00000000	0.00000000
altitude	0.00000000	0.00000000	0.00000000
verticalAccuracy	0.00000000	0.00000000	0.00000000
bearing	0.00000000	18.72018051	34.12737656
bearingAccuracy	0.00000000	0.00000000	0.00000000
speed	0.03311794	0.03473261	0.03424399
speedAccuracy	0.00000000	0.00000000	0.00000000
provider	ublox	ublox	ublox

6.2 Data analysis module

It should be noted that the development of ProActiveSafety is ongoing and its integration with the COGITO ecosystem will be gradual. The experimental version presented here does not entirely reflect how the final system will be operational within COGITO. As such, both the description and the current structure of the data analysis module are relevant only in the context of the development and experimental phases. The second version of the deliverable D4.6 will integrate with the IoT Data Pre-processing Module described in deliverable D3.6, a technology-agnostic component that "is able to fuse various Real-Time Location System (RTLS) techniques currently available in a unified and consistent manner". The data analysis module currently ingests location tracking data generated by the GNSS location tracking technology as well as hazard zones from the safety-enhanced SafeBIM. The following sections describe how ProActiveSafety interprets the data and how close calls are identified and processed.

Figure 25: Construction site visualised on a map (left) and an orthophoto is superimposed (right)

Figure 25 shows a construction site in a GIS map. To improve the data understanding we superimpose the map with an orthophoto showing the status of the construction. To visualise the trajectory all coordinates, need to be transformed into a common coordinate system. ProActiveSafety converts real-world coordinates into a local coordinate system. Figure 26 visualises the recorded locations on the orthophoto.

Figure 26: Full set of trajectory data over a period: squares represent machines and circles are pedestrian workers

Figure 27: A truck approaches the workers

While Figure 26 shows the locations over a period, Figure 27 displays the location of all resources at a specific time. At this moment, a hazard (truck highlighted in orange squares) arrives to the site. All workers have to leave the loading zone where the truck eventually stops (Figure 28). If a worker gets too close to the protective envelope of the truck, a close call is recorded and processed in ProActiveSafety.

The application also assesses hazardous events between static hazard zones and construction equipment. ProActiveSafety receives geometric information about hazard zones from the DTP. These zones have been computed by the SafeConAI module and are ingested by the DTP. Figure 29 shows the construction site including the hazard zone. The algorithm in ProActiveSafety transforms the geometry information into the local coordinate system corresponding to the location data and uses the latter to generate a protective envelope around the resources. These envelops are user-defined according to standards. For instance, ISO 5006:2017 [36] defines 12 meters as minimum distance. Figure 29 shows exemplarily close calls events.

Figure 28: The truck has arrived and now a hazard is represented by a protective envelope (orange)

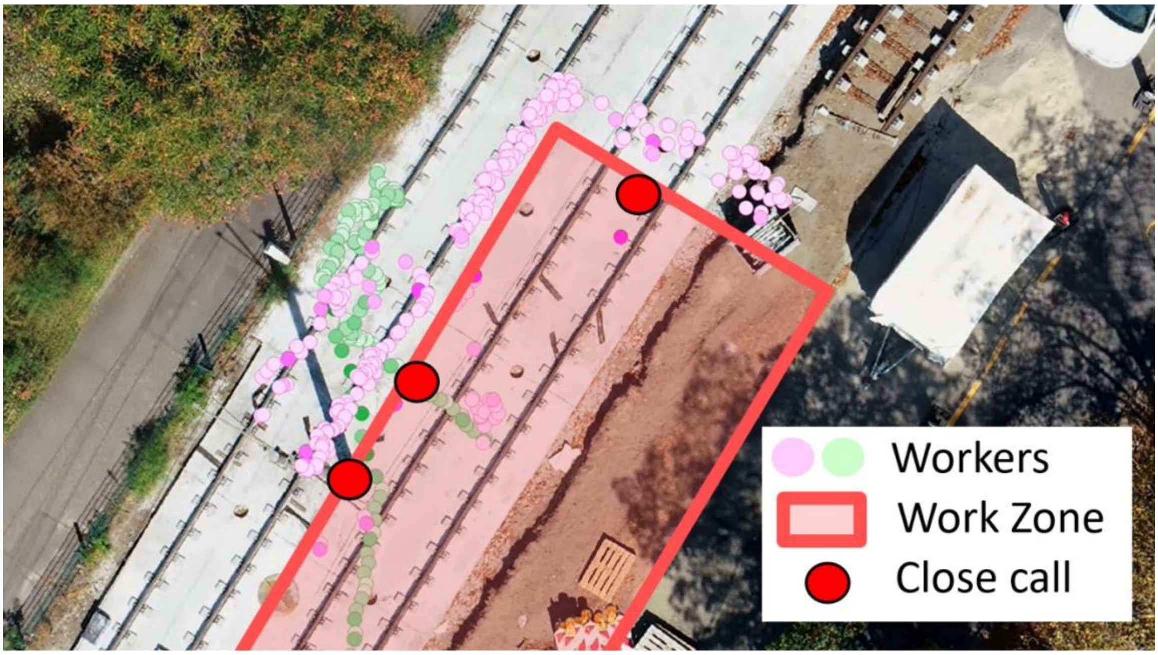


Figure 29: Hazard zones and entry points of workers are visualised

6.3 Trajectory prediction module

ProActiveSafety implements a trajectory prediction module. The following subsection first introduces the reader to the different trajectory prediction approaches in construction before section 6.3.2 introduces the concept of this module.

6.3.1 Trajectory prediction in construction

Trajectory prediction in construction refers to the short-term (i.e., 1 to 10 seconds ahead) spatial prediction of the path followed by a moving object and focuses on two main aspects. First, the development of proactive real-time safety systems based on proximity monitoring for accident prevention [17] and second, the transition of the construction industry to automation and autonomy, where trajectory prediction is critical for safety planning and collision avoidance in human-robot collaboration. Automation involves a set of human-defined functions performed by robots or equipment in construction, whereas autonomy refers to the state in which robots or equipment operate independently, without explicit instructions from a human operator. Although the future of automation and robotics in construction is promising [85], the majority of the identified publications in [86] focus on proximity monitoring for accident prevention rather than the automation of construction equipment operations. Three categories of input data were found to be used for trajectory prediction in the construction literature: vision-based data, raw location tracking data and 3-dimensional point cloud data from LiDAR sensors.

6.3.1.1 Vision-based data

Video recorded footage is used to predict the movement of workers and equipment in construction sites through vision-based object recognition. The tracked objects (i.e., workers and equipment) are identified in the frames using computer vision and the motion vector is then calculated. Short-term prediction is commonly performed based on Neural Network (NN) models and Kalman Filters (KF), whereas Hidden Markov Models (HMM) are less frequently applied being outperformed by NNs. A framework was proposed by [87] for computer vision-based estimation of position and short-term prediction of workers' and mobile equipment trajectories. The researchers assumed clear and high-quality videos with limited occlusions, which makes the framework susceptible to inferior quality input. To solve the tracking limitations in construction environments, Rezazaddeh Azar [88] developed a vision-based equipment tracking algorithm for automated camera control with predictive capability by estimating the motion vector and the speed of the tracked object.

To increase the accuracy of the predictive models, semantic and contextual information is used combining input from other sensorial technologies. For instance, A system was introduced[60] that uses footage from CCTV camera infrastructure and data from inertial sensors embedded on modern smartphones and applied the Social Force Model (SFM) to identify obstacles and other people in the scene, assuming that they affect the behaviour of human motion and represent their effect as repulsive forces. designed The Long Short-Term Memory (LSTM) model by [89] predicts worker trajectories in construction environments, considering additional contextual information, namely the distance to the nearest neighbour, the relationship between that neighbour and the tracked worker and the distance to destination. An LSTM network combined with a Mixture Density Network (MDN) for construction workers and equipment path prediction towards right time intervention of collision and intrusion was constructed by [90]. The model considers two contextual cues, namely the distance between moving and static objects and the type of objects (i.e., worker and vehicle) to predict their trajectory up to 2 seconds in the future. Although the model outperforms other existing trajectory prediction models, it is still limited by the dynamic visual occlusions due to other moving construction resources. Semantic information in the form of predefined hazard zones is also considered in the literature. Deng et al. [91] used Kalman Filters (KF) to predict the movement of workers in construction sites and the estimated trajectory is checked against a set of artificial danger zone boundaries to determine whether the prediction point lies inside or outside of the zones. Considering the occlusion limitations, the researchers performed multi-angle detection which, however, is limited by the camera resolution, especially when the workers are far from the camera position. Kong et al. [92] proposed a framework for workers' trajectory prediction in construction sites based on the Social LSTM architecture. The framework takes into consideration the workers' unsafe behaviour, defined as any movement towards predefined hazardous areas, and corrects the predicted trajectories using KF. One important shortcoming of that study is related to the validation of the pre-trained model, performed on their own dataset with limited scenarios, preventing it from being generalisable.

Only two of the identified publications focus on the future of construction industry, where human workers and robots co-exist and collaborate [86]. Kim et al. [93] proposed a framework based on Social Generative Adversarial Network (S-GAN) for trajectory prediction to tackle contact-driven hazards in construction between workers and autonomous trucks. Their results showed that longer observation periods do not necessarily lead to higher prediction accuracy, due to the inclusion of less relevant time steps in the prediction. In a later study, they evaluated the model on a controlled testbed, including a worker and a truck following three predefined movement patterns [94]. The LSTM model by [95] was expanded by [89], by implementing the A* path planning algorithm for autonomous robots in construction sites. However, the study validates the worker trajectory and path planning algorithms separately assuming a flat ground surface.

6.3.1.2 Location tracking data

GNSS refers to a set of navigation technologies that depend on the satellites orbiting around the earth. Existing studies have deployed low-cost GNSS technology for tracking construction resources to enhance construction safety, planning and management [96]. GNSS data have also been used as input to trajectory prediction models in construction applications. Rashid and Behzadan [97] developed a smartphone-based application for trajectory prediction of workers to prevent contact-driven accidents in construction sites. The underlying model is based on HMM. A risk factor is introduced and ranges between 0 and 1 depending on the angle between the trajectory and the centre of one stationary user-defined hazard zone [98]. The model was further developed to consider one static or dynamic hazard (i.e., moving between two points) and validated it by comparing to a benchmark Polynomial Regression model, showing better prediction accuracy [99]. Both models, however, are error-prone in predicting trajectories with sharp turns and are limited to a single pedestrian worker and a predefined hazard. Furthermore, the application considers outdoor construction activities due to the limitations of GNSS technologies in indoor environments. Another shortcoming is related to the large number of detected close-call events (n=369) and potential collisions (n=77) in a 30-minute experiment, which could hinder the users' situational awareness and trust in the warning system and lead to delays.

6.3.1.3 Point clouds

Point clouds are sets of data points in space that can represent 3-dimensional objects, where each point has its own set of x, y and z coordinates. In a recent study, a LiDAR sensor was utilised to acquire point cloud data to track the positions of heavy machinery and obstacles in a construction site [100], [101]. The raw point cloud data were analysed to first detect the heavy machinery (i.e., excavator) and then perform detection and clustering of other objects (i.e., workers and machinery) of a width greater than 0.4m, which is the average chest width of a human being. The Extended Kalman Filter (EKF) was adopted for predicting the position and velocity of the moving objects, whereas the excavator's predicted working area was calculated based on kinematics analysis and data from embedded stroke sensors and a rotational encoder [100]. In a later study, an Unscented Kalman Filter (UKF) was used to predict the non-linear motion dynamics of the moving objects. In both studies two safety indices are defined and used, namely the Time To Collision (TTC), and the warning index (x) defined as the degree of potential collision risks.

6.3.2 Trajectory prediction in ProActiveSafety

The trajectory prediction module is tasked to perform the short-term trajectory prediction of moving construction resources. For this, a long short-term memory (LSTM) model has been developed. Based on the review of the state-of-the-art in trajectory prediction in construction provided in the previous subsection, LSTM models are used to enhance safety by predicting the trajectories of moving heavy construction equipment and pedestrian workers. Our model is trained on 60% of the sample dataset, whereas the test is performed on the remaining 40% of the dataset.

Figure 30 illustrates the split train and test sets from the input dataset. For the prediction, the geographic coordinates (i.e., latitude and longitude) are converted to x, y Cartesian coordinates in meters with GeoPy by calculating the geodesic distance of each point to the ones of minimum longitude and minimum latitude respectively. The current set up of the LSTM model takes as input sequences of 12 steps in the past corresponding to 12 seconds of location tracking data and predicts 4 steps in the future (i.e., 4 seconds). This is performed for every data point in the training set. The concept of the trajectory prediction is depicted in Figure 31.

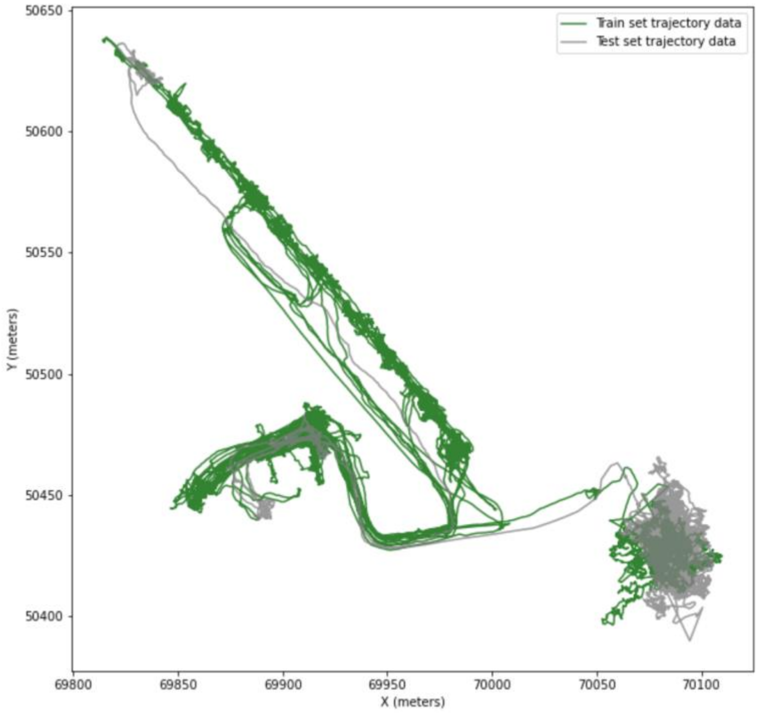


Figure 30: Test and train dataset split for the LSTM model for short-term trajectory prediction

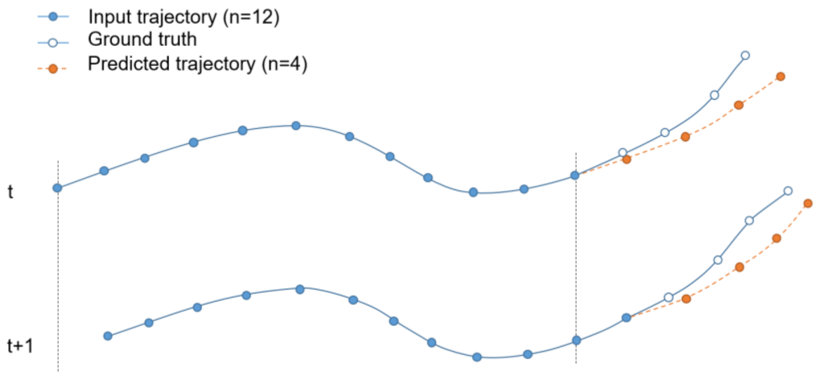


Figure 31: Short-term trajectory prediction

As the model predicts 4 steps in the future at each time-step, namely t, t+1, t+2 and so on, there are data points that are predicted up to four times. For each predicted data point, the mean of predicted (x, y) coordinates (in meters) is calculated as depicted in Figure 32, where $c_{x,y}$ denotes the (x, y) coordinates in meters and n is the number of predictions for each point.

$$m_{x,y} = \sum \frac{c_{x,y}}{n} \qquad (1)$$

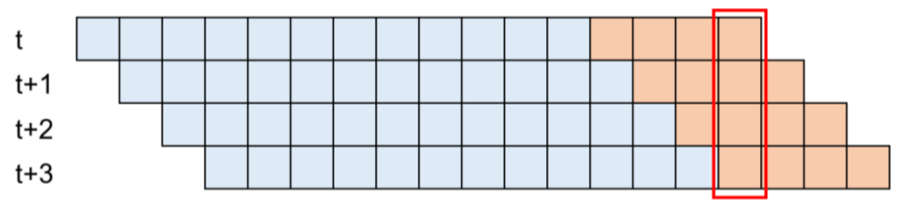


Figure 32: Calculation of the mean (x, y) predicted coordinates of each predicted point. Marked in red, are the four predicted (x, y) coordinates in four consecutive time-steps for the same trajectory point

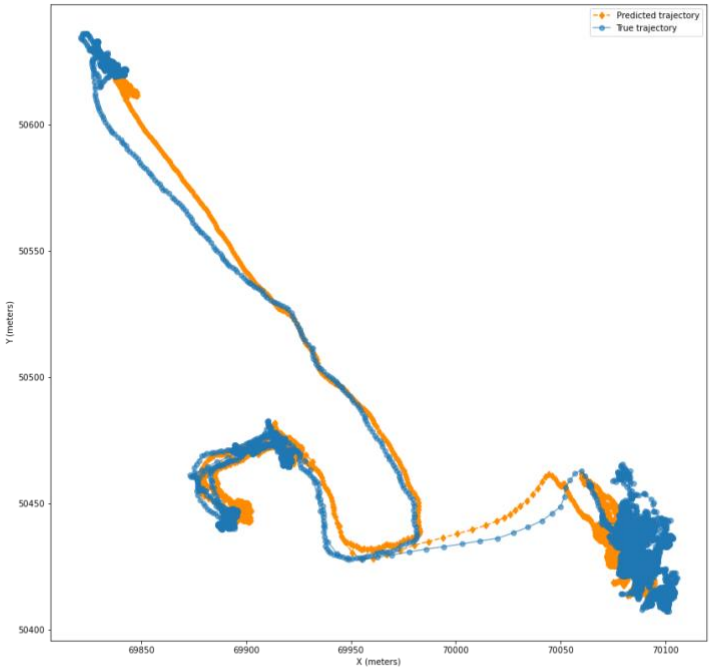


Figure 33: True and predicted trajectories on the test set of the sample dataset

The overall predicted trajectory is plotted over the true trajectory as illustrated in Figure 33. The dataset used to train the model is small and thus, there is large deviation in the predicted trajectory at locations that are not traversed in both the test and train set, resulting in poor performance of the model. An example of that can be seen in Figure 30 at the top left part of the trajectories, where the path of the test set trajectory has not been traversed within the train set trajectory. However, this is not the case at locations that exist in both sets. Therefore, the performance of the model is expected to increase significantly with further data collection.

6.4 Hazard zones checking

Hazard zones are inferred dynamically based on the analysis of proximity events. The individual points of recorded proximity events are currently visualised on OpenStreetMaps (OSM) mapping service using the leaflet JS library. An illustration of the input trajectory data, the short-term trajectory prediction and the identified, through the proximity events analysis, hazard zones is depicted in Figure 34. The identified hazard zones will supplement the prediction model described in the previous sub-section.

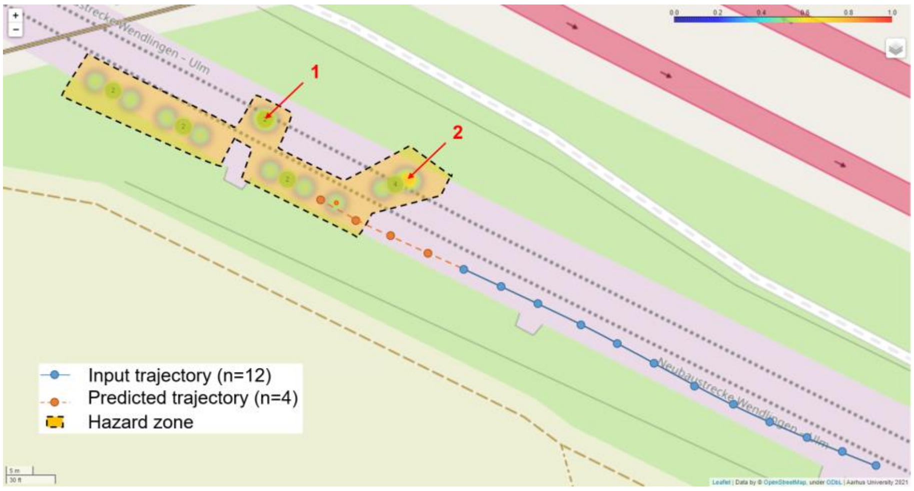


Figure 34: Hazard zone identification and trajectory prediction for proactive safety warning. Two occasions (1 and 2) where equipment reached into the other rail track which could potentially be dangerous

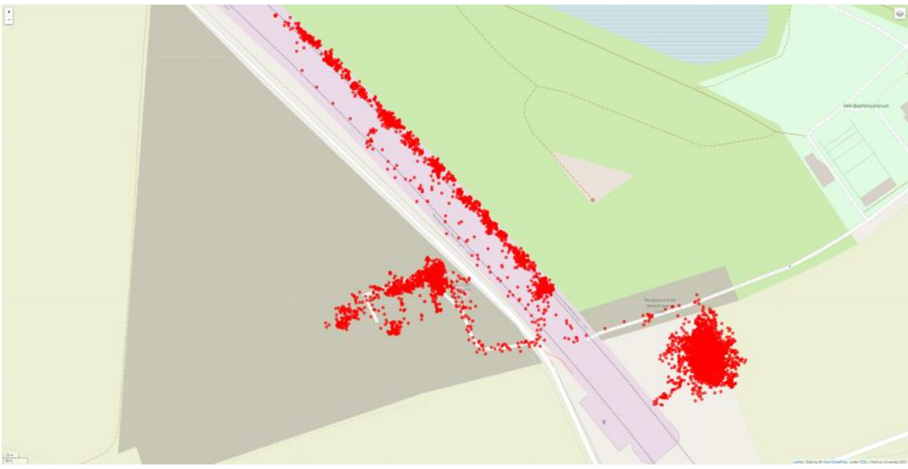


Figure 35: Visualisation of construction heavy equipment's trajectory working on a railway construction project

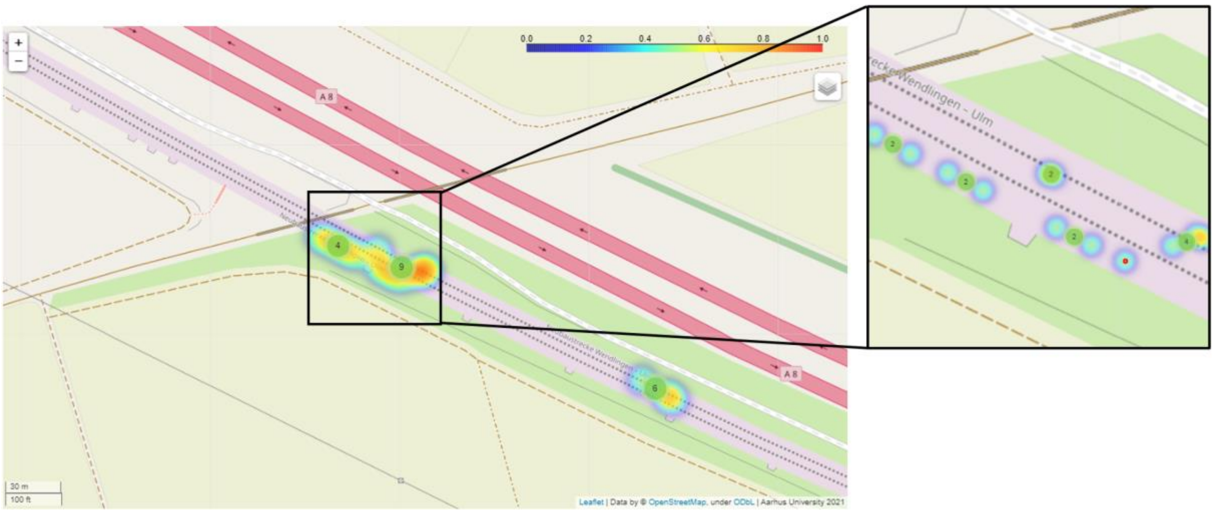


Figure 36: Heatmap of close proximity events between two construction heavy machinery objects. The relative number of close proximity events in each clustering area is represented in a colour

scale mapping in the zoom plot on the right, whereas the total number of the identified close proximity events in each clustering area is provided in numbers within coloured circles

ProActiveSafety analyses close call events and generates heatmaps (see Figure 36). These illustrate zones with a high emergence of close calls that eventually can be compared to hazard spaces (generated in D4.2).

7 Conclusions

The COGITO Deliverable D4.4 "Proactive Real-time Risk Monitoring and Detection Methods v2" reported on the state-of-the-art on research of the existing methods for enhancing safety in construction, including (a) the current state and the need of right-time safety in the construction phase, (b) a close call definition and the proposed close call reporting process, (c) the sensor-based methods for close call data collection and risk monitoring and detection, (d) the methods for intelligent close call data analysis and reporting and (e) the tools for accident prediction in regards to heavy construction equipment and pedestrian workers in the realistic, complex and dynamic construction environments. In addition, this deliverable also reports on the second iteration of the development activities within the COGITO Task T4.2 "Proactive Real-time Risk Monitoring and Detection" and documents the algorithms and techniques used in Proactive Real-Time Risk Monitoring and Detection application called ProActiveSafety.

The Proactive Real-time Risk Monitoring and Detection application, ProActiveSafety, enables eventually the prediction of potentially hazardous events through the analysis of close call events between pedestrian workers and heavy construction equipment as well as between pedestrian workers and hazard zones. ProActiveSafety implements state-of-the-art sensing for run-time location tracking data and machine learning techniques for data analysis in combination with construction semantic information queried from the COGITO Digital Twin Platform. Specifically, the application analyses trajectory data, superimposes them with hazard zones retrieved from the DTP and computes close call events and categorizes them by hazard weights (velocity, duration, orientation, deviation, distance). Moreover, sample location tracking data have been utilised to train a type of artificial recurrent neural networks (RNN) called LSTM network to perform short-term proactive monitoring of hazards of pedestrian workers and moving equipment in the dynamic construction environment.

This deliverable only deals with the underlying algorithms and methods used in the ProActiveSafety backend; its actual implementation, user interface (UI), and testing, are presented in the forthcoming deliverable D4.6 along with a detailed usage walkthrough to demonstrate its functionality.

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