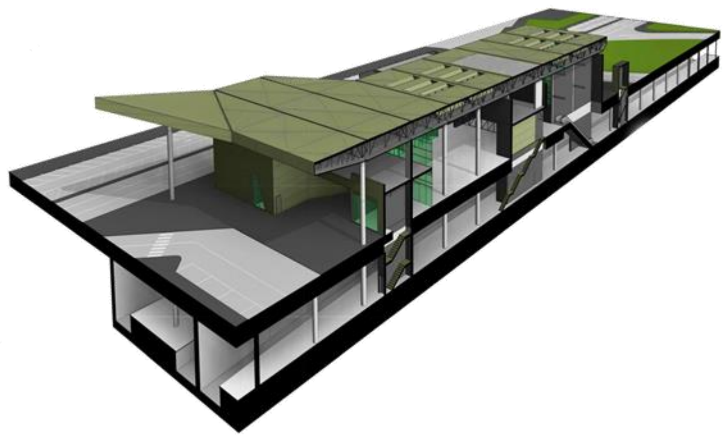

COGITO

CONSTRUCTION PHASE
DIGITAL TWIN MODEL

cogito-project.eu

D4.3 – Proactive Real-time Risk Monitoring and Detection Methods v1

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D4.3 – Proactive Real-time Risk Monitoring and Detection Methods v1

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Executive Summary

The COGITO Deliverable D4.3 "Proactive Real-time Risk Monitoring and Detection Methods v1" aims at documenting the state-of-the-art regarding the existing methods for enhancing safety in construction, focusing primarily on two areas relevant in the context of COGITO. First, the sensor-based methods for risk monitoring and detection and second, the trajectory prediction of moving, heavy construction equipment and pedestrian workers in order to enhance safety in complex and dynamic construction environments. This deliverable also documents the first version of the currently developed Proactive Real-Time Risk Monitoring and Detection application called ProactiveSafety. In addition, it reports on the first 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 developing 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. Trajectory prediction in construction refers to the short-term prediction of the path followed by a moving object within 1 to 10 seconds ahead and focuses on two main aspects. First, the development of proactive real-time safety systems based on proximity monitoring for accident prevention. Second, the transition of construction towards automation and autonomy, where trajectory prediction is critical for safety planning and collision avoidance in human-robot collaboration. Three categories of input data were found to be used for trajectory prediction in construction literature: vision-based data, raw location tracking data, and 3-dimensional point cloud data from LiDAR sensors.

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 risk analysis module. 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. 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
RaDAR	Radio Detection and Ranging
RNN	Recurrent Neural Networks
RTK	Real-time Kinematic
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]–[3]. According to laws in most industrialised countries, a safe workplace must be provided before any 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]–[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 equipment operations, multiple levels of consequences 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) on 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 reduce the opportunities for accidents. It requires identifying, registering and reviewing incidents that might lead to an accident or 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 have 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 has been carried out within WP4 towards designing, developing and delivering a first 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 location tracking data 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.

ProactiveSafety is responsible for communicating additional safety hazards to SafeConAI to enhance the safety analysis as well as for proactively issuing warnings through the Work Order Execution Assistance (WOEA) service. The identified health and safety hazards it is envisioned to be visualised both off-site and on-site. 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 undertaken 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*. Finally, the health and safety hazards will be utilized by the VirtualSafety application to create realistic training scenarios to improve safety culture and increase awareness of potential hazards in construction.

Quality Control"

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 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 3.7 presents the state-of-the-art on trajectory prediction methods for enhancing safety in construction, whereas in Section 4 the Proactive Real-Time Risk Monitoring and Detection application is presented in detail. Finally, Section 5 concludes this report and describes the future developments planned for the second iteration of the Proactive Real-Time Risk Monitoring and Detection module.

2 Existing Methods for Enhancing Safety in Construction

2.1 Hazard prevention

A variety of means exist during the design of construction sites [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 safest 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 minimise 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 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 that are worn by the workers, other research suggests 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 starts 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 its digitalisation, for example, through the use of Building Information Modeling (BIM) and virtual reality [14], [24], [25] methods. Such digital methods consider regulative 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]–[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].

While several conditions are adversarial to create 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), more than plenty of 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 found that decreasing vigilance results from 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 accidents 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 in the equipment cabin on monitor 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 as part of sociotechnical systems (STS) the interaction between humans and technology in workplaces. The data acquired simultaneously from, for instance, 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 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 1, based on their principle of operation, the various existing Sensor-based System (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.

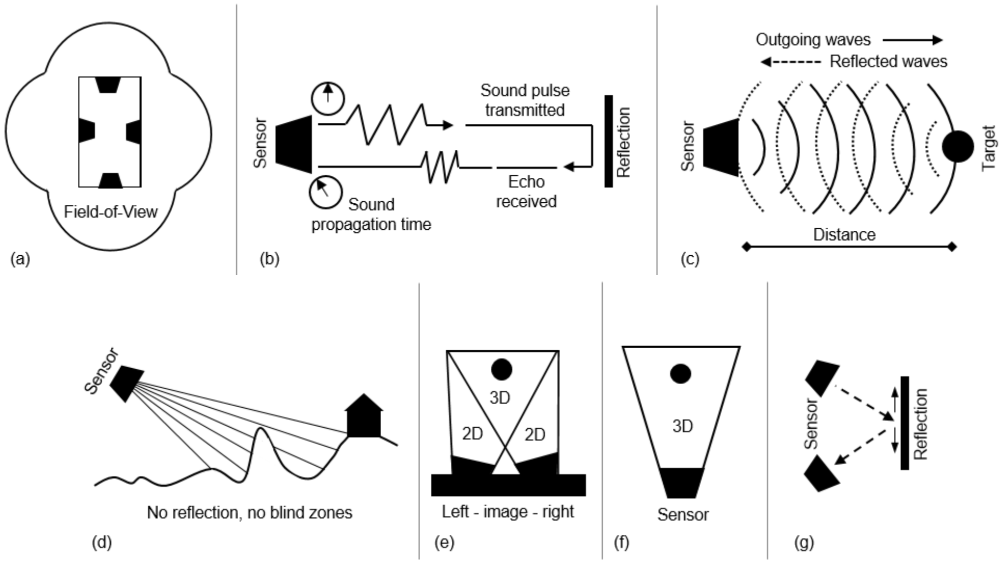

Figure 1 – Operating principles of Sensor-based Systems (SbS): (a) camera-monitor, (b) ultrasonic, (c) radar, (d) radio, (e) 3D camera, (f) 3D-TOF camera, and (g) LiDAR/LaDAR systems [17]

Camera-Monitor-Systems (CMS) 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 1a).

- *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 [44]. 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 [45]. 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 [46]. 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.

3.1 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 1b). 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.

3.2 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 1c). 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.

3.3 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 1d) 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 [47]. Radio systems have been successfully used in the underground mining industry [48], [49], with implementations in construction applications being investigated [32], [47].

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.

3.4 3D camera sensors

3D camera sensors (Figure 1e) 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 [50]–[54]. 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.

3.5 3D time-of-flight sensors

A Time-of-Flight (ToF) sensor (Figure 1f) 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 [55] 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.

3.6 Lidar systems

LiDAR or LaDAR (Light or Laser Detection and Ranging) (Figure 1g), 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).

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 by an asterisk were determined based on the findings in literature. For example, CMS scores 'medium' because the false alarm rate (operator could easily ignore a display screen) is higher 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.

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

3.7 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 [56], the majority of the identified publications in [57] 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.

3.7.1 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. Zhu et al. [58] proposed a framework 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 [59] developed a vision-based equipment tracking algorithm for automated camera control with predictive capability by estimating the motion vector and speed of the tracked object.

To increase the accuracy of the predictive models, semantic and contextual information is used combining input from other sensorial technologies. For instance, Papaioannou et al. [60] introduced a system 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. Cai et al. [61] designed a Long Short-Term Memory (LSTM) model to predict worker trajectories in construction environments, considering additional contextual information, namely the distance to the nearest neighbour, the relationship between that neighbour and the tracked worker and the distance to destination. An LSTM network combined with a Mixture Density Network (MDN) for construction workers and equipment path prediction towards right time intervention of collision and intrusion was constructed by Tang et al. [62]. 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. [63] 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. [64] 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 [57]. Kim et al. [65] 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 [66]. Hu et al. [67] expanded the application of the LSTM model developed by Cai et al. [61], 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.

3.7.2 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 [68]. GNSS data have also been used as input to trajectory prediction models in construction applications. Rashid and Behzadan [69] developed a smartphone-based application for trajectory prediction of workers to prevent contact-driven accidents in construction sites. The underlying model is based on HMM. A risk factor is introduced and ranges between 0 and 1 depending on the angle between the trajectory and the centre of one stationary and user-defined hazard zone [70]. 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 [71]. 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.

3.7.3 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 [72], [73]. 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 [72]. In a later study, an unscented Kalman filtering (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.

4 Proactive Real-Time Risk Monitoring and Detection

In 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 digital twin platform. For this, 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 moving workers and equipment in the dynamic construction environment.

4.1 GNSS location tracking technology

In the current experimental setup, GNSS location tracking technology has been deployed to provide location tracking data for the outdoor environment. GNSS is infrastructure-less technology and thus suitable for complex and dynamic environments such as construction sites. A prototype system developed by Rhomberg Sersa Rail Group was used for acquiring high-accuracy timestamped location datasets for 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 achieving better positioning accuracy [74]. 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 (see Figure 2).

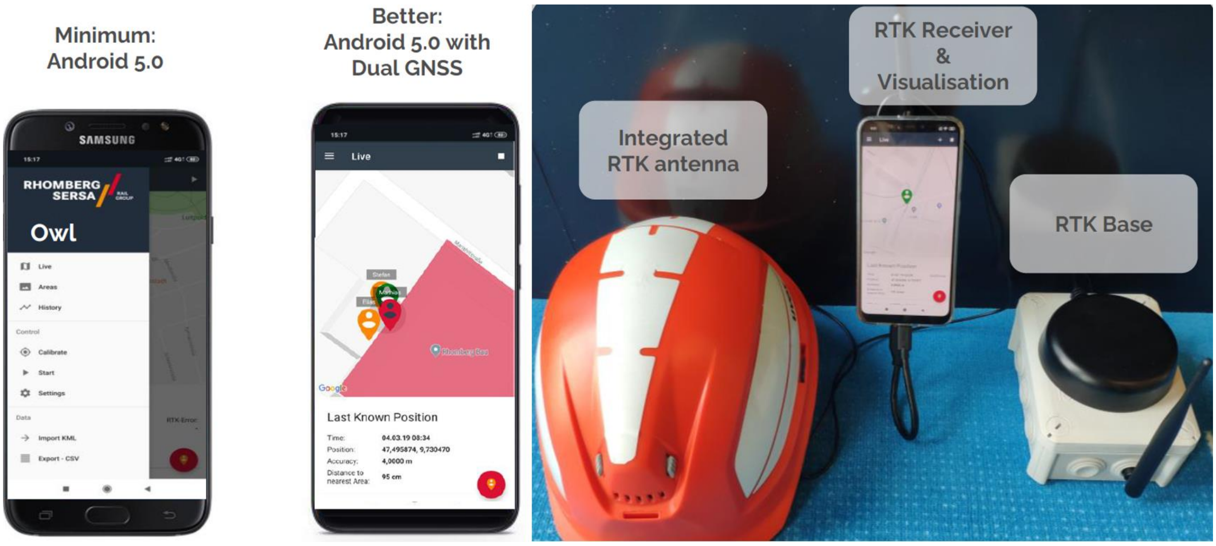

Figure 2 – 'Owl' system for on-site location tracking. Smartphone app (left) and RTK setup (right) for enhanced accuracy, including an integrated RTK antenna, RTK receiver and RTK base station [75].

The GNSS RTK system called 'Owl'[1] 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. Using a smartphone application and a GNSS tracker, the positions of construction workers and machinery are recorded and an overview is displayed at the web-based application. The web-based software application also facilitates direct, simultaneous communication between several people (see Figure 3). Every user has access to the current construction site overview and direct text messages can be answered on smartphones and smartwatches. All steps taken are automatically recorded in the running log. Potential danger zones can

[1] https://magazine.rhomberg-sersa.com/en/articles/excellent-improvements

be set up manually through the web-based application so that the system issues automatic messages. For example, if an unauthorised person approaches an excavator in operation, the person and the excavator driver both receive a warning. This also applies to the loading zones, crossings, assembly points and logistics routes; collision warnings are also issued to machines dangerously approaching each other. RTK-GNSS provides ground truth data of pedestrian workers and vehicles.

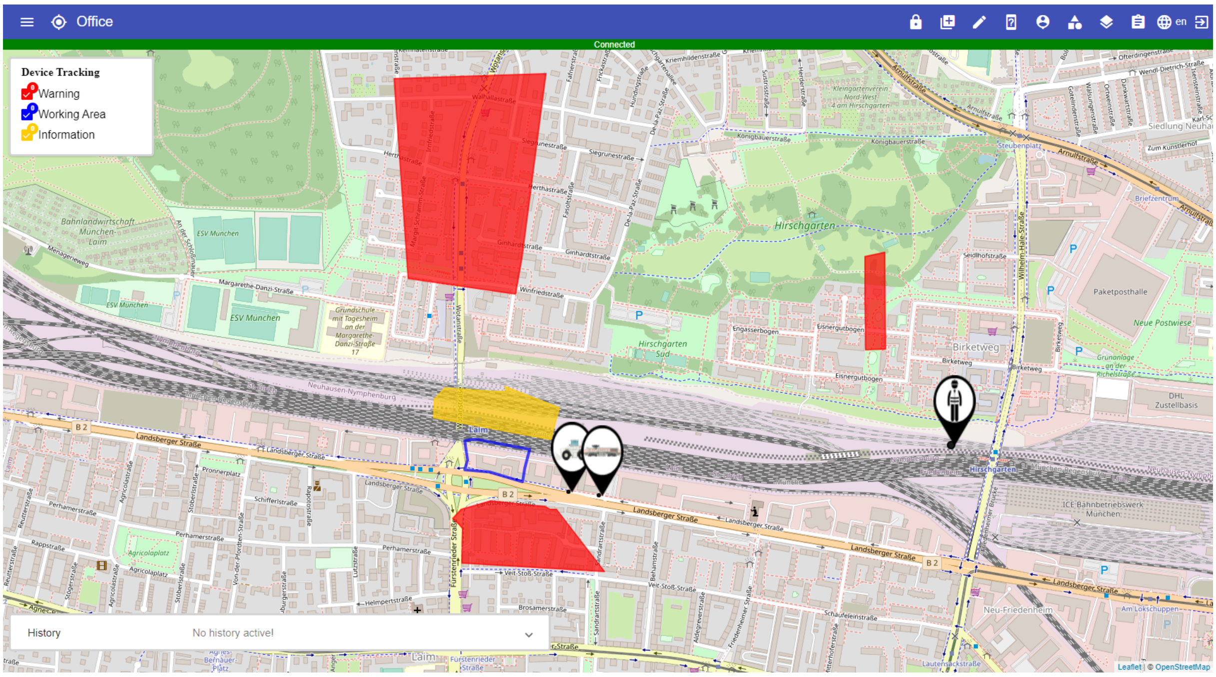

Figure 3 – 'Owl' system web-based platform for safety monitoring and coordination [75].

4.2 ProactiveSafety

The ProactiveSafety application receives location tracking data of the construction resources (i.e., pedestrian workers and moving heavy equipment) from the Digital Twin Platform and more specifically from the IoT Data Pre-processing module; it consists of four modules, namely (i) the data analysis module, (ii) the trajectory prediction module, (iii) the hazard zones checking module and (iv) the risk analysis module. ProactiveSafety is responsible for the proactive issuing of warnings through the Work Order Execution Assistance (WOEA) service; moreover, additional safety hazards (see Figure 14) are communicated to the SafeConAI to enhance the safety analysis. The additional safety hazards are identified through the close-proximity events analysis performed in the ProactiveSafety application.

In the second version of the Proactive Real-time Risk Monitoring and Detection application, construction semantic information (e.g., construction site layout plans) will be integrated by inferring and extracting from the BIM models existing hazard spaces (e.g., excavation pits). The identified hazard spaces will then be converted into geospatial elements (e.g., polygons) and ProactiveSafety will perform spatial analysis to identify and proactively alert pedestrian construction workers and mobile equipment heading towards those hazard zones. Figure 4 illustrates the components of ProactiveSafety and their dependencies to other modules and services. In the following sections each module is described in detail (with the exception of the risk analysis module that will be reported in the second version of the deliverable).

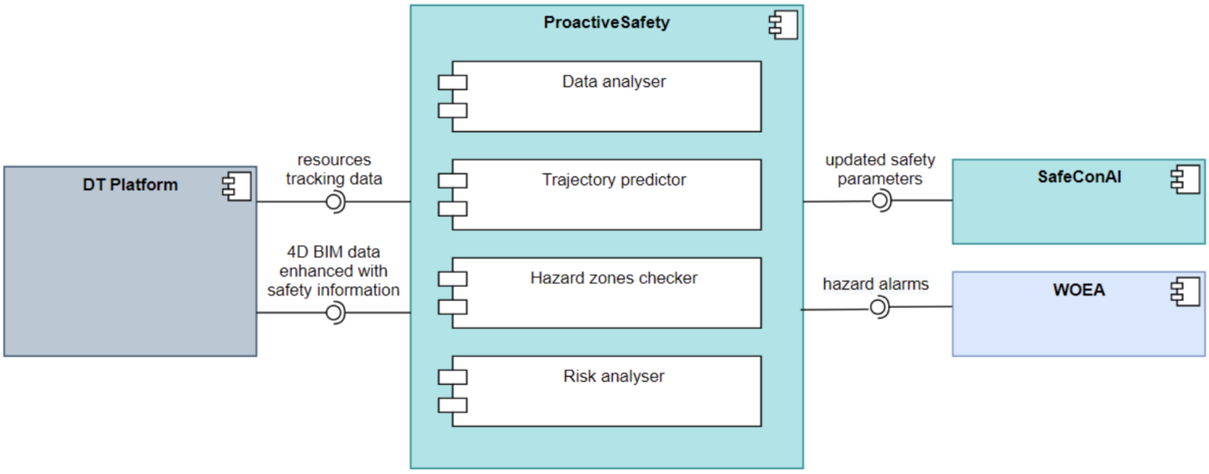

Figure 4 – Component diagram of the ProactiveSafety service as defined in deliverables D2.4 and D2.5.

4.2.1 Data analysis module

The current structure of the data analysis module is applicable only during the development and experimental phases. It should be noted that the development of ProactiveSafety and of the relevant COGITO components is ongoing and the integration will be gradual. Also, the experimental version of ProactiveSafety does not entirely reflect how the final system will be operation in COGITO. The second version of the deliverable will integrate the IoT Data-Preprocessing Module developed within the COGITO Deliverable 3.5 which is a technology-agnostic component that “is able to fuse various Real-Time Locating System (RTLS) techniques currently available in a unified and consistent manner”.

Currently, the data analysis module ingests location tracking data that have been generated by the GNSS location tracking technology. In some datasets, there exist initial points whose location is severely inaccurate. This is likely due to initialisation of the GNSS receivers and the time required to acquire signals from satellites in the first run. To overcome this issue in an automated manner, an initial outlier search and elimination is performed by calculating the difference of each point’s latitude and longitude coordinates with the mean values of coordinates for each dataset. The difference threshold is set to 0.5 degrees which is approximately equal to 35 km in longitude and 55 km in latitude. Although railway construction works often extend over several kilometres, data points exceeding the aforementioned distance threshold are most likely outliers. In order to confirm that the eliminated data points are indeed outliers, we perform a check to count the number of the eliminated data points, which vary from zero to two in some datasets. A selection of datasets with eliminated data points is presented in Table 2. In Figure 5 the start- and end-times of the location tracking for all imported datasets is illustrated providing an overview of the location tracking for each construction resource being monitored.

Table 2 – Eliminated data points in datasets as part of the initial data pre-processing within the data analysis module.

Dataset	Length_prev	Length_new	Delta
D1-WorkerB-20190603	42214	42212	2
D2-WorkerB-20190603	36096	36094	2
D3-WorkerC-20190603	39559	39558	1
D4-WorkerD-20190603	44451	44449	2

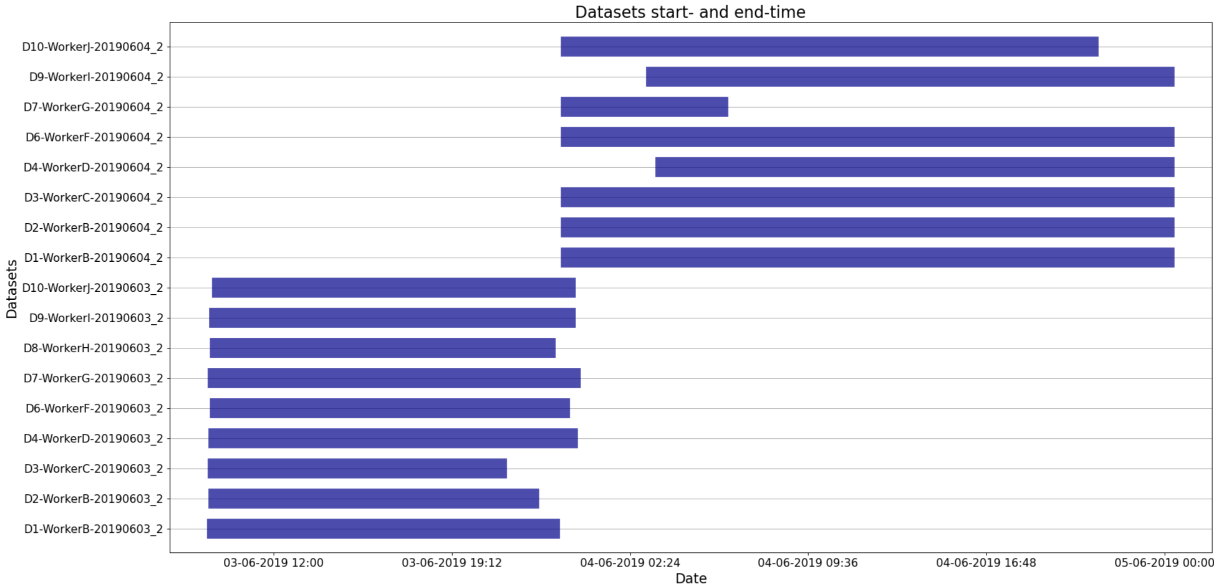

Figure 5 – Duration of the trajectory datasets to show the activity logging start- and end-times.

The trajectories corresponding to pedestrian workers and heavy machinery are visualised in ProactiveSafety using the OpenStreetMap mapping service under the Open Database License (ODbL) as shown in Figure 7. The close proximity analysis is performed by calculating the geodesic distance of each data point in the datasets to the data points of other construction resources recorded at the same time (i.e., matching timestamp). The calculation of the geodesic distance is performed with GeoPy[2] library for Python. The analysis is done for a user-defined distance rule that can be changed. For instance, 12 meters would represent the visibility circle as defined in ISO 5006:2017 [36]. The result of the analysis depends on the error of the raw localisation data. ProactiveSafety visualises the proximity events of user-selected construction resources on OpenStreetMap map as described previously (see Figure 8). The algorithm iterates over all available datasets and calculates the distances only once to minimize the computational expense. For this, the upper diagonal of the square adjacency matrix is used to represent all unique trajectory dataset combinations avoiding the redundant calculations. This process is illustrated in Figure 6.

Dataset	1	2	3	…	n
1	-	x	x	x	x
2	-	-	x	x	x
3	-	-	-	x	x
…	-	-	-	-	x
n	-	-	-	-	-

Figure 6 – Upper diagonal in the adjacency matrix of n available trajectory datasets used to iterate over all unique dataset combinations avoiding redundant calculations and thus, minimising the computational expense.

[2] GeoPy (Python) documentation available at https://geopy.readthedocs.io/en/stable/#module-geopy.distance

The results of the proximity analysis are exported and saved as text files, for further analysis. The current version of the algorithm can import the previously saved files without the need of repeating the analysis process.

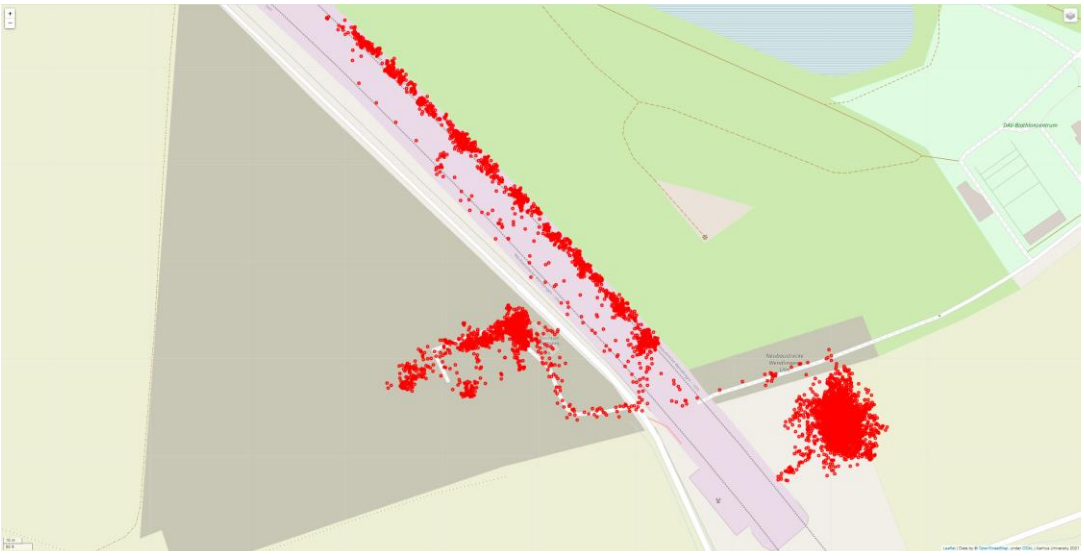

Figure 7 – Visualisation of construction heavy equipment trajectory working on a railway construction project.

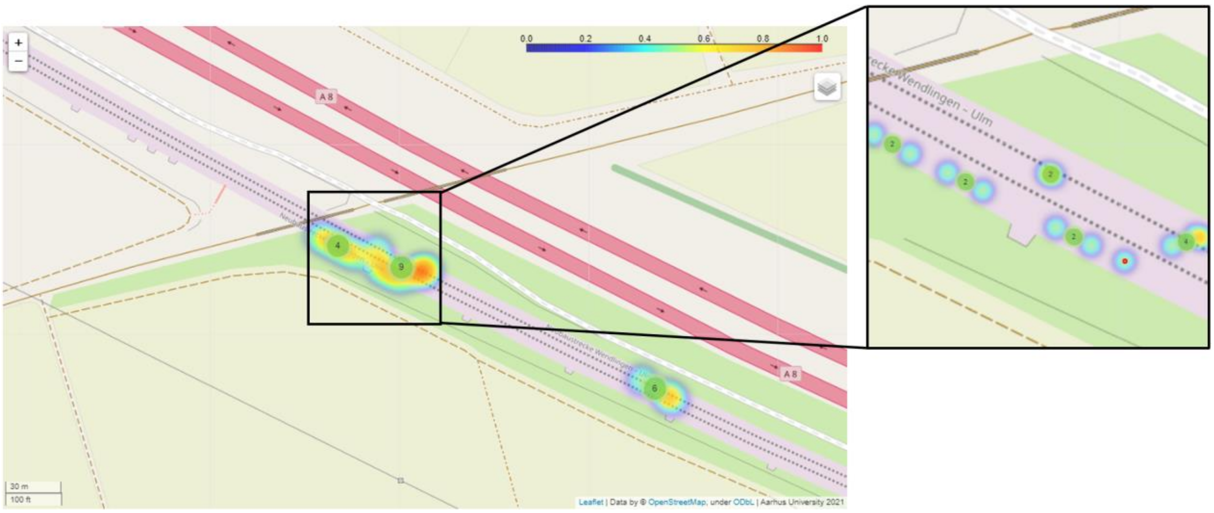

Figure 8 – Heatmap of close proximity events between two construction heavy machinery objects. The relative number of close proximity events in each clustering area is represented in a colour scale mapping in the zoom plot on the right, whereas the total number of the identified close proximity events in each clustering area is provided in numbers within coloured circles.

The performed data analysis includes the calculation of speed based on the recorded location tracking data and the corresponding timestamps. The calculated speed is compared to the "raw" GNSS recorded speed in order to validate the former's accuracy; the latter can be considered as the ground truth for validation. In Figure 9, the "raw" GNSS recorded speed and the calculated speed are depicted. Although the calculated speed follows the overall pattern of the GNSS recorded speed, it is shown that it significantly deviates from the ground truth. In addition, the deviation illustrated in the following figure, suggests that the internal dual-frequency GNSS sensor infers the speed without considering the location (i.e., longitude and latitude) and time for its calculation, otherwise the two plots would be overlapping. The significant deviation between the calculated and recorded speeds signifies the existence of noise in the dataset and highlights the importance of performing data filtering prior to the analysis. It is therefore noteworthy that the COGITO IoT Data Pre-Processing Module allows for data filtering as described in the corresponding deliverables D3.5 and D3.6.

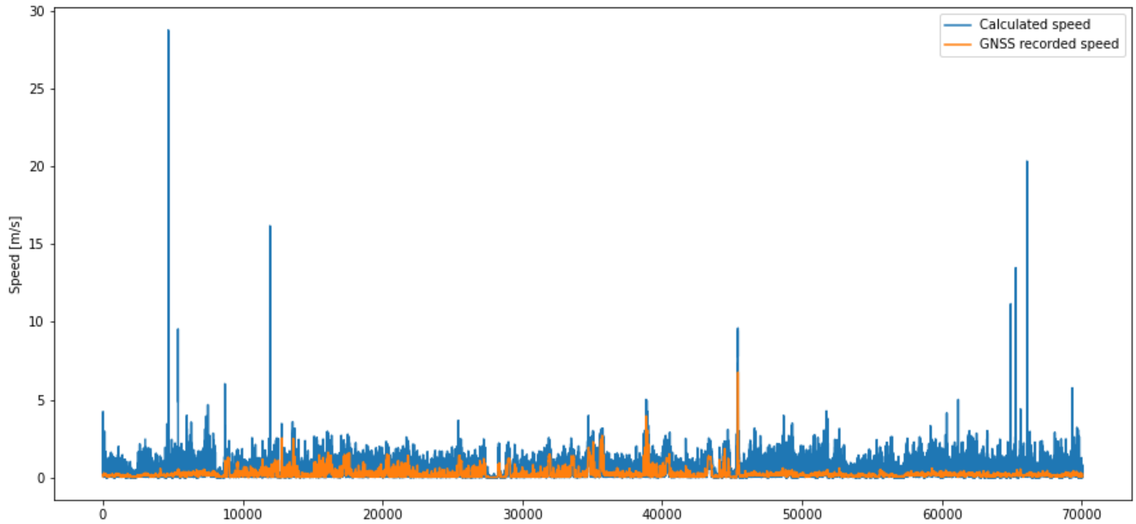

Figure 9 – Calculated and GNSS recorded speed.

4.2.2 Trajectory prediction module

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, 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 10 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.

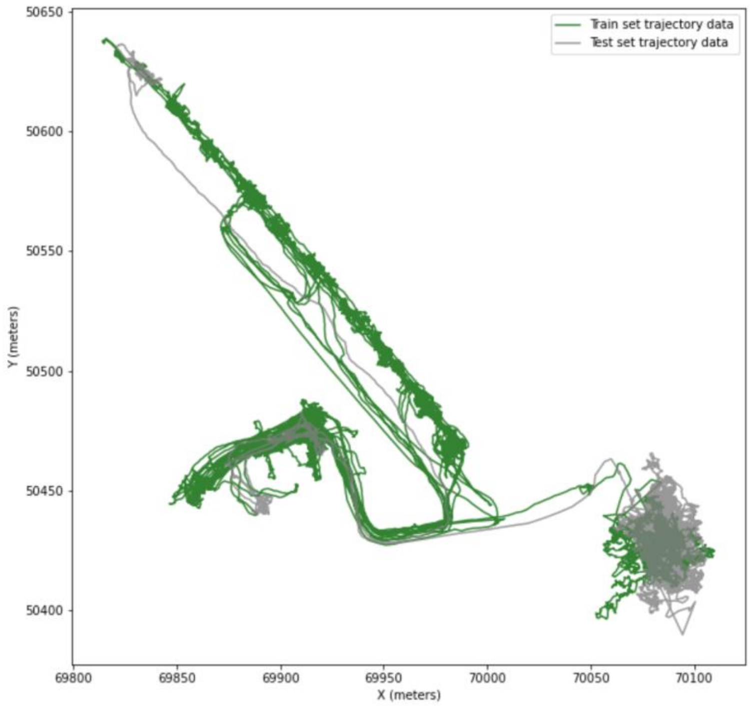

Figure 10 – Test and train dataset split for the LSTM model for short-term trajectory prediction.

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 11.

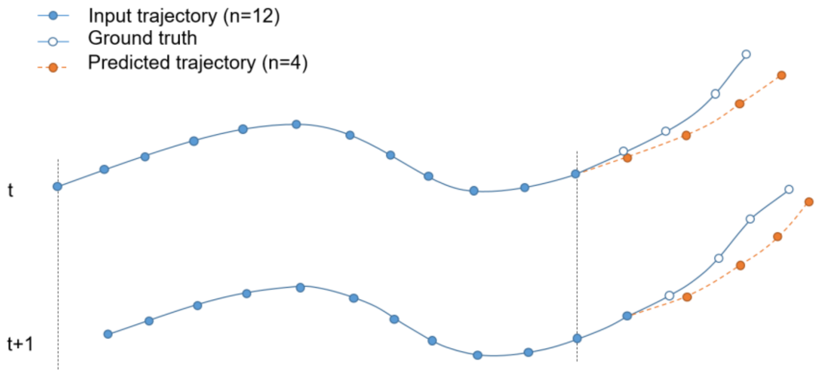

Figure 11 – Short-term trajectory prediction

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 12, where $c_{x,y}$ denotes the (x, y) coordinates in meters and n is the number of predictions for each point.

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

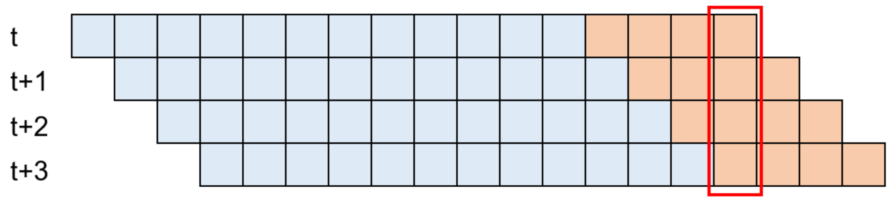

Figure 12 – Calculation of the mean (x, y) predicted coordinates of each predicted point. Marked in red, are the four predicted (x, y) coordinates in four consecutive time-steps for the same trajectory point.

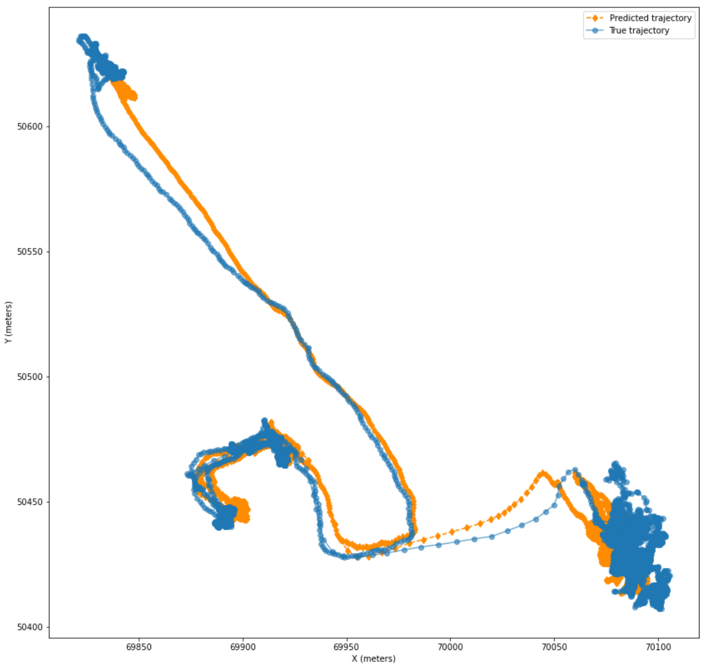

Figure 13 – True and predicted trajectories on the test set of the sample dataset.

The overall predicted trajectory is plotted over the true trajectory as illustrated in Figure 13. 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 10 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.

4.2.3 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 OSM mapping service and will be clustered according to user-defined spatial rules into hazard zones in the second version of this application prototype. 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 14. The identified hazard zones will supplement the prediction model described in the previous sub-section.

For future development of the ProactiveSafety tool, the integration with construction semantic information (e.g., construction site layout plans) is planned. To this end, existing hazard spaces, e.g., excavation pits, will be inferred and extracted from the BIM model and then be converted into geospatial elements (e.g., polygons). ProactiveSafety will perform spatial analysis using the geospatial elements to identify and proactively alert pedestrian construction workers and mobile equipment heading towards those hazard zones. Additional hazard zones will be provided by SafeConAI to further enhance the safety analysis.

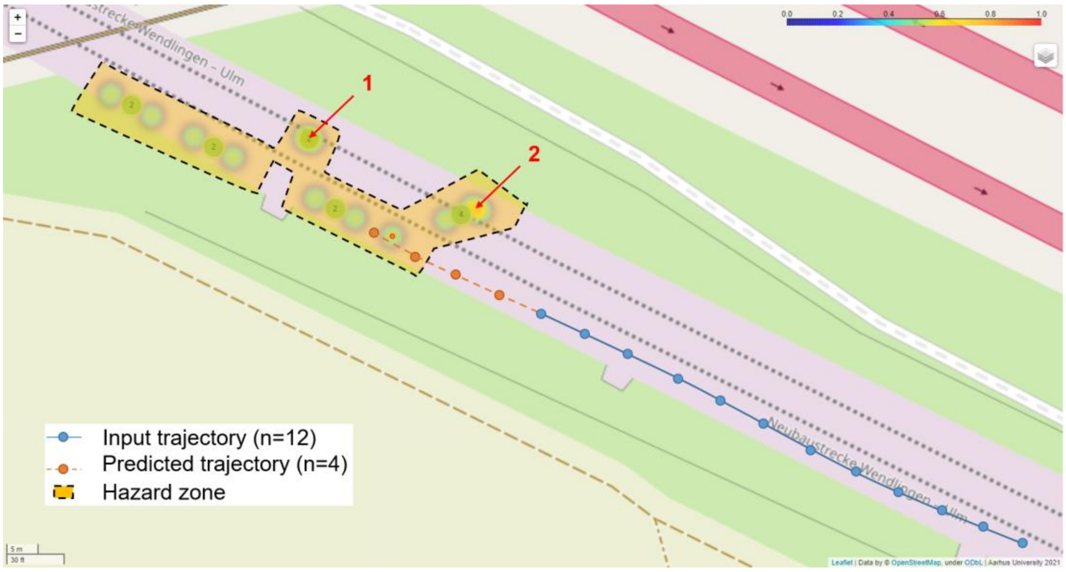

Figure 14 – Hazard zone identification and trajectory prediction for proactive safety warning. Two occasions (1 and 2) where equipment reached into the other rail track which could potentially be dangerous.

5 Conclusions

The COGITO Deliverable D4.3 “Proactive Real-time Risk Monitoring and Detection Methods v1” reported on the state-of-the-art on research of the existing methods for enhancing safety in construction, focusing primarily on two areas that are relevant for COGITO. First, the sensor-based methods for risk monitoring and detection and, second, on the trajectory prediction of moving, heavy construction equipment and pedestrian workers to enhance safety in complex and dynamic construction environments.

The Proactive Real-time Risk Monitoring and Detection application, namely ProactiveSafety, enables the prediction of potentially hazardous events through the analysis of close proximity events between pedestrian workers and heavy construction equipment. Furthermore, ProactiveSafety implements state-of-the-art machine learning techniques and up-to-date location tracking data and construction semantic information queried from the COGITO Digital Twin Platform. Specifically, sample location tracking data have been utilized 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. 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. The future developments will be reported in the second version of this deliverable.

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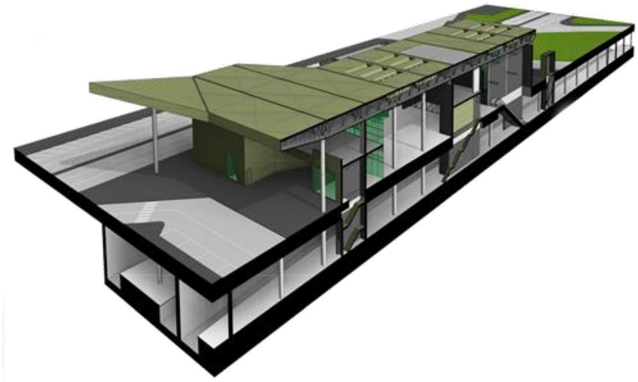

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