An Industrial IoT-based Feedback System for Collision Prevention in Worksites

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***Abstract*—With the advent of the Industry 4.0, the proliferation of IoT devices and artificial intelligence (AI) has accelerated the adoption of smart technologies in industrial safety, including accident detection and proactive risk management. However, conventional camera-based collision management systems suffer from blind-spot issues and high computational demands, which limit their practicality and result in high latency, making real-time operation difficult. In addition, sensor-based systems are constrained by limited positioning accuracy, often leading to reduced reliability and the generation of unnecessary alerts. To address these limitations, we propose the Intelligent Industrial Safety System (IISS), a ultra-wideband (UWB) and AI based feedback framework designed for proactive collision prevention. The IISS is consist of three subsystems: an indoor localization subsystem utilizing UWB anchors and tags for accurate positioning, a collision prediction subsystem employing an AI-based trajectory prediction, and a user feedback subsystem that delivers multimodal alerts through wearable devices. In this study, we designed and presented a proof-of-concept implementation of a IISS capable of predicting collision arising in blind-spot scenarios. In addition, tests were conducted in a worksite based on the proposed system. The results indicated that the system can predict potential collision scenarios and provide workers with intuitive feedback through vibration, auditory alerts, and context-aware text messages.**

***Index Terms*—Collision Prevention, Safety, Real-time Location System, Ultra-wideband**

I. Introduction

The rapid development of IoT devices has improved convenience across various domains, including industrial safety. Particularly in worksites, IoT devices are increasingly applied for real-time monitoring, accident detection, and proactive accident prevention. With the integration of Industrial IoT (IIoT), various sensors and wearable devices have been deployed. They enable worker localization, environmental monitoring (e.g., gas concentration and temperature), and supervision of heavy equipment. Such functions are directly related to enhancing safety, demonstrating the potential of IIoT to provide continuous and real-time situational awareness. Despite these advantages, most existing approaches remain reactive, focusing on detection rather than proactive prediction. In particular, among different types of accidents, collisions between workers and heavy equipment are reported as one of the most frequent and severe causes of injuries [1], [2], highlighting the urgent need for proactive collision prevention systems.

Currently, AI-based collision management systems commonly rely on cameras [3]–[6] and positioning sensors [7]–[9]. However, camera-based approaches suffer from critical limitations. Blind spots prevent reliable collision detection in certain areas [10], [11]. In addition, the use of images or videos as model inputs significantly increases the computational complexity of AI models [12]. This complexity reduces the real-time responsiveness that is essential for ensuring worksite safety, while also requiring high-performance server infrastructure for system operation. Moreover, sensor-based approaches such as Wi-Fi [13], Bluetooth beacons [14] and RFID [15] face inherent limitations due to restricted positioning accuracy, making it difficult to fully capture workers' intentions or movement patterns. As a result, these approaches struggle to provide precise predictions of potential collision scenarios. Furthermore, existing UWB Real-Time Location System (RTLS) collision prediction systems [16], [17] do not take into account the movement direction of objects and instead generate alarms solely based on predefined distance thresholds. However, such an approach may trigger unnecessary alerts regardless of the actual collision probability, which can undermine both efficiency and reliability in industrial work environments. This limitation highlights the urgent need for a more reliable and proactive collision prevention system.

To address these limitations, we propose a multi-modal, prediction-aware collision prevention framework for industrial environments, termed the Intelligent Industrial Safety System (IISS). Unlike existing reactive [17]–[19] or distance-threshold-based [20], [21] approaches, the proposed frame-

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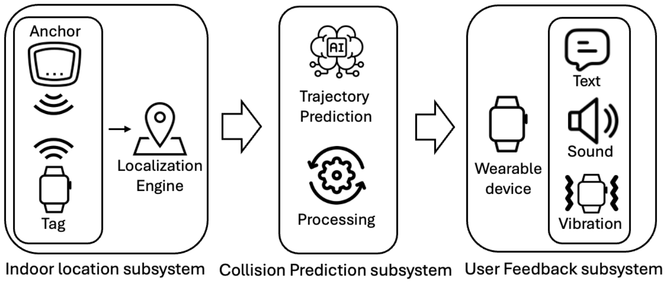

Fig. 1: Concept of Intelligent Industrial Safety System

work proactively estimates collision risk by integrating UWB-based positioning, learning-based trajectory prediction, and adaptive multi-modal feedback delivery. As illustrated in Fig. 1, the IISS is composed of three subsystems. The indoor location subsystem employs a localization engine to estimate the positions of workers and mobile equipment. The collision prediction subsystem utilizes an AI-based trajectory prediction model to forecast potential collisions based on predicted motion trends. Upon identifying collision risks, the user feedback subsystem delivers timely alerts through wearable devices in the form of text, auditory, and haptic notifications. To validate the effectiveness and practicality of the proposed framework, we implemented a proof-of-concept system and conducted evaluations in an actual worksite environment

The rest of the paper is organized as follows: Section II presents the architecture and subsystems of the proposed IISS, Section III covers the experimental setup and the proof-of-concept implementation, followed by a discussion of different aspects of the system. Lastly, Section IV provides the conclusion and discusses future work.

II. System Architecture of IISS

In this section, we describe the architecture and design of the Intelligent Industrial Safety System (IISS), a feedback system developed for proactive collision prevention. As illustrated in Fig. 1, the overall system structure comprises three subsystems: (1) The indoor location subsystem, (2) the collision prediction subsystem, and (3) the user feedback subsystem. The detailed data pipeline is depicted in Fig. 2. The pipeline begins with the location stream generated from the UWB RTLS, which is transmitted to Kafka for event-driven data handling. The stream is subsequently processed by Flink, which incorporates deep learning models for trajectory prediction. The processed results are then delivered to the user feedback subsystem, enabling real-time monitoring and alerting. The following subsections provide detailed descriptions of each subsystem.

A. Indoor location subsystem

Various indoor localization technologies such as Wi-Fi [22], [23], Bluetooth beacons [24], and UWB [25], [26] have been explored in industrial environments. However, Wi-Fi, Bluetooth beacons, and RFID systems often suffer from limited accuracy. Therefore, our system adopts UWB, which offers superior positioning accuracy and robustness in industrial environments. The indoor location subsystem employs UWB anchors and tags to provide accurate real-time positioning of workers and mobile equipment. Distances between a mobile tag and fixed anchors are estimated using Two-Way Ranging (TWR). This method refines the basic Time-of-Flight (ToF) measurement by eliminating clock synchronization errors between devices. Accordingly, the distance d is calculated as shown in Eq. (1).

$$d = \frac{c \cdot (T_{\text{round}} - T_{\text{reply}})}{2}, \tag{1}$$

where c is the speed of light, T_{round} is the measured round-trip time between the tag and anchor, and T_{reply} is the known response delay at the anchor.

With the distances d_i to at least three anchors at known positions (x_i, y_i), the tag's position (x, y) can be estimated using trilateration, defined by Eq. (2).

$$(x - x_i)^2 + (y - y_i)^2 = d_i^2, \quad i = 1, 2, 3, ... \tag{2}$$

where, (x, y) denotes the estimated position of the tag, (x_i, y_i) are the known coordinates of the anchors, and d_i is the distance between the tag and anchor i, calculated by Eq. (1).

Once the positions are estimated, these data must be reliably streamed for subsequent processing. To achieve this, the UWB location data are transmitted in real time to Kafka, which serves as the streaming middleware. Kafka buffers the incoming streams and reliably delivers them to the following modules, where trajectory prediction and collision risk assessment are performed. This ensures that the estimated positions can be seamlessly integrated into the subsequent collision prediction process, forming a coherent pipeline from localization to risk analysis.

B. Collision prediction subsystem

The collision prediction subsystem is designed to forecast future trajectories and identify potential collision risks in real time. As illustrated in Fig. 2, UWB RTLS data are processed

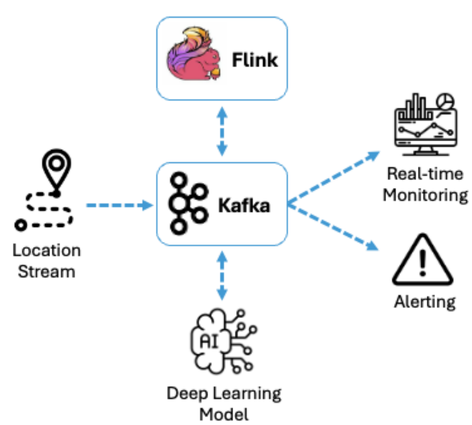

Fig. 2: Data Pipeline of IISS

through a Kafka–Flink streaming pipeline. The location data are first published to Kafka. Flink then performs three sequential operations: noise reduction, trajectory prediction, and collision risk assessment. In the first stage, a Kalman filter is applied to remove noise and enhance positional accuracy. Next, an LSTM model [27] predicts the future trajectories of workers and mobile equipment. Finally, Flink computes the minimum distance between predicted trajectories and generates a collision prediction alert event, which is transmitted to the user feedback subsystem through Kafka for multimodal notification delivery.

C. User feedback subsystem

The user feedback subsystem provides both real-time monitoring and multimodal alerting functionalities. Real-time monitoring is enabled through a safety management dashboard, which visualizes high-risk areas using heatmaps based on the frequency of predicted collisions. In addition, the dashboard continuously tracks the trajectories of workers and mobile equipment. This allows site managers to intuitively identify hazardous zones and implement proactive countermeasures.

Alerting is delivered directly to workers via wearable devices. Depending on the severity of the detected risk, alerts are provided in the form of text messages, haptic feedback, or auditory alarms. Moreover, our system's text notifications explicitly provide the direction and relative position of approaching mobile equipment.

This additional contextual information enables workers to more accurately perceive the risk and take precise, timely evasive actions. By combining multimodal alerts with context-aware feedback, the subsystem significantly enhances the effectiveness of collision prevention. This design also ensures immediacy and clarity in risk communication.

III. Experiments

In this section, we implement a proof-of-concept of the proposed IISS to verify its stability and effectiveness in a worksite. Fig. 3 illustrates the experimental scenario designed for collision prevention. The experimental setting includes racks, an office, and containers, with UWB anchors deployed to support reliable position estimation. In this environment, workers equipped with wearable devices and mobile equipment fitted with UWB tags moved along predefined routes that often intersect, thereby simulating collision-prone situations such as blind spots.

A. Experiments Setup

The experiments were conducted in the environment illustrated in Fig. 4. The mobile equipment was configured to operate at a speed of $2.0, \mathrm{m/s}$, while the worker moved at a walking speed of $1.5, \mathrm{m/s}$. We installed four UWB anchors at a height of 4.5 m within an area of $9, \mathrm{m} \times 14, \mathrm{m}$ to ensure accurate and stable position estimation. To reflect realistic worksite conditions, eight frequently used routes were selected, and approximately ten minutes of trajectory data were collected under this setup. The collected trajectory data were then used to train the LSTM model [27], which serves as the trajectory prediction module in the proposed IISS.

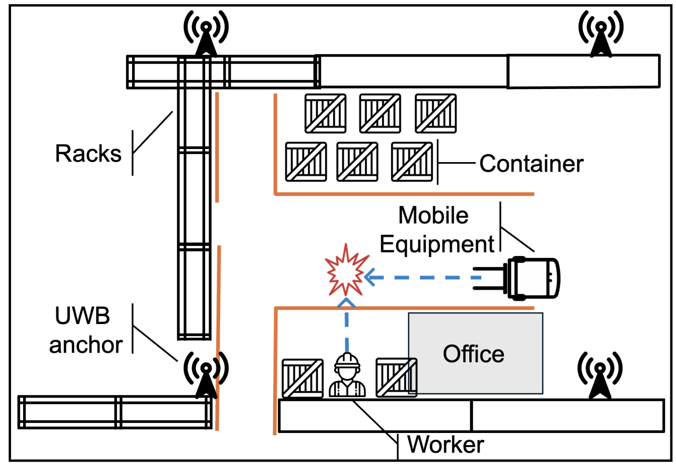

Fig. 3: Experimental scenario for collision prevention (bird's-eye view)

Fig. 4: Experimental setup for IISS operation, showing the UWB anchor, UWB tag, office, and mobile equipment (forklift). The driver's line of sight is occluded by the office, creating a blind-spot scenario.

B. Results

The proof-of-concept results of the IISS in the configured scenario are presented in Fig. 5. Fig. 5(a) illustrates a scene in which the forklift and worker move forward. In this situation, the driver's line of sight is blocked by the office structure, preventing direct recognition of the worker. Likewise, the worker is unable to visually detect the approaching forklift. Fig. 5(b) shows the wearable device receiving the collision prediction alert. The display indicates the predicted collision direction (Right) and distance (4.5 m). In addition, both haptic feedback and auditory alarms are simultaneously activated. Fig. 5(c) depicts the predicted trajectories of the forklift and the worker under potential collision conditions.

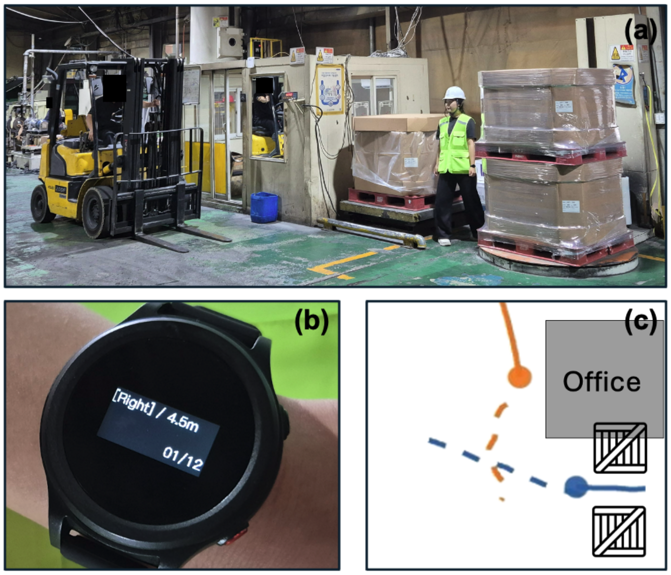

Fig. 5: Experimental results of the proposed IISS. (a) Scene showing the forklift and worker moving forward. (b) Wearable device displaying a warning message triggered by collision prediction. (c) Trajectories of the forklift (orange) and worker (blue) (dashed lines indicate predicted trajectories, solid lines represent the previously traveled paths)

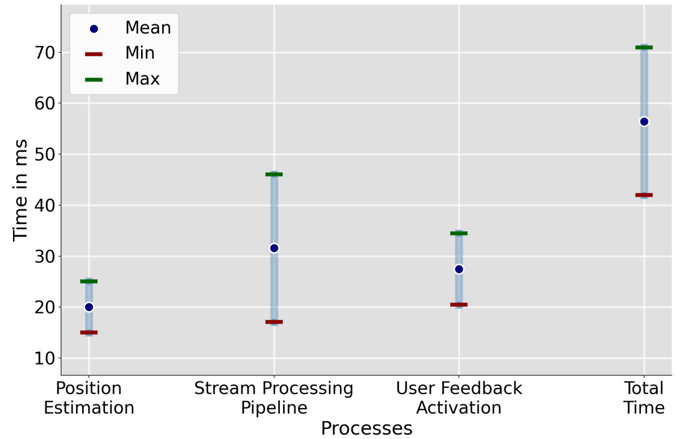

Fig. 6: Processing time for each process

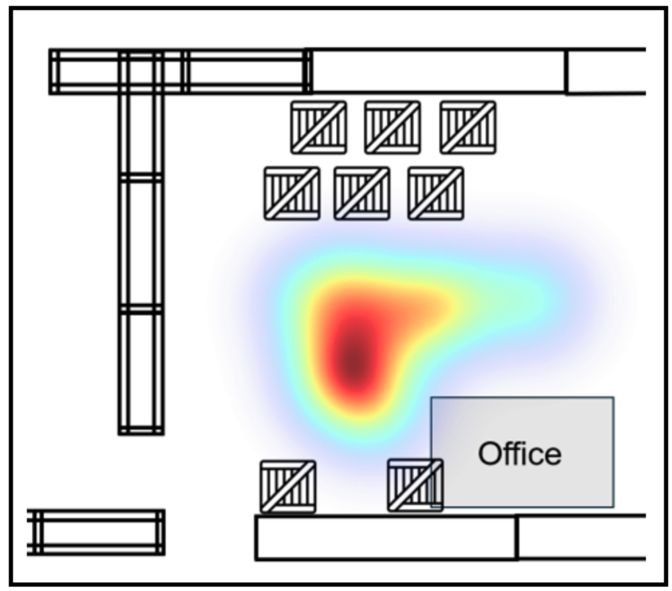

Fig. 7: Predicted collision heatmap generated by the real-time monitoring dashboard.

Real-time responsiveness is essential for collision prediction alerts to be effective in practice. To evaluate this aspect, the entire process was divided into three subprocesses: position estimation, stream processing pipeline, and user feedback activation. The processing time for each subprocess is summarized in Fig. 6, with position estimation requiring approximately 20 ms, stream processing pipeline about 31.5 ms, and user feedback activation around 27.4 ms. For a comprehensive understanding of the system, the end-to-end process completes in approximately 56.4 ms. This latency allows the system to generate up to 17 alerts per second when necessary.

Fig. 7 illustrates a heatmap generated by the real-time monitoring dashboard of the proposed IISS. The heatmap shows areas with a high frequency of predicted collision events, where red regions indicate higher risk levels compared to green and blue regions. These results confirm that collision-prone zones can be visually identified within the worksite. Furthermore, frequent collision locations can serve as objective indicators for preventive measures and the designation of hazardous areas. Leveraging such information allows site managers to intuitively recognize high-risk regions and implement proactive safety measures, thereby enhancing the overall level of worksite safety management.

C. Discussion

The proof-of-concept experimental results demonstrate the potential of the proposed IISS in addressing key limitations of conventional collision prevention systems. The system completes the entire process within approximately 56.4 ms, enabling the generation of up to 17 alerts per second and thereby ensuring that workers can respond in a timely manner to potential collision risks. Moreover, the trajectory-based approach effectively reduces false alarms and missed detections compared to simple distance-threshold methods, improving both reliability and usability while mitigating worker fatigue caused by unnecessary warnings. In addition, the use of UWB-based localization allows the system to overcome blind-spot issues and, combined with directional notifications and multimodal alerts, significantly enhances situational awareness and worker safety in industrial environments.

Despite these results, several limitations remain. The experiments were conducted within a confined $9\mathrm{m} \times 14\mathrm{m}$ area. Therefore, further investigation is needed to account for the complexity of large-scale worksites. In addition, further validation is required under multipath interference and complex indoor environments to ensure robustness. Moreover, the current evaluation focused on simplified movement patterns. To better reflect real-world conditions, additional data collection and model training are necessary to capture the diverse behaviors of workers in actual industrial environments.

IV. Conclusion

This study proposed the IISS to prevent collisions between workers and mobile equipment in industrial environments. The proposed system integrates UWB-based localization with an AI-driven trajectory prediction model to proactively assess potential collision risks and deliver timely feedback to workers. Specifically, it provides directional and distance-based text notifications, supplemented with haptic and auditory alerts, enabling intuitive and immediate responses. The proof-of-concept implementation demonstrated that the end-to-end process can be completed within 56.4 ms, allowing the system to generate up to 17 alerts per second when necessary. Furthermore, site managers can utilize the real-time monitoring dashboard, which generates heatmaps of predicted collision-prone areas, as a valuable tool for preventive safety management.

For future work, we plan to extend the system beyond position data by incorporating dynamically changing environmental factors to provide more context-aware feedback. In addition, we will expand the experimental scope by deploying a larger number of UWB anchors in large-scale industrial sites to further validate the scalability and robustness of the system.

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