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Automated classification of construction site hazard zones by crowd-sourced integrated density maps

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ABSTRACT

Current onsite safety management always relies on time-consuming predefinitions of hazardous zones based on the managers' personal capabilities. However, in a typical labor-intensive industry such as construction, the workers themselves can provide a wealth of information for hazard identification. Historical accident-free working locations on site provide a valuable means of recognizing safe workplaces. This paper presents an approach to the automated classification of construction site zones derived from the location tracks of workers collected from a real-time location system (RTLS). Through data mining, filtering and analysis, the location tracks are transformed into grid density maps and continuous density maps. These illustrate the characteristics of spatial-temporal activities onsite as well as providing a visual representation of the distribution of safe and hazardous individual workplaces. A personnel hazard map is generated automatically based on historical accident-free location tracks from a field project using the proposed approach. Compared with the actual workplaces in terms of accuracy, precision, sensitivity and specificity, the evaluation result reveals that the hazardous areas on a construction site can be automatically classified to improve the workplace management of individual workers. The contributions of this research include an automated zone classification algorithm and an evaluation framework consisting of four indicators for hazard awareness onsite.

1. Introduction

Identifying the changing hazards or controlling risks during construction activities is an important, but often quite difficult task. This is especially the case onsite, even when most of the activities are conducted repetitively [1], where it is almost impossible to avoid all the safety hazards in a workspace due to the complex nature of construction projects [2,3]. Construction sites are also highly dynamic, with exposed workspaces and their occupation constantly changing, exacerbating the already serious hazard identification problem for both the construction site and crew. Since it is uneconomical or ineffective to employ more safety inspectors, an efficient and automated approach is needed.

There is an increasing use of personal mobile devices integrated with geographic location tracking, context-awareness and wireless communication in the construction industry, and working habits are changing accordingly. This is providing the potential for accessing a wealth of information for evaluation, communication and collaboration onsite. Basic data concerning the continuously changing locations of communication devices onsite enables the geographic position and spatial-temporal behavior of workers, materials and equipment to be monitored by simple manipulation, providing managers and workers with opportunities for creative initiatives for the collection, tracking and visualization of onsite construction activities [4–9]. This has given rise to the introduction of location-based services (LBS) that offer value-added services for individuals in the form of new utilities embedded in their personal devices [10]. Properly leveraged, this rich spatial-temporal information has the potential to improve hazard identification and the control of risks onsite.

However, the increasing amount of research applying LBS to safety issues is mostly based on predefined unalterable manual rules. Proximity hazard indicators between workers, equipment and hazardous areas are widely employed in pro-active real-time construction systems due to the growing body of evidence indicating that potential

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risks and accidents can be reduced by avoiding working in, or close to, a dangerous location at a specific time [11–16]. The workspace requirements of labor and equipment operations in 3D BIM models are being generated with increasing precision to improve the efficacy of proximity alert systems and approaches [17,18]. Although these studies greatly assist in safety management onsite, pre-construction safety plans are still insufficiently adequate to cope with the dynamic and multiple objectives that occur during daily onsite activities. The whole hazard identification process needs to be involved prior to the application of these proximity approaches [2], otherwise, unidentified hazards will continue to threaten the health and safety of the workforce. Moreover, the situation is exacerbated by most planners being conservative and unable to provide timely updates of hazardous locations according to changing site conditions.

Since the construction process lasts so long, it is reasonable to consider the hazard zones to be static at short time intervals. Accordingly, this study aims to develop an automated approach to identifying, mapping and updating all of the area-restricted hazards or safe zones onsite in a timely manner. This involves deriving crucial historical locations deemed to be safe working zones, such as accident-free walk paths, by *crowd sourcing* (workers engaged in similar activities or in the same group) to assist in individual safety decision-making [19]. This exploratory approach attempts to classify the entire site into hazardous and safe zones through a novel *peer based* approach based on their frequency of occupation by workers, potentially providing an available means to reuse the historical data for further prediction in the short run. On the assumption that areas that have been occupied by accident-free workers are more likely to be safe areas than otherwise, the issue then becomes one of identifying such areas. The approach utilizes data mining and information technology to extract and integrate density maps from these areas to provide individual guides to safe zones in the form of personal hazard maps [20].

Consequently, to achieve the objectives of this paper that harness accident-free work trajectories and safety preferences by like-minded peers, the rest of the paper is structured as follows. Section 2 investigates the background of the research, containing traditional hazard identification approaches and potential issues in practice. Then the core proposed framework consisting of four modules is introduced in Section 3. Curial zones of workplaces are visualized via density maps to display their distribution and mark the characteristics of workers onsite. In Section 4, a field case study is described to demonstrate the capability to create an automated zone classification map for an individual worker and evaluate its accuracy. Finally, conclusions and future research possibilities are provided in the last section.

2. Background

Although the associated root causes of fatal/serious accidents are well known, including lack of attention, insufficient safety training, tiredness, poor quality materials and equipment [21], there nonetheless still exist unidentified hazards or risks that cannot be anticipated prior to their occurrence. From an external environment perspective, the hazards are a result of a variety of circumstances, including unexpected site conditions. The constantly changing dynamic of aggregated variables onsite also undermines hazard identification [2]. From an internal worker perspective, different workers share different safe and hazardous zones due to human factors [22,23]. For instance, a ditch on a site may be a safe working zone for an experienced excavator operator who understands the work method involved and uses appropriate personal protective equipment (PPE), but may be a hazardous zone for other workers. Both perspectives make it impossible to identify all the hazards involved completely in advance.

Commonly, most accidents onsite are regarded as the result of contact collisions mainly caused by low awareness and blind spots [12,24]. Thus, apart from site inspections, proximity safe alert systems based on real-time location systems (RTLS) have been extremely popular and unsafe-proximity identification is widely used to provide proactive safety management [1]. Spatial interference between personnel, related equipment and materials, such as the proximity of labor to operating heavy equipment or moving vehicles, can be detected or predicted [5,13], For example, based on onsite dynamics, the analysis of activities and related hazards, Guo has identified space conflicts by considering space constraints and path interferences to assist decision-making [25]; Sacks et al. has designed an algorithm to estimate the likelihood of spatial and temporal exposure to related hazards [1]; Lee et al. have developed a radio frequency identification (RFID)-based RTLS suitable for diverse sites to contribute to aggressive safety management [16]; and Marks and Teizer propose proximity detection between workers and equipment [12]. To enhance the efficiency of proximity safe systems, Kim et al. have developed a human-assisted obstacle avoidance system during equipment operation [26]; Wang and Razavi have constructed a low false alarm rate model by adding position, heading direction and speed attributes [15]; and Cheng et al. further propose to utilize the fusion of RTLS and physiological status as well as thoracic posture to activity analysis [27,28]. On the other hand, Vahdatikhaki and Hammad, Tantisevi and Akinci generate a dynamic equipment workspace [17,29,30]; Akinci et al. design a project-specific model to build workspace requirements at the activity-level [31]; with Zhang et al. then integrating BIM into the 3D visualization of the workspace requirements to promote the accurate calculation of proximity [18]. These studies all require the manual pre-identification of unsafe-proximity prior to applying field-testing, which is time-consuming and prone to invalidate the approaches due to unpredicted conditions.

Since it is impossible and uneconomical for managers to identify all the unsafe-proximity hazards before construction, a novel approach to extracting spatial-temporal information from historical location tracks is to use the wealth of information available of the locations of workers, materials and equipment [32]. This can be conveniently obtained by utilizing such advanced technology as UWB, RFID and GPS [4,33–35]. A few researchers have attempted to promote proximity safe alert systems through learning from the spatial-temporal proximity relationships of near misses. Wu et al., for example, have designed an autonomous system by considering the characteristics of near misses based on typical historical accident cases [24]; and Teizer and Cheng have collected and studied near-miss data to provide a proximity hazard indicator to identify obstacles for route searching and generate heat maps for safety planning [36,37], which enhances safety knowledge sharing among stakeholders [13]. These studies attempt to transfer safety knowledge from not only inspectors and managers but also the workforce itself. However, such approaches commonly view and serve workers as a community, with often-insensitive unsafe-proximity recommendations being provided for safety initiatives.

Therefore, an approach that automatically updates according to movement feedback from specific groups of workers onsite has a genuine potential to provide the responsiveness required sufficiently and efficiently. However, a major problem with historical location resources is that enormous amounts of information have to be examined in order to find the relevant pieces needed. If the working area of a worker is safe, then it should also be safe for similar workers undertaking similar activities at a similar time. Thus, integrating the density maps of historical accident-free locations should provide a much better alternative than increasing the number of safety managers onsite.

3. Framework of automated zone classification

The framework of the proposed approach is represented in Fig. 1. The origin dataset is cloud-stored and contains historical locations, real-time locations, layout and predefined special zones. It is not compulsory to input the data in the dot boxes since sometimes workers are new to the site or adequate detailed information of the geographic attributes of sites cannot be obtained before construction. The essential assumptions