Spatio-Temporal Assessment of Workers' Lung Exposure to Workshop Dust using Multi-Channel Optical Sensing and a Dynamic Occupational Disease Risk Early-Warning Model based on Graph Neural Networks

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Abstract: There is dust pollution in industrial production workshops, which is one of the main causes of occupational lung diseases. Traditionally, the methods used to measure dust mostly focused on a specific area or only measured the concentration occasionally, failing to present the actual exposure situation of workers in complex environments. This document presents an optical sensor network system with multiple channels, combined with worker time and movement path analysis, and then combined with graph neural network technology to construct the corresponding assessment and expectation framework. The first step is to use distributed optical sensors to form a spatial field of dust concentration in the workshop, thereby recording the dispersion of particles and having a very high resolution; the second step is to combine indoor positioning technology to reproduce the path that each worker has walked, and then estimate the cumulative damage to their entire respiratory tract in that concentration field, thus completing the calculation process from both time and space aspects. Remove the situations such as when workers encounter each other, changes in their positions, and the amount of things they have come into contact with as data in the graph structure, and then use the characteristics of graph neural networks that are good at handling relationships to create a dynamic alert model for occupational disease hazards. This model not only considers how much exposure a single person has received, but also finds the hidden patterns of the spread and accumulation of risks within the population, providing new methods for the comprehensive improvement of the occupational health protection.

Keyword: *Occupational Dust Exposure, Multi-Channel Optical Sensing, Spatio-Temporal Assessment, Graph Neural Networks (GNN), Dynamic Risk Early-Warning*

1. INTRODUCTION

Occupational lung diseases such as pneumoconiosis are among the most serious workplace diseases worldwide. In industries like mining, construction materials, and metal processing, large amounts of production-related dust pose long-term harm to workers' health. The conventional preventive measures mostly rely on installing sampling devices throughout the workshop and conducting regular tests on the total dust or respirable dust content to carry out health risk assessments. However, their obvious drawback is that they treat the complex workshop environment as several isolated points, without considering the significant differences in dust concentration across different spaces and the drastic fluctuations over time. Moreover, they are unable to link these concentration data with the actual activity trajectories of the workers.

The actual situation is that a worker will visit many workstations within an 8-hour workday, from material feeding to grinding and packaging. The dust concentration varies at each location. The actual amount of dust that enters his lungs is the sum of the duration he stayed at each place, the instantaneous concentration at that time, and the average concentration at the fixed points. Measuring the exposure risk using the average concentration at fixed points is equivalent to using the average temperature of the entire city to determine whether someone will suffer from heatstroke. This is a seriously inaccurate assessment.

In response to the aforementioned issues, this paper proposes a new systematic solution. Its main idea consists of three parts. Firstly, in the aspect of perception, a large number of photovoltaic sensing networks are used to create a high-resolution and low-cost spatial-temporal field of dust concentration in the workshop, converting the invisible dust clouds into visible images. Secondly, at the evaluation level, the location information of employees at that time is combined with the concentration field in terms of time and space to calculate the "spatial-temporal exposure dose" that each person's lungs are exposed to, moving from the concentration in the environment to the inhalation volume by the person. For the warning level, it does not merely focus on a single individual but views all the workers in the entire workshop as a whole that is interconnected through spatial movement and work collaboration. Using advanced technologies such as graph neural networks, a dynamic alarm model for occupational disease risks in the group is constructed, aiming to identify the "super spreader" risk points and high-risk clusters prone to infectious diseases in advance, thus shifting from post-event remediation to pre-event prevention.

II. MULTI-CHANNEL OPTICAL SENSING NETWORK AND RECONSTRUCTION OF DUST SPATIOTEMPORAL FIELD

To achieve spatiotemporal evaluation of worker exposure, the first technical prerequisite is to obtain a high spatiotemporal resolution workshop dust concentration distribution map. The traditional weighing method is time-consuming and labor-intensive, and cannot be monitored in real time; Although single point light scattering or beta ray direct reading instruments can achieve continuous monitoring in time, their spatial coverage capability is very limited. Therefore, this article proposes a low-cost, multi-channel optical sensor array scheme.

The core sensing unit can adopt a small particle sensor of light scattering type. After the dusty airflow passes through the photosensitive area of the sensor, some of the laser beam will be scattered by the particles. The intensity of the scattered light is directly proportional to the mass concentration of the particles and linearly correlated within a certain range. Within the workshop, using a certain strategy to arrange dozens, even hundreds, or even more of such sensor nodes forms a dense monitoring network. Each node is equivalent to an independent "channel" that continuously and uninterrupted delivers concentration data to the data center.

The deployment strategy is not uniform distribution, but adopts a "risk oriented" deployment approach, strengthening deployment at high-yield dust sources such as crushers, screening machines, and belt transfer points to form a "source capture zone". Deployment is carried out according to rules at workers' permanent operating locations, inspection routes, rest areas, etc., constructing a "crowd contact zone", implementing deployment at entrances, exits, and ventilation openings, and creating a "boundary monitoring zone". In this way, through the array layout of multiple regions and levels, a data foundation has been formed for accurately characterizing the entire lifecycle of dust from occurrence to discharge.

Dozens of sensors produce discrete point time series. To turn these data into a continuous spatial concentration field for the entire workshop, spatial interpolation and data fusion techniques are required. Geostatistical methods such as kriging can provide optimal unbiased estimates of the concentration at unknown points by analyzing the data from known points and their spatial correlations. But this can only be static.

The diffusion of dust is a process influenced by multiple factors such as airflow organization, temperature difference, and mechanical motion. To more accurately reproduce the spatiotemporal field, multi-source data fusion is necessary. The real-time data collected by the sensor network can be regarded as observation data, and combined with the pre-set flow field knowledge of computational fluid dynamics simulation. After real-time data correction, the dust concentration value at any coordinate point in the workshop at any time can be obtained. Just like conducting a real-time, high-definition "CT scan" of the entire workshop, obtaining a dynamic three-dimensional view of dust concentration provides a good environmental foundation for subsequent individual exposure calculations.

III. METHOD FOR ASSESSING EXPOSURE OF WORKERS TO AIRBORNE SUBSTANCES

With the concentration field in place, the questions to be answered are "Who, when, where, and how much dust was inhaled". That is, the worker's spatiotemporal behavior data needs to be precisely coupled with the concentration field.

By obtaining the workers' trajectories, the goal of individual exposure can be achieved. When dealing with complex workshop environments, in indoor positioning technology, a combined approach is adopted, integrating Bluetooth angle seeking technology and inertial navigation system. Lightweight positioning tags are attached to the workers' safety helmets or badges, and positioning base stations are set up at important locations in the workshop. The system can instantly calculate the two-dimensional or three-dimensional coordinates of each worker, thereby generating a continuous spatiotemporal trajectory, clearly indicating when the worker is at a certain location and how long they stay beside a certain piece of equipment. It is necessary to operate in accordance with privacy protection principles, de-identify the personal identity data before using it, and only use it to ensure health protection.

By "immersing" a person's continuous trajectory line into a changing dust concentration field, the instantaneous concentration value corresponding to each point on that trajectory line at that specific time and location can be extracted. The dose received in the lungs is not just a simple average concentration; instead, it is the result of integrating the instantaneous concentrations over time and space according to the worker's walking trajectory.

The system creates a dynamic exposure profile for each worker. When they enter the high-concentration area, their cumulative exposure curve becomes very steep. Once they return to the rest area, the curve becomes relatively flat. The total exposure for the entire day is the sum of the amount of dust inhaled through each small section of the worker's activity path during that day. This allows for the accurate separation of the exposure situations of workers in different positions or the same position but with different operation methods. For example, if someone enters the core area to clean dust while the equipment is running due to a violation, the exposure pulse within just a few minutes can become the main part of the total exposure for that day. This meticulous insight is beyond what traditional methods can achieve.

IV. A DYNAMIC EARLY WARNING MODEL FOR OCCUPATIONAL DISEASE RISKS BASED ON GRAPH NEURAL NETWORKS

Accurately assessing individual exposure doses has solved our problem of risk quantification, but what we really need to address is the issue of prediction and prevention. Occupational diseases, especially pneumoconiosis, have a long incubation period and are chronic and collective problems. The risks faced by workers depend not only on their personal exposure history, but also on the overall level of protection of their work team and the mutual influence among workers. Therefore, we hope to establish a group oriented dynamic risk warning model using graph structured data and graph neural networks.

We consider the personnel in the workshop as independent points on a dynamic graph, and the lines connecting these points represent the intricate relationships between them. These relationship patterns differ greatly, and when combined, they form a 'workshop social physical' landscape.

Firstly, it is the fundamental spatial coexistence relationship. Within a certain time window, if two people are in close proximity and the duration exceeds a certain threshold, it is considered that there is a connection between them, and the edge can be weighted based on the duration of coexistence. People can identify groups within high-density areas. Secondly, there are social contact relationships, which are formed through the position of individuals, indicating whether they are communicating or exchanging tools, thus generating social contact behavior, reflecting mutual learning of safety behaviors or verbal transmission of bad habits. The third type is the device personnel membership relationship, which considers the device as a special node. If the same person operates the same device, the group not only shares the same physical exposure source, but also follows the same operating standards and safety culture together.

The traditional deep learning methods deal with data that are some regular data in Euclidean space, such as images or sequences, etc. They cannot handle graph data with relatively complex topological structures very well. However, graph neural networks can fill this gap. The basic idea of it is to use a process called "message passing", enabling the information carried by each edge on the graph to be transmitted and fused with each other, thereby obtaining a feature vector representing the node.

In the context of occupational disease risk prediction, there is a natural explanatory advantage. The individual characteristic vector of a worker not only includes information such as his own exposure dose, age, and working years, but also incorporates information about his colleagues around him, the equipment he uses, and even the colleagues of his colleagues. Therefore, when the current personal exposure dose of a certain worker is still within the safe range, but his closely related colleagues have frequently experienced high exposure incidents recently, the model can infer from his position on the graph that there may be issues such as lax management or poor atmosphere in that area, and accordingly increase the risk score to issue an early warning.

We regard each worker as a target node, whose characteristics consist of dynamic features and static features. The dynamic features include the sequence of spatial-temporal exposure doses in the recent period, the working sequence pattern, the entropy value of the movement trajectory, etc.; the static features include age, years of service, position, past medical history, etc. We use the prediction task of "Will this worker have a higher overall risk level in the next evaluation period (such as the next week or the next month)?" for training.

The core of the model lies in the graph convolutional layer or the graph attention layer. Among them, the graph attention mechanism is the most crucial part. It enables the model to autonomously learn and assign different attention weights to different neighboring nodes when aggregating information. Just like a newly hired young worker, the model can automatically discover the current behavior pattern and risks of this person, and the part most susceptible to the direct leader, that is, his supervisor, will be given a very large attention weight. After stacking multiple layers of graph neural networks, the information can skip more nodes, thereby capturing more complex network effects.

During training, we divided the historical data into individual time slices. We used the graph structures and node attributes of the earlier time slices to guess the risk levels of the subsequent time slices, enabling the model to learn how to identify typical patterns that indicate the aggregation of risks. The model might itself discover such a dangerous subgraph structure: a group of experienced employees are all risky, an old machine is prone to failure, and some new employees who are not well-informed have close connections, which might indicate a "risk spark" where many people will have health problems in the future.

After the trained model is deployed online, the system enters a real-time or near-real-time dynamic warning mode. Whenever there are new sensor data and location data, the exposure profile of each worker will be updated once, and the relationship network diagram of the workshop will also change accordingly. The warning system will use the graph neural network model to predict the risk level faced by each worker at regular intervals, and then sort them according to the risk level from high to low.

The warning information is presented visually to the managers. On the map of the workshop, the workers are represented as different colored dots. Green indicates safety, yellow indicates caution, and red indicates danger. The thicker the connection between nodes, the closer the relationship. The managers can see that a red dangerous node is surrounded by a circle of orange nodes. Clicking on the community will reveal "Zhang San (High Risk), the individual's recent exposure dose has exceeded the limit, and the 'broken team' where he is located, the number of people in this team has exceeded half and the risk index has risen. The No. 3 crusher of the 'broken team' has had a higher number of dust source sensor alarms in the past week."

This diagnostic-type early warning will significantly advance the time when problems are identified. Managers will not only know "who" has the problem, but also understand "why the problem exists" and "how the risk spread", thereby achieving targeted and comprehensive intervention that combines both individual and overall solutions. This involves mandatory physical examinations for individuals, changing their work positions; conducting specialized safety training for the entire shift; and immediately repairing the equipment that has been identified as faulty. This forms a complete intelligent cycle system from perception to assessment, from prediction to intervention.

CONCLUSION

The innovation of the system described in this article lies in advancing occupational health protection from the previous "environmental average concentration qualification theory" to a new stage of "accurate measurement of individual spatiotemporal exposure and intelligent estimation of group risks". The multi-channel optical sensing network makes intangible killers tangible, and the fusion of individual trajectories and concentration fields achieves true individualized exposure evaluation. The application of graph neural networks opens up a new perspective on the collective and networked transmission laws of occupational disease risks, integrating macro management with micro intervention. The practical dilemma of this methodology lies in the difficulty of data collection and integration, the testing of long-term predictive validity of the model, and considerations of privacy ethics. In the future, when the Internet of Things, artificial intelligence, and health big data merge, perhaps we can foresee that proactive, precise, and intelligent defense systems like this will be part of smart factories, enabling workers who sweat profusely in dust to completely escape health crises and bringing warmth to technological innovation.

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