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Occupant-centric robotic air filtration and planning for classrooms for Safer school reopening amid respiratory pandemics

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A B S T R A C T
Coexisting with the current COVID-19 pandemic is a global reality that comes with unique challenges impacting daily interactions, business, and facility maintenance. A monumental challenge accompanied is continuous and effective disinfection of shared spaces, such as office/school buildings, elevators, classrooms, and cafeterias. Although ultraviolet light and chemical sprays are routines for indoor disinfection, they irritate humans, hence can only be used when the facility is unoccupied. Stationary air filtration systems, while being irritation-free and commonly available, fail to protect all occupants due to limitations in air circulation and diffusion. Hence, we present a novel collaborative robot (cobot) disinfection system equipped with a Bernoulli Air Filtration Module, with a design that minimizes disturbance to the surrounding airflow and maneuverability among occupants for maximum coverage. The influence of robotic air filtration on dosage at neighbors of a coughing source is analyzed with derivations from a Computational Fluid Dynamics (CFD) simulation. Based on the analysis, the novel occupant-centric online rerouting algorithm decides the path of the robot. The rerouting ensures effective air filtration that minimizes the risk of occupants under their detected layout. The proposed system was tested on a 2 × 3 seating grid (empty seats allowed) in a classroom, and the worst-case dosage for all occupants was chosen as the metric. The system reduced the worst-case dosage among all occupants by 26% and 19% compared to a stationary air filtration system with the same flow rate, and a robotic air filtration system that traverses all the seats but without occupant-centric planning of its path, respectively. Hence, we validated the effectiveness of the proposed robotic air filtration system.

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1. Introduction

The COVID-19 pandemic has lasted for more than a year and has impacted more than 180 countries worldwide, dramatically changing the way of life for millions of workers for foreseeable future. Massive lockdowns have proven to be effective in reducing the chance of person-to-person transmission and community spread [1]. However, lockdown comes with the price of profound economic impact, and is ineffective for essential operations and facilities that cannot shutdown. In the post-pandemic era, additionally, whatever being closed will eventually reopen again, with the risk of sporadic outbreaks due to the long incubation period of the disease. To this end, reopening schools and universities has received particular attention in the U.S. due to the concerns of online instruction quality, accessibility to high-speed internet, and implications for childcare. As a prerequisite for reopening, maintaining a safe indoor environment has commonly been the top priority for schools [2].

Robots are naturally resilient to the virus-contaminated environment, which makes them applied to a wide variety of areas [3, 4] including cleaning and disinfection [5–8], teleoperated healthcare [9,10], logistics [11], and manufacturing [12]. Among them, cleaning and disinfection robots take up approximately 1/6 of the total documented applications [3]. Despite the success of robotic disinfection services during the onset of the pandemic — using ultraviolet light [13–18] and chemical spraying [19,20], difficulties exist in the translation to classroom environments: while the aforementioned methods kill the pathogens effectively, they are inappropriate for human-occupied spaces and pose possible
irritation or harm to students and teachers. Yet, operation of the aforementioned disinfection methods when the room is vacant does not guarantee the protection against face-to-face airborne spread of the pathogen among occupants [21,22]. Although the public has shown high acceptance to service and collaborative robots (cobots), especially during the COVID-19 pandemics [11, 23], this team is aware of no deployed robotic solutions for the safe disinfection of human-occupied spaces in socially-distanced settings. Therefore, this paper is intended to propose a solution to irritation-free disinfection as a service that enhances student safety in reopening classrooms, through means of a cobot with a specially designed air filtration payload.

Pathogens become airborne when exhaled in the respiratory droplets of breaths, coughs, or sneezes. In a classroom where the students are stationary seated and socially-distanced, most of the droplets naturally precipitate to the floor prior to penetrating the spatial separation between students [24]. However, the remaining portion of smaller droplets form a bioaerosol that remains airborne for a prolonged period. Depending on ventilation and room characteristics, these droplets permeate the space, posing a significant risk of transmission through inhalation [21], which accumulate over time. A potential solution to block such transmission without irritating the occupants is to capture bioaerosol droplets with air filtration — the exact mechanism of masks. Applying air filtration technology as a public service for pandemic prevention in a classroom, however, has two principle requirements. (a) The technology should ensure contaminant locality, that pathogens are cleaned without affecting other occupants or exciting already-settled contaminants; and (b) the technology should also cover all occupants despite their spatial–temporal distribution.

Conventionally, air filtration systems are stationary, and designed with the particle filtering efficiency (particle removal rate) and flow rate (clean air delivery rate) to satisfy filtration rate requirements for a given room [25]. However, the high flow rate results in excitation and spreading of the contaminant due to the airflow [26] incurred by the fan of the air cleaner, which violates requirement (a). Alternatively, if the air cleaner is robotic and automatically moves to the location of the bioaerosol, the flow rate of the air cleaner can be reduced since only the regional air needs filtration. As a result, the contaminant locality is easier to achieve. Robotic air filtration deals with pathogens in the fluid air. Therefore, robot motion and the shape of the robot are coupled in the influence on the surrounding airflow. Specifically, the pathogens can be entrained in the shedded vortex [27] from the robot as it moves, and spread further around the room, if the robot velocity is dominant compared to the natural air draft. Consequently, the geometric design of the filtration system needs to suit the fluid dynamics associated with robot motion, such that less disturbance to pathogen distribution is induced from the motion of the filtration system.

The mobility of robots has been proven to improve coverage in the service area despite different layouts, as in the case of UVC robots [16]. However, whether its combination with air filtration has similar effects to multiple occupants – thus addressing requirement (b) – is not studied before. In addition to the resilience to the virus-contaminated environment, mobility is another asset of robots that is currently underdeveloped in pandemic response. Compared to on-demand deployment at different sites with manual decisions [15,17,18], studies on improving the efficiency and coverage of disinfection through mobility and automation [16,28] are scarce.

To further explore the efficacy of mobility, the trajectory and speed of the robotic air cleaner are planned considering the complex spreading dynamics of the pathogen-carrying droplets. Since only humans can be the source or victim of these droplets, and air filtration reduces the number of droplets regionally, the planning is subject to the timely distribution of occupants in the room. To this end, literature has combined control of robots with Computational Fluid Dynamics (CFD), but either did not alter the distribution of airborne substance [29] or was simulated offline, without timeliness requirements [30]. The combination of a robot with an air cleaner is seen in [31,32], however, none of them are targeted for high-consequence pathogens, and therefore did not consider the spreading of particles and influence zone from a fluid dynamics standpoint.

Driven by these requirements, the Purdue Campus Patrol Robot (PCPR) is developed to protect people in a classroom setting using mobile air filtration [28]. This paper is an expansion of [28] by confirming the augmentation of robot mobility to air filtration, such that risks from scattered sources of airborne pathogen are reduced for arbitrarily-seated occupants. The air filtration system atop the mobile robotic base is designed to work with the robot’s motion, such that disturbance to the surrounding air is minimal. The robot is automatically rerouted based on the estimated spreading dynamics under the detected occupant layout. Analysis and approximations of the CFD results of a coughing person are used to find the risk-optimal trajectory and speed profile, instead of computing the airflow of the entire room with multiple occupants, which enables on-site evaluation of the optimal path.

As an overview, the contributions of this paper are:

- Presenting the Purdue Campus Patrol Robot — a modular cobot system with a novel design of the air filtration module. By combining robotics, the efficacy of air filtration is improved, in that the risk of indoor occupants transmitting airborne pathogens is reduced.
- Analyzing the CFD simulation results of a coughing source for the spreading dynamics of saliva droplets, and derive the regional influence on which under robotic air filtration on a parameterized path. Upon servicing multiple occupants, on-site optimization of the path for minimal risks (expectation of worst-case dosage) of occupants is made possible, based on the analysis and detected occupant layout.

The remainder of the paper is organized as follows: Section 2 illustrates the design of the air filtration module for a robot and the hardware setup of PCPR. Section 3 analyzes the spread of pathogen-carrying droplets from a human cough based on CFD simulation, which is used in Section 4 to derive the influence of mobile air filtration. To improve the filtration effectiveness, the path of the robot is optimized in Section 5 given the live spatial distribution of occupants. Section 6 demonstrates the system at work and validate its efficacy. Finally, Section 7 concludes the findings.

2. Design of the purdue campus patrol robot for mobile air filtration

Since the air filtration module is given mobility and coverage by the robot, it needs to be designed with motion in mind, such that the locality of contaminant can be preserved. The robot, correspondingly, needs to deliver the task-specific autonomy and mobility without losing expandability for general-purpose tasks that require fast adaptation. To address the first concern, we present the Bernoulli Air Filtration Module, with a novel design that prevents excessive disturbance to the surrounding air when the module moves. The PCPR, as shown in Fig. 1, is developed with a “robotic base + payload” modular design to address the second concern. This section will elaborate on the design of the air filtration module, and how its functionality is achieved with the complementary capabilities of the robotic mobile base.
From our preliminary work [28], air filtration and robotic mobility combined can service stationary, socially-distanced occupants at the scale of 10. The indoor space is therefore divided into segments of at most 30 m² for each robot. As basic requirements, the robot should cross the spacing between socially-distanced seating, and has a continuous operation time of 4 h. The robot should possess a maximum moving speed of no less than 0.5 m/s for timely cleaning. The filter, on the other hand, should reduce the airborne particle from the intake by at least 95%. The robot velocity, coupled with the intake area of the filter, requires a flow rate of approximately 50 L/s for sufficient air collection.

### 2.1. Novel Bernoulli air filtration module

Airborne infectious bioaerosol droplets with diameters ranging from 0.1 to 10 μm, that can suspend in the air for hours, pose a major threat for horizontal transmission through inhalation [21]. To capture the bioaerosol droplets, the PCPR employs the Bernoulli air filtration module to augment the effectiveness of air filtration with robotics. Addressing the bio-hazard of the droplets, the Bernoulli air filtration module brings medical-grade air treatment – a combination of particle filtration (a High-Efficiency Particulate Air, HEPA filter) and enclosed ultraviolet light (UV) disinfection – to classrooms, aiming to trap and inactivate the infectious bioaerosol droplets.

In our setup, the module has a flow rate of $Q = 47$ L/s of filtered air. The filtration efficiency of the module is $f \geq 99.3\%$ for particles larger than 0.3 μm, measured by the percentage reduction of the particles at the outlet compared to the inlet of the filtration module. The power consumed by the fan is monitored by the module as an indicator of pressure drop at the filter, which relates to the remaining lifespan of the filter. In case the fan power consumption exceeds a threshold, a maintenance text message for filter replacement is issued to the fleet manager. In the filtration pipe of the Bernoulli filtration module, two germicidal 2.5 W UV lamps with surfaces irradiation of 5 mW/cm² are adopted as a complimentary disinfection system to the air filtration module. All the filtered air in the module is exposed to the germicidal UV radiation. The UV light source is contained in a cylindrical enclosure and is safe to occupants nearby.

The flow tract design of the Bernoulli module, i.e. the AeroMINE (Motionless, INtegrated Extraction) technology, originates from wind energy applications [33]. Using a pair of mirrored, perforated airfoils and a perforated cylindrical filtration pipe, a low-pressure zone is created between the airfoils, which helps to drive the air from surroundings into the intake of the system. The air is then driven by an axial fan in the cylinder through the HEPA filter (Fig. 2a). The AeroMINE design yields a large intake area and a large swept volume that traps the pathogen as the robot moves, which helps the filtration efficiency. Notably, the large intake area is achieved without using a large-diameter fan, thus reduces the disturbance (wake) to its surrounding airflow. The design of the Bernoulli module is fine-tuned to optimize the efficiency of this module in air sampling. The optimization were performed iteratively with modifying the following parameters: (1) distance between the airfoils, (2) relative size of the airfoils to the central cylinder, (3) the angle between the two airfoils, and (4) the thickness (camber) of the airfoils. A combination of these configurations were tested with computational fluid dynamics (CFD) simulations, and the most efficient design were selected for the Bernoulli module.

To illustrate the benefits of this novel design in reducing the wake, the airflow around the Bernoulli Air Filtration Module is compared to that of a commercially-of-the-shelf box-shaped air purifier with the same intake area, a common design for stationary air cleaners. As shown in Fig. 2b, c, the air filtration modules are moved by the robot at a speed of 0.5 m/s, with the contour of the relative velocity of surrounding air generated with CFD simulations. Here, the moving speed of 0.5 m/s is chosen as a typical order of magnitude for robot motion speed indoors, as it ensures 1.5 s of reaction time before hitting any person or obstacles in a socially distanced layout. Additionally, the magnitude of speed yields a Reynolds number in the 10⁴ order, which is representative to a large realm of indoor robot motion. Ideally, the relative speed of the airflow equals the speed of the robot, 0.5 m/s, should no disturbance of the air is incurred by the filtration modules. We determine that severe disturbance occurs in areas where variation in relative velocity exceeds 50% (below 0.25 m/s or over 0.75 m/s). The disturbance area is 0.294 m² for the Bernoulli Air Filtration Module, compared to 2.14 m² for the box-shaped design. The wake caused by the module shape leads to entrainment of the particles with the robot as it moves [27], and minimizing the wake means less disturbance to the air in the environment. Consequently, the motion-induced diffusion and excitation of the pathogens is minimized, which preserves locality requirements while obtaining the benefits in coverage from the robotic perspective. Notably, the desired aerodynamic benefits is only achievable when the robot is moving forward.

### 2.2. Holonomic mobile base

To combine robotics with air filtration in an indoor classroom scenario, not only does the air filtration module need to be designed with mobility in mind, but the robot should also be a complementary component that suits the air filtration task. The main requirements for the robot are four-fold: sufficient payload capacity (≥40 kg) for the air filtration module; agile motion (steering radius <0.5 m, max speed ≥0.5 m/s) for limited spaces between rows of seats indoors; modular and expandable design for other emerging and specific tasks in the future; cost-friendly for massive deployment.

Based on the requirements above, an holonomic mobile base is built, with four powered caster wheels driven by eight motors, which addresses the payload capacity and agility requirements.
The base has a footprint of 62 cm × 62 cm, and a weight of approximately 90 kg. The parallel configuration of multiple powered caster wheels empowered its payload capacity of >50 kg and top speed of 1 m/s. Although external batteries can be added, the inbuilt 1670 Wh battery can provide 5 h of continuous operation. The base can climb slopes below 15°, which complies with the accessible design standards in buildings. Each set of powered caster wheels are rolled and steered independently, enabling holonomic motion of the vehicle, which is a critical capability of maneuvering in narrow spaces. The holonomic motion eases the constraints on path planning for directional payloads such as the air filtration module as well. An operational space controller [34] is adopted to cope with the over-actuation induced by the eight motors.

From the reports [8] we observe a fragmentation of applications where robots are deployed. As the applications become specific and risk-averse, the versatility of robots and their payloads is threatened. As a result, time, cost, and resources are wasted on re-engineering the entire system for each specific application, and retraining operators on different robots and tasks. The fragmentation of application-specific robots hampers their agile deployment for emergencies. Therefore, our robot is based on a modular design, where the payload atop the base is self-contained in power and functionality. A general-purpose protocol is developed for communicating telemetry and commands between the robotic base and the payload, with plug-and-play capability. Hence, the payload can be added or swapped for multimodal disinfection/manipulation tasks while sharing the same mobility and navigation stack (Examples of different configurations as shown in Fig. 3).

Due to the modular design concept, the robotic base needs to be self-contained in its functionality of precise motion. To lower the cost of the robotic base for massive deployment while ensuring technical-readiness, the robot uses a wheel odometer and a planar LiDAR sensor, along with the wealth of packages for map-based navigation and planning on Robotic Operating System (ROS). The RGB-D camera (Intel RealSense D435i) is used in addition to provide surrounding information on suspending structures such as desks, and to detect the presence of occupants. For localization, the Adaptive Monte-Carlo Localization (AMCL) package is used. The odometer referred to by the AMCL is fused from both the wheel odometer and a visual odometer, using an extended Kalman filter. The wheel odometer is calculated from the encoders of the eight motors as a byproduct of the operational space controller. To reduce odometry drift, the visual odometer is obtained from the LiDAR using a range flow approach [35]. The planning part is based on the move-base package on ROS. Timing is critical to dosage in many cleaning tasks, including the mobile air filtration task as explained in Section 5. As a result, the timed elastic band (TEB) local planner [36] is adopted to generate a path from the current location of the robot to its goal, with time consumption penalized. The TEB planner also accounts for both stationary and dynamic obstacle avoidance, which makes the robot suitable for working around people.

Apart from map-based navigation, the robot is also capable of hybrid navigation — switching between map-based and target-based navigation. Target-based navigation is essentially a visual servoing process toward a goal location with a PD controller, thus achieves high relative precision and prevents drift in localization. The sensor input involves either the planar LiDAR or the RGB-D camera on board. The combination improves the adaptability of the robot to a large variety of indoor spaces, such as door thresholds and isles, which has narrow clearance and tends to cause trouble for map-based planners.

For the mobile air filtration task, the occupant information is also provided by the RGB-D camera, as the robot passes in front of each seating position. In this case, the camera faces the side of the robot due to task requirements and the constraint on the field of view of the camera. The camera is angled such that if an occupant presents at a seating position, the person can be captured by the camera as the robot is traversing each seat. As a result, the robot does not need to stop and steer when detecting occupants, which shortens the duration of the initial pass and preserves the designed orientation of the Bernoulli Air Filtration Module.
3. CFD simulation for bioaerosol droplets spreading from a human cough

By mechanism, the concentration of pathogens in the surrounding air affects the performance of robotic air filtration — robotic air cleaners can actively move to and clean the plume of bioaerosol droplets before it spreads out and affects more people. Therefore, the planning and resultant effectiveness of robotic air filtration is related to the spreading dynamics of saliva particles from a human cough. This section thus serves two purposes — to illustrate the necessity of mobile air filtration even under the social distancing guideline, and being a basis for deriving the effect of mobile air filtration. Specifically, we are interested in the coughing case since it is a common symptom of COVID-19 [37] and more frequent compared to sneezing, while having similar jet velocity [38]. We also consider a worst-case scenario when no facial covering is present, as people tend to relax precaution over time. For convenience, the indoor air is assumed stationary in the CFD simulation, since the background flow is less than 0.2 m/s according to the NIOSH standards which is insignificant compared to the robot motion. The temperature and humidity used in the simulation are also compliant with the NIOSH standards (24 °C, 50% relative humidity) [39].

With ANSYS Fluent 2019, the simulation domain is built as a rectangular domain of $4.5 \times 5 \times 3.5$ m (width $\times$ length $\times$ height). A box as a mock-up human is placed on the symmetry plane along the width edge. Conditions in [40] are used — the mouth of the human is a 21 mm-diameter circle at 1.6 m above the ground, and emits 14,000 droplets horizontally at 1.6 m above the ground. The droplets have diameters from 1 µm to 500 µm and following Rosin–Rammler-Logarithmic distribution. The Lagrangian method was used to track saliva droplets with hybrid implicit and trapezoidal schemes. The transient speed profile of air jet from the mouth $U(t)$ is based on previously performed measurements [41,42], lasting 0.61 s with a peak velocity of 22.06 m/s occurring at $t = 0.066$ s. For simulating the turbulent airflow within the coughing jet, the Reynolds Average Navier–Stokes (RANS) with the Remorization Group (RNG) k-$\varepsilon$ turbulence model was used [43].

The total time of analysis is 600 s with non-uniform time steps for both discrete (droplets) and continuous phases (air), such that the droplets from a coughing source are well-decayed and influence ends. Specifically, the distribution of droplets projected onto the horizontal plane, in two snapshots taken from the simulation, is shown in Fig. 4 to illustrate the penetration depth of >2 m, and the complex spreading dynamics of the particles. The predicted spreading of saliva droplets using RANS simulations was compared with the experimental results reported by Wei and Li in [44].

In their experiments, Wei and Li [44] determined the streamwise penetration ($X_p$), which is the variation of the longest flow distance along the streamwise direction, as a function of time for several inlet velocity profiles. They defined the characteristic velocity of the real-human cough flow ($U_c$) as:

$$U_c = \frac{1}{t_f} \int_0^{t_f} U(t) \, dt,$$  

where $t_f$ is the time that a cough flow last. The characteristic Reynolds number is given by:

$$Re_c = \frac{U_c D}{\nu},$$

where $\nu$ is the kinematic viscosity of the fluid, and $D$ is the diameter of the nozzle (mouth). To validate our numerical model, we used two sets of experimental data results that corresponds to two real cough time-dependent velocity profiles described as case 9 and case 10 in [44]. In [44] Wei and Li determined the streamwise penetration in two stages of the cough, the starting-jet stage (when the cough starts and follows the time-dependent cough profile) and the interrupted-jet stage (after the velocity supply in the time-dependent cough profile is finished). The results of the comparison between the RANS simulations and experiments are shown in dimensionless form in Fig. 5(a) and Fig. 5(b) for the starting and interrupted jet stage, respectively. In Fig. 5(b) two constants, the virtual origin in the interrupted jet stage ($X_v$) and ($t_u$) the extrapolated temporal origin in the interrupted jet stage, are introduced to compare the results from (0, 0) in the cartesian plane. It can be seen from Fig. 5(a) and Fig. 5(b) The RANS simulations predictions of the cough are in good agreement with the experimental results reported in [44].

4. Analysis on the influence of mobile air filtration to particle spread from a single source

Efficient cleaning depends on intentionally encountering the region with highest plume concentration, driven by fluid dynamics which is time-costly to compute directly. Albeit, due to the covert nature of the disease, the source of transmission is hidden and the probability is uniform among all occupants, which compifies the problem of solving the entire indoor flow field directly. As an approximation, the unperturbed one-shot CFD results from Section 3 is used as the basis to estimate the regional effect of robotic air filtration under different regional paths — near each individual occupant. As a result, the path optimization workflow can refer to an accelerated estimation of the influence of spread from each occupant, that is based on CFD results but avoids repetitive CFD computations, which enables online evaluation.

4.1. Influence evaluation from a recipient standpoint

Before quantifying the benefits of robotic air filtration, we need to develop a realistic evaluation method of how many virus copies a human will inhale as the bioaerosol plume spreads and diminishes, given the position of the person and the distribution of the pathogen-carrying droplet particles. Because the particles are discrete, the virus concentration, measured in copies/m$^3$ of air, is calculated in a grid-wise manner by summing the volume...
of particles that enters a given grid. For particles with diameter below 60 µm, which penetrates beyond the social distancing bound, the precipitation effect is not obvious. Hence, they spread out and distribute more evenly in the vertical direction from ground to the height of \( H = 3 \) m, compared to larger particles [24, 45]. Therefore, an averaging of particle counts along the vertical direction is used to project a 3-D simulation to a 2-D evaluation of influence. Denote the concentration of virus in saliva as \( c \), and the grid size for summation as \( l \times l \), the grid cell is then \( G(x, y) = [l(x + \frac{1}{2}, x + \frac{1}{2}) \times l(y - \frac{1}{2}, y + \frac{1}{2})] \). The granularity of the grid summation is determined by breathing behavior of humans, which has been standardized. A normal human breaths in about \( V = 0.5 \text{L} \) of air at the rate of 12 per minute (or \( f_b = 0.2 \text{Hz} \)) at rest [46]. Because the volume per breath equivalents to that of a sphere with 0.1 m diameter, we set the grid size to be \( l = 0.1 \text{m} \).

The virus concentration (air) in grid cell \( G \) and at time \( t \) after the emission is then:

\[
c_d(x, y, t) = \frac{c}{H^2} \cdot \frac{4\pi}{3} \sum_{P(t) \in G(x, y)} (kr_p)^3,
\]

where \( P(t) \) is the set of airborne particles at time \( t \), and \( r_p \) denotes their radii, which are obtainable in both numerical simulation and experimental cases. To account for virus condensation due to liquid evaporation in the droplets, a scaling factor \( k = 3 \) is added [42]. Here, we set \( c = 7 \times 10^6 \text{ copies/ML} \) [47] in the analysis followed. The total dosage \( D \) the observer receives through an exposure period of \( t_e \) is thus obtained by integrating the product of air exchange rate \( f_b \) and virus concentration in the air \( c_d \). Because the particles drift freely in the air, to better capture the worst case in the dosage estimation in case of body motion of the observer, a maximum value of the integral among a \( 3 \times 3 \) grid pattern (0.09 m²) centered at the observer at \((x, y) \) is obtained:

\[
D_{(x,y)} = \max_{k=x-l+1}^{x+l-1} \int_0^{t_e} c_d(\bar{x}, \bar{y}, t) f_b \text{ dt}.
\]

The dosage metric in (4) is a function of position and exposure time, with the parameter of initial saliva virus concentration \( c \). Since Watanabe et al. [48] has revealed the relation between risk of infection and dosage of exposure to the pathogen, the dosage as evaluated in (4) is used to evaluate the risks of the occupants in a pathogen emission event.

### 4.2. Assumptions

Although mobile air filtration applies to static indoor gatherings in general, this paper specifically focuses on the application in a classroom scenario during school reopening. We limited our study to classrooms, excluding lecture halls, because the latter often have fixed seating that prevents our robot from approaching arbitrarily-seated students. This section will lay out the assumptions we will be using in the remainder of this paper. These assumptions play a key role in simplifying the evaluation of particle spread in a room with multiple occupants and the robot following a parameterized path.

#### 4.2.1. Geometry

Without losing commonality, the seating pattern in a classroom is assumed to be a grid, i.e. the seats are placed with fixed spacing \( (d_x, d_y) \), being either occupied or unoccupied, as shown in Fig. 6. A total of \( N \) occupants are facing the same (+\( d_x \)) direction, with an equal probability of being the source. To decouple the interaction between coughs from different occupants, we assume:

**Assumption 1** (Independence). The emission events (simulated coughs) happen at a low spatial and temporal frequency, such that sets of airborne particles from each emission, \( P(t), i = 1, 2, \ldots, m \), are independent. The overall airborne particles are:

\[
P(t) = P_1(t) \cup P_2(t) \cup \cdots \cup P_m(t),
\]

with the positions, velocities, and diameters of each particle \( p \in P \) unchanged.

We identify that the risk of airborne transmission lies in two factors – a healthy occupant is either close to, or in the spreading sector of the source. We further assume that the influence of the plume decreases monotonically with respect to the distance from the source [24], so the highest influence will happen at the neighbors of the source. In a grid pattern, we hence are interested in two types of neighbors of the source: a) among the occupants outside the spreading sector, being closest to the source (Distance Neighbors, DN); b) among the occupants inside the spreading sector, being closest to the source (Spreading Neighbors, SN). The two types of neighbors are determined to be at risk during an emission event from the corresponding source, where the influence of the emission is thus evaluated/measured.

Regarding the high consequence of the substance we are cleaning, the worst-case dosage among all occupants during an emission event is our interest. Based on the assumptions and definitions regarding how DN and SNs are selected, the worst-case dosage must be captured by one of the neighbors. As a result, the influence of occupant \( i \) being the source is the highest dosage registered among the two types of neighbors:

\[
D_i = \max_{j=DN,SN} D_{(x_j, y_j)}.
\]
4.2. Filtration dynamics

Because the shape of the Bernoulli Air Filtration Module is specially designed to minimize its disturbance to surrounding air, even on a moving robot, the following assumptions are made to simplify the interaction between the robotic air cleaner and the particles:

**Assumption 2 (Locality).** The immediate effect of robotic air filtration is local. In the control volume $V_i$ encapsulating the robot, with the filtration module having flow rate $Q$ and filtration rate of $f$, the virus concentration in the air $c_a$ at location $x$ follows:

$$\frac{\partial c_a(x, t)}{\partial t} = D_a \Delta c_a - \nabla (\nabla \cdot c_a) - Q c_a - \frac{Q f c_a}{V_i} (x \in V_i), \quad (6)$$

where $I$ denotes the identity function, which equals to 1 when the input condition is true and 0 otherwise. $D_a$ is the diffusivity of particles, $P_a$ is the precipitation coefficient, and $v$ is the velocity field, which follows:

**Assumption 3 (Stealth).** The velocity field $v$ is not affected by the presence of the robotic air filtration system.

4.2.3. Robot motion

Under the locality assumption, the robot influences the spread of the plume only when it is near the source. To further analyze how its path influences the spread, parameters of the robot path are extracted when it enters the region. The robot is designed to move in a cyclic cleaning path having a period of $\tau$ and cycle distance of $l$. Occupants (students) are assumed to be quasi-static, i.e., their layout among the seats, although not fixed, remain unchanged over a time range with magnitude of 10$\tau$. The robot is defined as near occupant $i$, if the robot is within the rectangle $\{(x_i, x_i + d_x) \times (v_i, -v_i + \frac{l}{2})\}$. The duration the robot spends near occupant $i$ in each cycle is denoted as $q_i$, where $q_i$ is defined as the time quota. For the safety of indoor occupants, an upper limit of robot speed is specified as $v_{\text{max}}$. Limits are also placed on the closest distances, $r_{\text{min}} < r_i < r_{\text{max}}$, such that the robot passes between two rows with sufficient margin.

Since air filtration reduces particle counts proportionally from inlet to outlet, the most effective cleaning path shall travel through the region with the highest particle concentration, i.e., the front of the source. Under the “pass in the front” scheme, the simplest passing pattern near the source is to move in a straight line in the “row” ($y$) direction. Given the straight-line pattern, the closest distance that the robot passes occupant $i$ is denoted $r_i$, where $i = 1, 2, \ldots, N$. The robot speed near the source is thus $v_i = d_y / (q_i \tau)$. The path and speed profile of the robot near an occupant $i$ is uniquely defined by the triplet $(r_i, q_i, \tau)$, as we assume passing direction is irrelevant.

4.3. Approximating the influence of robotic air filtration to dosage accumulation

As we have parameterized the robot path near the source, the relation between regional path parameters that guide the robot through the plume and the dosages at neighbors remain unknown at this point. Although CFD simulation yields precise results, they are extremely computationally intensive – e.g. propagating the simulation of particle spread in Section 3 for 600 s takes approximately 21 h of computation on a modern 36-thread processor (Intel Xeon Gold 6140). If the path segment of the robot near every occupant needs to be optimized and each containing three degrees of freedom, a typical optimization problem will involve several tens of degrees of freedom and needs several thousands of evaluations with different parameters. The brute-force CFD approach will, in this case, incur computational load in 10 ExaFLOPS scale, that even the top supercomputer in the world will take tens of minutes to solve. Therefore, directly solving brute-force CFD for robot path optimization, which requires timeliness of solution as well, is infeasible. One may argue that only a few derived values (dosages) at specific locations of the flow field is of our concern, which means learning-based techniques may speed up the evaluation. However, purely generating the data required for learning by brute force CFD involves magnitudes higher amount of computation. Therefore, the evolutionary dynamics of the particles under different path parameters of the robot need to be first simplified, before any further acceleration in evaluation is possible.

4.3.1. Approximation of robotic air filtration

The purpose of this section is to reliably estimate the spreading pattern of the coughing plume under different path parameters that the robot follows near the source, without repeatedly calculating the CFD setup of the problem. To circumvent the repeated computation of CFD, a low-order approximation of the robotic air filtration is proposed. Based on the Independence assumption (Assumption 1), the simplification will focus on the influence of the robot on one source, when the robot is near the source. The magnitude of influence is related to the path parameters of the robot. From the single-source CFD simulation in Section 3, the unperturbed (no robot) spreading dynamics is obtained from snapshots of the particle distribution at different times. Denote the dynamics that drive the evolution of particle distribution in CFD as:

$$\frac{\partial c_a(x, t)}{\partial t} = D_a \Delta c_a - \nabla (\nabla \cdot c_a) - P_a c_a \equiv F(x, t)c_a. \quad (7)$$

Therefore, the problem of approximating the effect of robotic air filtration becomes solving (6) given (7), on all grids where the dosage is calculated from particle distribution. Assume $Qf / V_i \ll 1$, such that gradients of the identity function can be neglected when discretized to the grid for dosage calculation. Since the velocity field is not changed by the robot, linearize (6) at $(x, t)$ yields:

$$\frac{\partial c_a(x, t)}{\partial t} \approx F(x, t)c_a - \frac{Q f c_a}{V_i} I(x \in V_i), \quad (8)$$

with the same initial conditions as (7), $c_a(x, 0) = \hat{c}_a(x, 0)$, since the coughing source is not affected by the robot.

In practice, both CFD and dosage calculation are executed on discrete time steps. We set $V_i = 0.5 \text{ m} \times 0.5 \text{ m} \times h$, given the size of the robot and the filter, which yields $Qf / V_i \approx 0.05$. Results from the CFD simulation are ported out at every 1 s from $t = 0$ to $t = 5 \text{ s}$, and every 5 s of simulation time afterward. Substeps to calculate (8) also need to be taken, due to the low-order nature, between two consecutive snapshots of CFD results. When
calculating sub-steps, CFD results are interpolated linearly in the
time domain. Denote δt = c(t) − c0(t), and the position of the
robot relative to the source is (x(t), y(t)). The discretization of
(8) with respect to t yields:
\[ c_d(x, t + Δt) ≈ c_d(x, t) + Fc_d Δt \cdot \frac{c_d - δt}{c_d} = \frac{QF}{V} l(V, t) Δt, \quad (9) \]
where:
\[ Fc_d Δt = \hat{c}_d(x, t + Δt) - \hat{c}_d(x, t). \quad (10) \]
Therefore, the computation sequence in Algorithm 1 is derived to
approximate the effect of mobile air filtration during a cleaning
session. The approximation focuses on the interaction between
the robot and the plume from a single coughing source. The robot
passes near the source once every cycle time. The path parame-
ters of the robot are given to the procedure, which yields the
dosage on grid cells at each time step.

**Algorithm 1 Low-order approximation of the effect of robotic
filtration to a spreading plume.**

1. **Dataset:** CFD snapshots (\(c_d(t_j) : j = 1, 2, \ldots, n\))
2. **Input:** \(r_i, q_i, \tau, c_0(0)\)
3. **t** ← 0; \(x_i, y_i, y_r, y_r^\prime = -d_r/q_i; \hat{δ}_t \leftarrow 0\)
4. **while** \(t < t_r\) **do**
5. \(Δc_d \leftarrow \frac{c_d(t_j) - c_d(t)}{t_j - t} Δt\), where: \(t_j ≤ t < t_{j+1}\)
6. \(Δc_d \leftarrow Δc_d \left(\frac{a_j(t_j) - δ_j}{c_d(t_j)} \right) - \frac{QF}{V} l(V, t) Δt\)
7. \(\hat{δ}_t \leftarrow (\hat{c}_d(t) + Δc_d) - (c_d(t) + Δc_d)\)
8. \(t \leftarrow t + Δt; y_r \leftarrow y_r + \frac{d_r}{q_i} Δt\)
9. **if** \(y_r > \frac{d_r}{q_i}\) **then**
10. \(y_r \leftarrow -\frac{d_r}{q_i}\) **end**
11. Interpolate \( \hat{c}_d(t) \leftarrow \frac{(t_k+1-t_k)\hat{c}_d(t_k)+(t-t_k)\hat{c}_d(t_{k+1})}{t_k+1-t_k} \), where: \(t_k ≤ t < t_{k+1}\)
12. \(c_d(t) \leftarrow \hat{c}_d(t) - \hat{δ}_t\)
13. **Return:** \(c_d(t)\)

### 4.3.2. Accelerated evaluation of dosage with fitted neural network

To assess the risks of the neighbors of the source, dosages are
calculated on the grid locations of the neighbors based on (4).
The integration ranges from 0 to 600 s with a step size of 0.2 s,
such that the dosage converges. Even under the approximated
Algorithm 1, the integration process takes 1 s to complete on a
desktop CPU and is not parallelizable. As a result, the execution
time for thousands of evaluations is still too long for on-site
execution. To further accelerate the evaluation process, the state
space spanned by \((r_i, q_i, \tau, x_i, y_i)\) is randomly sampled, and the
resultant dosage at the neighbor is fitted with nonlinear neural
networks — where \((x_i, y_i)\) indicates the relative coordinates of the
dosage evaluation points from the source. The range of sampling
are:

\[0.3 < r_i < 1.7 (m), \quad 0 < q_i < 0.5, \quad 20 > τ > 300 (s), \quad -1 < x_i < 4 (m), \quad -2 < y_i < 2 (m).\]

By fitting the model for arbitrary evaluation positions, the fitted
evaluator can address different room layouts — when \(d_r\) and \(d_r^\prime\)
change, or even when the seats are in a different pattern.

To address the statistical difficulty on the distribution of dosage
under random sampling — where the change caused by filtration
is relatively small compared to the wide range of possible
dosages, two neural networks are fitted separately, with one
modeling \(\hat{D}_r\), the dosage at the neighbor when no filtration is
present (computes from \(\hat{c}_d\) and takes \((x_i, y_i)\) as inputs only),
and the second modeling the reduction of dosage caused by the
passing of the robotic air cleaner at the specified set of para-
eters (takes in all five variables). Both networks have two layers.
The first (hidden) layer consists of 128 neurons, and the second
(output) layer has one neuron. All neurons are fully-connected
and use the sigmoid activation function with biases. The 100,000
samples of (un-filitrated dosage, change due to filtration) pairs
within the range are split into 70% for training – 15% for testing
– 15% for validation, and the model is trained with the Levenberg–
Marquardt approach. The structure of the network is shown in
Fig. 7(a), with fitting results shown in Table 1. Through the neural
network, the evaluation time over the same time period is further
shortened from 1 s to 0.002 s, with accuracy retained.

### 4.4. Analysis of the CFD result and approximated influence of the
robot

Despite the complex spreading dynamics of the particles, nu-
merical analysis can be made to abstract features that simplify
the spreading procedure. Specifically, the distribution of droplet
distance and azimuth from the source over time, weighted by the
droplet volumes (referring to Section 4.1), is shown in Fig. 8. In
Fig. 8(a), the error bars indicate 1–σ intervals of distance distri-
bution, while Fig. 8(b) depicts the change of standard deviation in
azimuth distribution over time. From Fig. 8(a) we observe that the
plume needs to spread for a certain duration before affecting the
neighbors of the source, where the duration is monotonically
longer with the distance of the SNs. The CFD simulation also confirms
the spreading dynamics of plume — The plume generally lies within
a sector with central angle of 120° (2–σ) facing front (Fig. 6),
and does not spread backwards (>-3–σ) [42]. These findings are

---

**Table 1**

| Estimated terms | Train R | Test R | Validation R |
|-----------------|---------|--------|--------------|
| log(\(\hat{D}_r\)) | 0.9960  | 0.9962 | 0.9964 |
| log(\(\hat{D}_r - D_r\)) | 0.9957  | 0.9948 | 0.9958 |
consistent with the identification of neighbors (DN and SN), who have the highest risks of dosage accumulation.

As the spreading distance increases, although the concentration of the pathogen decreases, the moving speed of the plume also decreases. As a result, the infectious plume will cause continuous exposure to the adjacent people even with social distancing enforced. An evaluation of (4) using the CFD-generated particle positions and diameters yields 15.47 copies per emission event at a distance of 1.85 m (6 ft). As a reference for the severity of exposure, studies of SARS-CoV indicates a 5% chance of developing illness from the virus when exposed under a virus dosage of 10 copies [48]. These results reveal the need for air filtration that can effectively capture the droplets before dispersion.

From the Locality assumption (Assumption 2), the robot needs to make at least one pass near the source before the majority of the plume spreads to the neighbors, to achieve satisfactory effects. As a result, the cycle time of the robot is limited by the smallest distance of SNs from their corresponding source, who is an arbitrary person among all occupants:

$$\tau < \tau_{\text{max}} \left( \min_{i=1}^{N} d_{SN,i} \right) \equiv \tau_{\text{max}}(d_{SN}).$$

The purpose is to ensure that whoever is the source, all occupants are safe before the robot passes once in front of all occupants. A fitted relation between the upper bound of spreading distance versus time is obtained from the CFD results. Hereby we take the 1-σ upper bound of particle spreading distance as shown in Fig. 8(a) and fit a linear model on the distance ranging from 1.75 m to 4 m. The distance range assumes that people obey social distancing guidelines and will not enter too close into the spreading sector of each occupant. The fitted model gives a limit on the cycle time with respect to the global nearest distance of SNs:

$$\tau_{\text{max}}(d_{SN}) \approx 133.6d_{SN}^2 - 216.3: \quad 1.75 \leq d_{SN} \leq 4,$$

where $d_{SN}$ is measured in meters and $\tau_{\text{max}}$ is measured in seconds. The fitted bound is shown as the red dashed line in Fig. 8(a).

Three-dimensional slices of the evaluated dosage with two given variables are shown in Fig. 7(b), 7(c), to illustrate the highly nonlinear trend of how each path parameters in the $(r_i, q_i, \tau)$ triplet affect the dosage at a neighboring location from the source. As the evaluation results suggest, the effectiveness of robotic air filtration is more significant when the robot moves closer to the neighbors (with higher $r_i$), but not to the source. The reason for the phenomena can be explained by the decaying spreading speed of the plume. As the robot passes further away from the source, although the plume is slightly more dispersed, the significant decrease in spreading speed increases the likelihood of the robot to move through the portion with peak concentration. Shortened cycle time of the robot also plays a positive role in the cleaning effect, as the number of passes through the plume is thus increased, weaving a denser cleaning “net” through the plume as the plume spreads. A decrease in cycle distance $l$ (product of robot velocity and cycle time) reduces the dosage because the time quota $q_i$ for a specific occupant is increased, hence the portion of air surrounding the occupant that is filtered also increases. Occupants that are more than 4 m away from the source are barely affected by the source emission (estimated dosage less than 0.001), which is consistent with empirical findings in [24].

To summarize, the effect of robot passing to dosage reduction of the neighbors is nonlinear. All three parameters in the $(r_i, q_i, \tau)$ triplet affect the spreading pattern of the plume, hence changes the worst-case dosage at neighbors, i.e. $D(r_i, q_i, \tau)$. The passing distance affects the chance of intercepting with the spreading plume, and the time quota affects the speed of the pass, which further affects the volumetric portion of local air that is cleaned. Cleaning cycle time limits the worst-case spreading case (with the largest delay from emission to the first pass) and the maximum length of the cyclic trajectory under the speed limit.

5. Occupant-centric risk-driven path planning and optimization

Because the vulnerability to infection lies in all occupants and the source is hidden, the path of the robot needs to be planned based on the actual occupation status of the seats in the room and cover every person. Particularly, making the robot linger around only a few people, or traverse through every seat without any difference, are both unwise approaches. The analysis in Section 4.4 also shows that, although spending more time near a specific person is good for his/her neighbors, the result involves reduced time quota at other occupants or increased cycle time. Both factors will increase the risks at the neighbors of other occupants. To best utilize the benefits of mobility, the cleaning path needs to base on the actual distribution of occupants, hence “occupant-centric”. The speed and passing distance near each occupant, and the cycle time, need to be optimized based on the distribution of neighbors around each occupant, which is not trivial.

5.1. Overview

Fig. 9 gives an overview of the optimization procedure. The robot initially follows a general coverage path that passes in front of all the seats at a uniform speed. During the initial pass, an occupant detection procedure is executed to determine whether a seat is occupied. The path of the robot is then re-generated and optimized based on the estimated influence of a coughing plume on nearby occupants, should an arbitrary occupant becomes the
source. The robot then follows the optimized path for a specific duration (e.g., the duration of a class), before re-detecting the occupation status of each seat, in case the occupant layout has changed.

The optimization objective of robotic mobile air filtration in a classroom setting is to find the set of regional path parameters \((r_i, q_i, \tau)\) for each occupant and the shared \(\tau\), such that the risk of all occupants, should an arbitrary occupant become the source of the infectious coughing plume, is minimized. Statistically, the risk is expressed as the expectation of the loss function — in this case, the worst-case dosage \((5)\) among the neighbors of the source. Under the assumption that each occupant has an equal chance of being the source, the expectation of worst-case dosage becomes an algebraic average of \(D_i\) in \((5)\) among all occupants. As discussed in Section 4.4, the generated cleaning path must meet constraints on passing distance, maximum robot speed, and cycle time, which are translated to the linear constraint of \(r_i\) and nonlinear constraints of \(\tau\) and \(q_i\). As a result, the optimization problem can be formulated as:

\[
(r_i^*, q_i^*, \tau^*) = \arg \min_{r_i, q_i, \tau} \sum_{i=1}^{N} D_i(r_i, q_i, \tau) / N. \tag{13}
\]

subject to:

\[
\begin{align*}
q_i & \leq \frac{l - Nd_y}{v_{\max} \tau} \\
\frac{1}{v_{\max} \tau} & < q_i < \frac{l - d_y}{v_{\max} \tau}. 
\end{align*} \tag{14}
\]

The detailed flowchart that regenerates the robot path based on the detected layout of occupants is shown in Fig. 10. From the analysis in Section 4.4, a shorter path length promotes cleaning efficiency, hence a distance-optimized traverse sequence through all occupants detected by the robot is first found. Then, the path parameters near each occupant, \((r_i, q_i)\), and the overall cleaning period \(\tau\), are optimized with \((13)\) given the shortest traverse cleaning sequence. Based on the approximated influence of robotic filtration, the estimation of worst-case dosage is encapsulated in the neural network as discussed in Section 4.3.2 for fast evaluation. Trends of the influence based on the analysis in Section 4.4 further simplifies the optimization of the re-generated path, such that on-site execution is possible.

The following sections will illustrate the necessary procedures to obtain information, simplify, and solve the path optimization problem \((13)\).

5.2. Occupant detection

Occupant-centric online path planning relies on precise localization of the occupants in the room. The occupants in the room may change, temporally, hence the detection of occupants must be conducted on-site before each air filtration session begins. Detecting occupants in a room require image-based identification, which is then cross-matched with the known map of the room to determine which seats are occupied.

The robot is equipped with an RGB-D camera that scans the room. Using the images captured by this camera, instance segmentation is conducted to identify the objects of interest, i.e., humans and chairs. Instance segmentation removes the background and derives bounding boxes for each object in the frame while overcoming difficulties posed by occlusion and overlap [48]. Using the Mask R-CNN object detection algorithm [49] trained on the COCO dataset [50] with ResNet-50 as feature extractor, the pixel-wise masks of the objects in the image are obtained. This segmentation is then cross matched with the depth values obtained of the image to localize the object in the map of the environment. Specifically, when the robot is moving in its initial path through all seats, if the location of a detected person is at the seat where the robot is near, the robot will identify the seat as occupied.

The method achieved 96% accuracy through the color images alone — in 48 out of 50 images the humans were correctly masked. The Mask R-CNN detector failed on two images due to the pose and location of the face being near the image edges. The application of an RGB-D camera instead of a color-only camera reduces the likelihood of false-positives. The masks in the color channels are cross-checked by the depth value of the corresponding region. If the region has depth values different from the background, the detection is determined to be a false positive and is ruled out.

5.3. Generation of traversal sequence

The objective of the cleaning path is to traverse all occupants in a shortest distance, which is a traditional Traveling Salesman Problem (TSP). Since the robot is moving in a grid layout, distances between occupants are measured in Manhattan distance. The distance between two occupants that are \(n_x\) rows and \(n_y\) columns apart is thus:

\[
d_{xy} = d_x|n_x| + d_y|n_y| + 1.5d_h(n_x \neq 0), \tag{15}\]

where the term \(1.5d_h(n_x)\) is the distance penalty for the robot shifting to a new row and passing the destination occupant from the front. The additional distance incurred when \(r_i\) — the passing distance for different occupants — changes, is omitted because it is minor compared to the motion passing the cleaning zone. Finding the global optimal solution for TSP is proven NP-hard, therefore a near-optimal solution is obtained with integer linear programming.

Since now the occupant layout across the room is known, the minimal distance of SN among all occupants can be obtained. The total path length \(l = \sum d_{xy}\) is then compared with \(v_{\max} \tau_{\max} d(z_{\text{SN}})\). If the generated path cannot be completed within the cycle time even at the maximum allowable speed, the path is deemed infeasible. In this case additional robots are needed because either too many seats are assigned to the robot, or the occupants show significant clustering behavior, which a robot cannot handle efficiently in one continuous cycle.
5.4. Optimization of path parameters

For \( N \) occupants, directly solving the optimization problem (13) involves a \((2N + 1)\)-dimensional design space, where the constraints involve nonlinear boundaries, and the objective function is nonlinear and not globally convex. As a result, the optimization problem needs to be decoupled to resolve the nonlinear constraints, and simplified on certain dimensions for on-site solution.

The variation in cycle time will change the overall cleaning effect, while the time spent near each occupant, summing up to be the cycle time, affects the local cleaning effect. As a result, the constraints on \( q_i \) depend on \( \tau \) as shown in (14), which complicates the optimization process. To decouple \( q_i \) and \( \tau \), the optimal passing distances \( r_i^* \) and time quotas \( \tau_i^* \) are first optimized under a given \( \tau \) (inner loop). This sub-optimal solution is iteratively updated as \( \tau \) seeks its optimal (outer loop), i.e.:

\[
(r_i^*, q_i^*, \tau^*) = \arg \min_{\tau} \left( \arg \min_{r_i \in \mathcal{R}_N, q \in \mathcal{Q}_N} \frac{\sum_{i=1}^{N} D(r_i, q, \tau)}{N} \right).
\] (16)

As a result, the constraints for both inner and outer loops are now linear. In implementation, the inner loop adopts an interior point method, while the outer loop uses a binary search approach.

Further simplification of the optimization problem involves grouping similar spatial patterns of neighbors, and exploring the convexity of the objective function based on previous analysis in Section 4.4. The former approach reduces the dimension of the problem, while the latter reduces the number of iterations needed for solving the optima.

To reduce the dimensions of the design space, instead of optimizing with respect to every individual occupant, the optimization problem in (16) is solved with respect to different neighbor distribution patterns. Since only DN and SNs are of our concern for worst-case dosages, within the 4 m distance of significant spread the dimension of the optimization problem (16) is bounded. Given \( d_c = 1.8 \) m and \( d_o = 1.5 \) m, the number of unique SN distances is 5, and the number of unique DN distances is 2. As a result, the maximum unique \( B \) is 18 (including the absence of SN or DN in the 4 m range), which bounds the dimension of design space below 37. Further reduction is possible when a repeated seating pattern (e.g. the SN being the first person to the front and DN being the first person to the left) occurs, which is common when most of the seats are occupied. The reduced dimension in design space saves iterations and improves stability of the result, hence enables the feasibility of on-site computation.

Moreover, analysis in Section 4.4 shows that the relation between estimated dosage and the passing distance of the robot is concave. Therefore, the expectation is also concave with respect to the set of \( r_i \), hence minima of estimated dosage must be achieved at one of the two boundaries of \( r_i \) for each occupant. As a result, the optimization converges faster due to the simplification on \( r_i \) dimension by addressing its convexity.

To summarize, the cleaning path of the robot is designed to minimize the risks of the occupants, mathematically expressed as the expectation of worst-case dosage among all occupants. To achieve the objective, the path is planned and optimized based on the approximated spreading dynamics of the plume from CFD results. Evaluation of the spread is based on detected seating distribution of the occupants. The techniques of accelerated evaluation of dosage at the neighbors, and the formulation and deduction of the optimization problem enables on-site computation.

6. Experimental validation on the efficacy of robotic mobile air filtration

The experiment serves as a validation to the proposed robotic air filtration system. Specifically, an experiment with mimicked coughing source and the actual robotic air filtration system is carried out on a small-sized classroom to verify the efficacy of the optimization.

6.1. Experiment setup

As shown in Fig. 11, we align chairs in a room of 5 m \( \times \) 7.5 m, following social distancing guidelines at Purdue, with \( d_c = 1.8 \) m and \( d_o = 1.5 \) m. Among the six seats, five (all except Front Right, FR) are occupied. We make the center occupant at the rear happen to be the Source (S), which yields his spreading neighbor being the occupant in the Front Center (FC) position, and his distance neighbors being two occupants at Left (L) and Right (R) positions. To measure the dosages at neighbors and non-neighbors, five particle counters (ExTech VPC300) are placed at the seats adjacent to the source. Since the magnitude of emission velocity affects spreading speed of the plume, hence affects the cleaning efficacy of the robot, the horizontal velocity of the emission should match that of a normal human cough as discussed in Section 4. The number of particles emitted, however, can be scaled up to obtain better signal to noise ratio over the background particle counts.

In the experiment we use a vector fogger with pitch-up angle of 65° and copper mesh at the nozzle to obtain a peak horizontal speed of 22 m/s. A plastic bag loosely covers around the nozzle and the mesh to collect the backflow and the droplets within. The source was turned on for 2 s each, and the measurements of dosage last for 10 min. The particle counter reads the accumulative counts for particles of diameters 0.3, 0.5, 1.0, 2.5, 5.0, and 10 \( \mu \)m, hence the 10-minute dosage based on volume of inhaled
particles can be calculated with (4). The background is measured and subtracted prior to the start of each cumulative measurement series. Since the number of particles is scaled up compared to a normal human cough, we compare the relative dosage by scaling the highest value observed down to 1.

Four different setups of air filtration with the same filtration module, and one control group with no air filtration, are experimented. The four setups involve: (a) a stationary air cleaner placed by the wall (worst-case, 3.7 m in front of the source); (b) a mobile air cleaner following a general coverage path; (c) a mobile air cleaner that detects the seating of occupants and follows the optimized path from Section 5; and (d) a stationary air cleaner placed near the source (best-case, imagine the source is known, 1.3 m in front of the source). The best-case is impossible to reach in actual deployment, since the source is hidden, but serves as a reference on the upper bound of air filtration performance. Based on the layout of the room, the speed limit of the robot is set to 0.7 m/s (yielding the shortest cycle time), and pass at 1.3 min front of every seat path makes the robot move at 0.7 m/s (yielding the shortest cycle time, and pass at 1.3 m in front of every seat (despite whether it is occupied) to obtain the best performance of its class. The optimized path of the robot is obtained as illustrated in the following Section 6.2.

6.2. Occupant detection and path optimization

Initially, the occupation statuses at each seat are unknown, and the robot follows a general coverage path that passes amid the space between each row. An Intel Real-Sense D435i camera captures the RGB and depth images, which traverses every seat. The detection result, obtained as described in Section 5.2 and as shown in Fig. 11(b), will change the occupation statuses of the corresponding seat. Based on the occupation status of each seat, a cleaning sequence with potentially the shortest cycle distance is generated by solving the TSP in Section 5.3. The speed and distance profile under the shortest cleaning sequence is further optimized by solving (16), which is evaluated on-site with the accelerated dosage evaluator in Section 4.3.2. The optimized trajectory and associated velocities on each leg is shown in Fig. 11(c) and Table 2. The optimization process takes 8.2 s on an Intel i5-6300U processor, which is acceptable for on-site execution in a classroom scenario.

The optimized path is followed by the robot using the TEB local planner [36], by sequentially setting the next target point. The weight_optimaltime parameter is set to 100 to penalize the robot for moving slower than the designated speed. The variation of robot speed is achieved by dynamically changing the speed limit max_vel_x parameter during run-time. Since the local planner detects and avoids dynamic obstacles, the robot chooses a shortest alternative path or requests teleoperation assistance upon moving students or blocked isles (such as when students stretches their legs out).

6.3. Comparison of measured dosage

The normalized dosages at the five observers in different cases are shown in Fig. 12. The data is clustered based on different setup of air filtration method, and within each setup, dosages at each seating positions are measured. The blue shadow behind the bars indicate the worst-case dosage experienced among the five seats (other than the seat of the source), given each filtration setup. Among the five seats we identify FC to be the Spreading Neighbor and L and R to be the Distance Neighbors, according to Section 4.2.1. The seat FR is unoccupied. From the results we conclude that both mobility and the optimization process reduces the worst-case dosage among all occupants. With mobility alone, the worst-case dosage is 9% lower than the worst case with stationary filtration. The worst-case dosage under the optimized cleaning path generated by our approach is further reduced by 19% from the case with the same robotic air cleaner traversing all seats without difference. The optimized path yields a greater 26% improvement in worst-case dosage compared to the worst case with the same but stationary filtration module, and 36% compared to the case without air filtration. The robot only spent 36% of its time near the source (22% designated to the source, and two via-passes accounting for 7% each), but yields 75% the reduction of worst-case dosage at neighbors (from the no-filtration case) compared to the ideal but impossible best-case scenario. The result highlights the coverage and efficiency of air filtration being improved when combined with mobility of robots.

6.4. Discussions and future work

The distribution of dosages in the experiment meets our estimation in general, that the occupant at FC location receives the highest dosage compared to other occupants. The experimental result outperforms that expected from the optimization evaluation, and the Distance Neighbors experience higher dosages than expected from numerical simulations, which we discuss as follows:

6.4.1. Effects of the wake induced by the robot

Although the wake induced by the Bernoulli Air Filtration Module has been minimized by design, the robotic base still disturbs the airflow to some extent. The effect of the wake is two-sided: it entrains the particles which enhances the cleaning effect; the entrained particles are released when the motion of the robot changes. While the modular design of the robot does not require aerodynamics design of the robotic base, the effect of wake is not considered and compensated in the approximation and optimization process, which is a limitation of this paper.

| Table 2 | Optimized path parameters and computed speeds for each segment within the shortest cycle path. |
|---------|---------------------------------------------------------------|
| Segment | $i$ | $r_i^*$ (m) | $q_i^*$ | Speed (m/s) |
| 1 → 2 | FL | 1.3 | 0.0699 | 0.699 |
| 2 → 3 | FC | 1.3 | 0.0699 | 0.699 |
| 3 → 4 | via | – | – | 0.700 |
| 4 → 5 | S | 1.3 | 0.2215 | 0.221 |
| 5 → 6 | via | – | – | 0.700 |
| 6 → 7 | R | 1.3 | 0.1053 | 0.464 |
| 7 → 8 | via | – | – | 0.700 |
| 8 → 9 | L | 1.3 | 0.2215 | 0.221 |
| 9 → 1 | via | – | – | 0.700 |

Total $r^* = 30.69$ s

Fig. 12. Cumulative dosage comparison of the five assessment locations under different filtration settings.
6.4.2. Real-time environment assessment for pathogens to optimize cleaning efficiency

PCPR seeks to integrate biosensors for pathogen detection, which in real time assess the robot surroundings. The real-time environment information will be invaluable to dynamic planning and optimizing the efficiency of air and surface disinfection, in closing the loop from spread estimation to path optimization.

6.4.3. Environmental and psychological implications

The robot moves around in close proximity to humans in an occupied classroom during class. Therefore, practical considerations such as noise, occlusion, human behavior, and psychological factors will affect its public acceptance. Specifically, the noise level of the robot as measured at 1 m away is 40 dB during normal operation. While the value can still be further improved by industrially re-designing the fan module and adding more insulation, it is below the speaking volume of approximately 50 dB. Comparatively, a commercial 142 L/s stationary air purifier has a noise level of 63 dB, which is annoying to students sitting nearby. The interruptions caused by the robot such as visual occlusions have shown to increase the mental strain of occupants [51]. However, interruptions also make the participants more willingly to interact with the robots [52]. To this end, how to make the robot more psychologically acceptable in real classrooms is still an open question.

7. Conclusions

The Purdue Campus Patrol Robot combines the mobility granted by robots with efficient air filtration optimized for dynamically occupied shared indoor spaces. Using advanced Computational Fluid Dynamics-based simulations, we analyzed the spread of the particles in a cough plume to identify the people at risk. The simulation was used as the basis for analyzing the effect of the mobile robotic air filtration and helped derive an upper bound for the cycle time of the robot for efficient and effective coverage. Further, the novel occupant-centric path planning of the robot contains pathogen spread in a classroom setting. The path planning addresses the spreading dynamics of bioaerosol droplets under the detected layout of occupants, while capable of on-site execution. Notably, as mobility alone reduces 9% of pathogen accumulation among neighbors in a given layout, the novel path planning yields a further reduction of 19% from that of the former unoptimized path. The synergistic combination minimizes the risk to occupants while achieving effective and human-safe cleaning of indoor air. Hence, the proposed occupant-centric robotic air filtration system grants an effective solution to allow people, especially vulnerable groups such as students and teachers, to coexist in the COVID-19 pandemic.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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