CAVisAP: Context-Aware Visualization of Outdoor Air Pollution with IoT Platforms

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Abstract—Air pollution is a severe issue in many big cities due to population growth and the rapid development of the economy and industry. This leads to the proliferating need to monitor urban air quality to avoid personal exposure and to make savvy decisions on managing the environment. In the last decades, the Internet of Things (IoT) is increasingly being applied to environmental challenges, including air quality monitoring and visualization. In this paper, we present CAVisAP, a context-aware system for outdoor air pollution visualization with IoT platforms. The system aims to provide context-aware visualization of three air pollutants such as nitrogen dioxide (NO$_2$), ozone (O$_3$) and particulate matter (PM$_{2.5}$) in the city of Melbourne, Australia. In addition to the primary context as location and time, CAVisAP takes into account users’ pollutant sensitivity levels and color vision impairments to provide personalized pollution maps. Experiments are conducted to validate the system and results are discussed.

Keywords—context-aware, location-based, data visualization, air pollution, Internet of Things, environmental monitoring

I. INTRODUCTION

Air pollution has become a rapidly growing concern in the past decades with the growth of pollution sources worldwide. According to the European Environment Agency (EEA), pollutants are released to the air from a wide range of sources including transport, agriculture, industry, waste management and households [1]. Industrial growth and rapid urbanization exacerbate the problem, with a pressure felt severely in big cities [2]. World Health Organization (WHO) reports that 92% of the world’s population lives in areas that exceed ambient air quality limits. Moreover, statistics show that outdoor air pollution alone causes 3 million deaths annually [3].

Public awareness of air pollution can contribute to both reducing emission levels and decreasing exposure. Moreover, the air quality information is required by scientists and policymakers to enable them to make savvy decisions on managing the environment [4]. Despite the importance of measurements, in many cases, monitoring alone may be insufficient for the purpose of fully defining population exposure in the environment. Therefore, monitoring often needs to be combined with other objective assessment techniques, including modeling, personalization, and visualization of measurements.

In this paper, we present Context-Aware Visualization of Air Pollution Maps with IoT Platforms (CAVisAP) system, implemented to visualize outdoor air pollution according to users’ context. The main focus of the paper is to provide personalized context-aware visualization. The system considers various context information such as location, time, users’ sensitivity to different pollutants and color vision impairments to visualize air pollution data and provide a personalized experience. The paper presents an algorithm to define pollutant-specific sensitivity levels according to a predefined set of questions. Moreover, we develop context-aware visualization modeling and situation reasoning algorithms based on Context Spaces Theory [8]. Lastly, we implement the CAVisAP system to provide personalized air pollution visualization which takes into account users’ color vision impairments as a context. This is critically important since the misinterpreting of air pollution colors can lead to uncompromising health issues. The developed system was tested for a set of scenarios considering a variety of user profiles with different pollutant sensitivity levels. The experiments justify the importance of considering user profile since the same level of air pollution is proven to be very hazardous for one user while another can feel only a little discomfort. The experiments are tested for the city of Melbourne, Australia using air pollution data from the Environment Protection Authority of Victoria - with control of user profile data to demonstrate the feasibility and functionality of the proposed model. The remainder of this paper is organized as follows. Section II provides background information on the Internet of Things and context-aware computing and discusses the Australian EPA standard of assessing outdoor air quality. Section III reviews related work. Section IV presents a context-aware visualization model. Section V describes a system architecture and implementation. Section VI demonstrates experiments, analysis, and results. Section VII presents the discussion and conclusions of this study.

II. BACKGROUND

In the last decades, the Internet of Things (IoT) is increasingly being applied to environmental challenges, including air quality monitoring, visualization, and prediction. Introducing IoT into the field of environmental monitoring provides an opportunity to get more accurate data in near real-time [5]. However, there are numerous challenges of adopting IoT for environmental issues.

Data generated by billions of devices might not have any value unless it is processed and interpreted. Numerous data collection, modeling and reasoning techniques are evolved to add value to raw data coming from IoT devices. One of the fields which gained increased significance on processing raw data is context-aware computing. Context-aware approach deals with meaningful context information which can
characterize the user’s situation. Location, time, user and activity can be considered as primary context types. A system can be considered as context-aware if it uses context to provide relevant information according to the user’s current task [6]. Application of the context-aware approach to outdoor air pollution monitoring enables systems to understand user’s needs and provide relevant information.

III. RELATED WORK

Numerous researches are conducted to address issues of air quality monitoring and visualization. We review and compare state-of-the-art literature to identify open research questions.

A. Environment Type

According to [8], an average person spends 80% of their time indoors. Therefore, many of the existing studies focus on indoor air quality monitoring. For example, [9], [10] and [11] present different solutions for indoor air quality monitoring, prediction, and control. Numerous works propose systems to monitor and predict ambient air pollution. Studies in [12] and [13] demonstrate various solutions for outdoor air quality, while other papers such as [14] and [15] consider both environment types.

B. Physical Air Characteristics

In addition to air pollutants, different air quality characteristics can affect pollution levels of the environment. For example, the air exchange rate inside a room or wind outside enables air movement. [11] considers temperature and humidity to estimate human discomfort due to heat and humidity levels. From the reviewed literature [9] considers the air exchange rate (AER) and [12] considers wind speed when measuring the outdoor air pollution rate.

C. Air Pollutants

Air quality is measured by sensors that record the concentrations of the major pollutants. Air Quality Index (AQI) is a commonly accepted standard to interpret raw measurements. In this research, we use Australian standards specified by Australian National Environment Protection Measure for Ambient Air (NEPM) [7]. Methods of calculation can be found on the website of the NEPM. Table I illustrates The AQI levels and gives a brief description of each category.

| Category   | AQI range | Description                                      |
|------------|-----------|--------------------------------------------------|
| Very good  | 0-33      | Air quality poses little or no risk              |
| Good       | 34-66     | Air quality poses little or no risk              |
| Fair       | 67-99     | There may be health concerns for very sensitive people |
| Poor       | 100-149   | Air quality is unhealthy for sensitive groups.  |
| Very poor  | >150      | Air quality is unhealthy, and everyone may begin to experience health effects |

[10] and [12] cover the majority of the key pollutants such as particulate matter (PM2.5 and PM10), ground-level ozone (O3), nitrogen dioxide (NO2) and sulfur dioxide (SO2). However, pollutant types are not specified in several studies such as [13] and [16]. Overall, findings from the review show that the large part of the studies considers carbon oxides or particulate matter which demonstrate the significance and widespread nature of the pollutants.

D. Context-Awareness

An increasing number of IoT devices and their computing capacity bring a new benchmark for smart devices. Nowadays, devices are expected to give relevant information according to the user’s current situation. This is the main task of context-aware applications. In spite of the fact that a huge number of solutions proposed in the area of environmental monitoring, only a few consider the context-aware approach. Most papers consider basic context information such as current location, time and pollutant type. [15] provides information based on location and time. [10] and [11] consider more context information such as environment and user’s personal health features, however, both studies are oriented on indoor air quality.

Assessment of exposure to air pollutants is a reasonable measure of health risks. However, the same dose of pollution may affect each person differently. Therefore, they may experience dissimilar health effects. Review findings show that a few papers consider user’s health problems and age when providing air quality status for indoor environments. However, there is still a research gap in applying a context-aware approach to outdoor air pollution monitoring. Moreover, the user’s visual perception context such as eyeight impairments, color-blindness, and others are not considered for data visualization.

E. Data Acquisition

A variety of data acquisition methods are used in different studies. The most common practice is an installment of different gas sensors or sensor nodes with several built-in sensors. For example, authors in [9] and [11] use individual pollutant sensors. [13] and [16] work with historical air pollution datasets and [16] further considers traffic datasets to estimate more accurate pollution rates. Crowd-sensing is another widespread approach to monitor air pollution. For example, authors in [14] and [17] collect data from participants. Open-source data, national weather, and pollution monitoring centers, and Internet-connected monitoring stations are other forms of data sources in the literature [12],[15],[16].

F. Data Visualization

Many studies already have proven the importance of data visualization to understand trends and make a decision over a given dataset. For example, in [18] authors use datasets with identical statistical parameters to generate dissimilar graphs and demonstrate the importance of graphical representation method. The majority of papers present numeric indices for air quality [9],[12] where they illustrate the levels of pollution with respective colors (i.e. good-green, bad-red) [19]. Moreover, in [16] authors provide additional meaning by using descriptive words such as “good”, “non-critical”, “warning”, “alert”, or “alarm”. [15] and [17] visualize data with pollution heatmaps. [13] and [15] provide pollution-based routes from origin to destination. [10] and [19] and visualize real-time and historical data with line charts. Review findings show that diversity of visualization methods can be used to present air pollution data, however, there is a little justification of the methods chosen. Moreover, the user’s
preferences and vision impairments are not considered when providing visualization services.

IV. CONTEXT-AWARE AIR POLLUTION VISUALIZATION MODEL

Context modeling in this research is based on Context Spaces Theory (CST) introduced in [8]. The main idea of the approach is to represent context as a multidimensional space. The CST provides an abstraction that enables one to achieve a coherent context representation. In addition to the aim of comprehensively and insightfully representing context, the theory addresses the challenges of reasoning about the context in uncertain environments.

A. Context Attributes

To model context using CST, first of all, context attributes used for reasoning must be defined. The following set of context attributes is chosen for the proposed system CAVisAP.

- **Current location.** This attribute represents the current location of the user’s query for air pollution information.
- **Time.** This attribute represents the current time of the user’s query for air pollution information.
- **Pollutant type.** This attribute provides information on considered air pollutant type.
- **Pollutant value.** This attribute provides information on the last available value of the respective pollutant type.
- **AQI.** To identify the health concern of user to air pollution levels, AQI needs to be calculated from raw air quality measurements.
- **User ID.** This context attribute is necessary to store user profile data and provide context-aware service to the user.
- **Pollutant sensitivity level.** This attribute defines the user’s personal sensitivity to each pollutant.
- **Color blindness.** This context attribute provides information on the user’s ability to differentiate colors assigned for AQI levels. In case, if a user has color vision deficiency, specific colors should be used to provide a user with meaningful information.

B. Situation Reasoning

Situations spaces in CST represent real-life situations which are defined by context attribute values. In our model, we define the following five situation spaces according to the users’ pollutant sensitivity levels and AQI values.

- **Good Air Quality.** Air pollution has a little or no health risk and air quality is considered satisfactory.
- **Unhealthy Air Quality.** This situation implies that a person can experience gentle health effects and respiratory irritations.
- **Very Unhealthy Air Quality.** In this situation, users can experience more serious health effects. Problems with breathing may occur and users can feel high levels of discomfort.
- **Hazardous Air Quality.** This situation implies severe air pollution conditions and emergency conditions. Users can experience serious health effects and a strong feeling of discomfort.

**Very Hazardous Air Quality.** This situation is specific for users with high and extremely high pollutant sensitivity levels, meaning that effects can lead to death if not immediate rescue from the place. Table II presents the situation spaces of the CAVisAP system.

### TABLE II. SITUATION SPACES.

| Situation | Neutral | Low | Moderate | High | Extremely high |
|-----------|---------|-----|----------|------|----------------|
| 0-33      | Good    | Good| Good     | Good | Good           |
| 34-66     | Good    | UH  | UH       | UH   | UH             |
| 67-99     | UH      | UH  | VUH      | VUH  | Hs             |
| 100-149   | VUH     | VUH | VUH      | Hs   | VHs            |
| >150      | HS      | HS  | HS       | VHs  | VHs            |

* Pollutant sensitivity levels of users

Depending on the value of color-blindness context attribute we change the color hue used for data visualization. Table III presents color schemes and codes in our system.

### TABLE III. COLOR SCHEMA FOR DATA VISUALIZATION.

| AQI          | Normal vision colors | Color-blind safe colors |
|--------------|-----------------------|-------------------------|
| Good         | #00FF00               | #FEE5D9                 |
| Unhealthy    | #FEFF00               | #FCAE91                 |
| Very Unhealthy| #FF7F00              | #FB6A4A                 |
| Hazardous    | #FF0000               | #DE2D26                 |
| Very Hazardous| #000                 | #A50F15                 |

V. IMPLEMENTATION

CAVisAP system architecture comprises four layers: Data Acquisition, Data Aggregation, Data Processing and Data Visualization. The data acquisition layer is responsible for outdoor air pollution data retrieval from sensing devices and external data sources. The data aggregation layer provides a service for aggregation and storage of historical data. The data processing layer is responsible for context information retrieval, situation reasoning, and data sharing. Finally, the data visualization layer provides a user interface and up-to-date visualization of air pollution data. Fig. 1 illustrates the CAVisAP system architecture and its components.

A. Data Acquisition and Aggregation

Air pollution data for Melbourne is obtained from web service provided by the Environment Protection Authority of Victoria. The agency provides open access to air quality measurements for all operating sites in the Victoria state. The APIs provide information on the hourly readings as well as historical data for a range of pollutants such as CO, O₃, NO₂, SO₂, PM₂.₅, and PM₁₀.

The acquired data from the above-mentioned source is ingested into the IoT platform. The platform of choice for this study is ThingsBoard [21].
The ThingsBoard is an open-source IoT platform for data collection, processing, visualization, and device management. It is licensed under Apache License 2.0. The platform provides the administrator user with a rich web interface to register and manage devices which makes the platform easy to use. To provide secure access to the devices the platform uses access tokens. The incoming device data is processed with rule engines based on message content or entity attributes. The platform supports HTTP, CoAP and MQTT protocols for device communication and for connection to external data sources. It stores data received from devices as telemetries, which are time series of key-value pairs of data associated with specific devices. Attribute updates and time series data are stored into internal data storage via telemetry plugin which is configured in system level. The platform uses SQL, NoSQL, and hybrid databases to store data.

In the platform, we created virtual devices representing real-world stations. Each device adopts attributes such as name, latitude, and longitude from the Victoria EPA air pollution monitoring station. Then we ingest air pollution data on particulate matter, ozone and nitrogen dioxide obtained from the stations to the respective virtual devices. This is done via the configuration of HTTP API calls inside the rule engine to ingest telemetry data to the respective devices. In addition, we created virtual devices with simulated attributes and time series data to demonstrate situations which were not possible with data obtained via Victoria EPA API. The platform allows us to configure APIs to each device and to provide access to time series data. Fig. 2 shows an example of virtual devices created in the ThingsBoard platform.

### B. Data Processing

The data processing layer comprises of two parts. First, defining a user profile to further define user context. Second, situation reasoning based on user context and air pollution data. To obtain context attributes such as user’s age, sensitivity level to pollutants and color vision impairments a simple set of questions is developed.

In the context model, we consider three pollutants such as NO$_2$, O$_3$, and PM$_{2.5}$. Different studies found that older adults, children, and people with lung diseases are more sensitive to all three pollutants, while people with heart diseases tend to be more sensitive to particulate matter. Moreover, active people of all ages who exercise or work vigorously outdoors are at increased risk for ozone pollution [8]. As proof of concept, we developed a set of questions to define users’ NO$_2$, O$_3$, and PM$_{2.5}$ sensitivity levels. The set contains a wide variety of questions related to social status, age, lifestyle and habits of a user. However, the identified sensitivity levels are used as proof of concept and cannot be utilized as a reference to relate to the actual pollutant sensitivity of a person. Questions have multiple answers. The answers have weighted value from 0 to 4 which relates to the sensitivity levels for each pollutant such as neutral, low, moderate, high and extremely high. Weights are assigned according to the relevancy of a question to a pollutant and severity of its effects. Fig. 3 illustrates an example of a question, answers and pollutant-specific weights for answers from the set.

After getting the responses, weights for each pollutant are collected into arrays. Then number of pollutant-specific weights is counted. If there is at least one answer with sensitivity weight 4, then pollutant sensitivity level is defined as extremely high. Because weight 4 is assigned to answers which confirm that the user has a lung or heart diseases and they are extremely sensitive to pollutants. Next, if there are more than three answers with weight 3 then the sensitivity level is extremely high and in case if this number is between zero and three then the level is considered to be high and so on. Algorithm I presents the full process of pollutant sensitivity calculation. For example, we consider a set of 20 responses and count NO$_2$ sensitivity weights. There might be seven answers with weight 0, four answers with weight 1, seven answers with weight 2, two answers with weight 3 and zero answers with weight 4. Then according to the algorithm, the sensitivity level to NO$_2$ is defined as high since there are more than five answers with weight 2.
Algorithm I: Pollutant sensitivity levels calculation

**INPUT:** responses to the set of questions, pollutant sensitivity weights for each answer (0, 1, 2, 3, 4), pollutant sensitivity levels (neutral, low, moderate, high, extremely high), pollutant types (NO₂, O₃, PM₂.₅, PM₁₀)

**PARAMETERS:** pollutant sensitivity weights array

**METHOD:**

```javascript
for each element of responses do {
  for each pollutantType do {
    push pollutantSensitivityWeight to WeightsArray}
  for each element of WeightsArray do {
    for each pollutantSensitivityWeight do {
      count number of pollutantSensitivityWeight;}
    for each pollutantType do {
      if (number of pollutantSensitivityWeight (4) > 0) {
        return extremelyHigh;
      } else if (number of pollutantSensitivityWeight (3) > 3) {
        return extremelyHigh;
      } else if (0 < number of pollutantSensitivityWeight (3) <= 3) {
        return high;
      } else if (0 < number of pollutantSensitivityWeight (2) <= 5) {
        return moderate;
      } else if (0 < number of pollutantSensitivityWeight (1) <= 7) {
        return low;
      } else return neutral;
    }
  }
}
```

After defining the sensitivity levels, a user is asked to answer a binary question on color blindness. This is needed to further provide color-blind safe data visualization. Lastly, the user is asked to give access to the current location and the profile is saved with a unique id. Fig. 4 illustrates an example of the user’s profile information.

![User profile sample](image)

Fig. 4. User profile sample.

Defining user profile enables us to further provide context-aware air pollution data visualization. This is crucially important in the case when the same air quality levels can be safe for one person and might be vitally dangerous for another. Moreover, visualizing air pollution levels with colors visible for people with normal vision might not give any value to a color-blind user. Therefore, being aware of user context makes it possible to provide critically valuable information to users in a comprehensive way.

The next step is to identify the user’s current situation with regards to the air pollution levels in the nearby places. Users are provided with a choice to change the proximity radius to see air pollution in their current location. Further, a query is made to the IoT platform to get locations of the devices within the proximity radius. After getting the nearby device details, we query ThingsBoard for the latest telemetry data from each of the stations. Then AQI for each pollutant is calculated.

Next, we calculate the user’s current situation taking into account their sensitivity to each pollutant and respective pollutant AQI value. As it was introduced in the previous thesis chapter, there are five situation spaces in our model. Algorithm II illustrates the situation reasoning based on Australian air quality index standards.

![Algorithm II: Current situation reasoning based on Australian AQI](image)

The data processing layer and data visualization layer are implemented in NodeRED [20]. NodeRED is a flow-based development tool for visual programming developed for wiring together hardware devices, APIs and online services as part of the Internet of Things. The NodeRED allows interconnecting physical input/output, cloud-based systems, databases, and API’s. The Node-RED is based on flow-based programming and the flows are managed by the different type of “nodes”, where each has a well-defined function; the node receives data, then processes the data, and then it passes that data on to the next node in the flow or completes the data processing. The tool is implemented in JavaScript and the majority of nodes have pre-built configuration, which requires minimum programming skills. However, specific nodes provide an interface to write scripts for more complex solutions. The CAVisAP data processing layer consists of several nodes in NodeRED which make HTTP calls to ThingsBoard APIs, process user profile information, model context and reason situation of a user.

C. Data Visualization

To provide context-aware visualization, the first user profile needs to be obtained. Users are given an opportunity to select their pollutant sensitivity levels when registering to the system. For this purpose, login and registration interfaces are developed. In addition to the simple registration form where users can select from dropdown menu sensitivity levels (neutral, low, moderate, high and extremely high), we provide a link to the set of questions that can help users to define their...
sensitivity to NO$_2$, O$_3$, and PM$_{2.5}$. Further users are transferred into the main interface of the system which contains a personalized air pollution map in the current location of the user. The map uses different colors to provide the same level of pollution for users with different sensitivity levels as defined in the context model. Moreover, the set of colors differs for color-blind and users with normal vision. A number of techniques are used to visualize air pollution levels such as heat maps, colored air pollution spots maps, pinpoints and pinpoints with indices. The interfaces of the system are implemented using dashboard nodes in NodeRED which enable the extension of pre-build interface functionality. Fig. 5 shows a segment of workflow in NodeRED.

VI. EXPERIMENTS AND RESULTS

To evaluate the developed system, we simulated different users’ profiles with different sensitivity levels. Moreover, since the real-life data streams obtained from Victoria API showed relatively good levels of air pollution, we created extra virtual devices with generated data. These devices are used to test the system for severe air pollution levels. In the first set of experiments, we test the difference in the visualization of the same AQI for users with different sensitivity levels. We create five user profiles with different sensitivity levels to PM$_{2.5}$ and neutral sensitivity to NO$_2$ and O$_3$. Table IV illustrates the user profiles.

| Users | NO$_2$ sensitivity | O$_3$ sensitivity | PM$_{2.5}$ sensitivity |
|-------|--------------------|-------------------|------------------------|
| user1 | neutral            | neutral           | neutral                |
| user2 | neutral            | neutral           | low                    |
| user3 | neutral            | neutral           | moderate               |
| user4 | neutral            | neutral           | high                   |
| user5 | neutral            | neutral           | extremely high         |

In the first experiment, we consider five stations with good to very hazardous AQI levels. Table V shows the details on station names and respective PM$_{2.5}$ and AQI values at each station.

| Stations | Address           | PM$_{2.5}$ value | AQI  |
|----------|-------------------|------------------|------|
| st_1     | Woolworths Burwood | 10.2             | 25.5 |
| st_2     | Lundgren Reserve  | 14.9             | 37.25|
| st_3     | St Scholastica    | 30.9             | 77.25|
| st_4     | Hawthorn Art Centre | 45.8          | 114.5|
| st_5     | Unity of Melbourne | 67.5             | 168.75|

Fig. 6 shows locations of the stations on the map and situation at each node for a user with neutral sensitivity for all pollutants. Table VI presents situation reasoning for all five users calculated with the aforementioned algorithm.

| Users | st_1 | st_2 | st_3 | st_4 | st_5 |
|-------|------|------|------|------|------|
| user1 | good | good | unhealthy | very unhealthy | hazardous |
| user2 | good | unhealthy | unhealthy | very unhealthy | hazardous |
| user3 | good | unhealthy | very unhealthy | very unhealthy | hazardous |
| user4 | good | unhealthy | very unhealthy | hazardous | very hazardous |
| user5 | good | unhealthy | hazardous | very hazardous | very hazardous |

Fig. 7 presents the visualization of the air pollution data for the first set of experiments. As can be seen, the situation at Woolworth Burwood remains good for all five users, while at Lundgren Reserve it is unhealthy for all users who have at least a low level of sensitivity to PM$_{2.5}$. Moreover, the situation at St Scholastica changes from unhealthy to hazardous and at Hawthorn Art Centre from very unhealthy to very hazardous depending on the users’ pollutant sensitivity levels.

| Users | st_1 | st_2 | st_3 | st_4 | st_5 |
|-------|------|------|------|------|------|
| user1 | good | good | unhealthy | very unhealthy | hazardous |
| user2 | good | unhealthy | unhealthy | very unhealthy | hazardous |
| user3 | good | unhealthy | very unhealthy | very unhealthy | hazardous |
| user4 | good | unhealthy | very unhealthy | hazardous | very hazardous |
| user5 | good | unhealthy | hazardous | very hazardous | very hazardous |

Fig. 7. Visualization results for users with different PM$_{2.5}$ sensitivity levels.
At the second experiment, we consider only one user but with different sensitivity levels to all three pollutants, NO$_2$, O$_3$, and PM$_{2.5}$. Table VII presents the user profile.

| Users | Sensitivity levels          |
|-------|-----------------------------|
| user6 | NO$_2$ sensitivity          |
|       | O$_3$ sensitivity           |
|       | PM$_{2.5}$ sensitivity      |
| user6 | neutral                     |
|       | moderate                    |
| user6 | extremely high              |

At the second scenario, we consider five stations with different situations depending on the pollutant type. For example, at the station Unity of Melbourne air quality is good regarding NO$_2$ and O$_3$ values. However, the level of particulate matter is very hazardous. Hence, the overall situation of the user6 is very hazardous. Moreover, at Deakin Burwood Co. user’s situation is unhealthy with regards to particulate matter but there is a very unhealthy ozone level for moderate sensitivity groups. Therefore, the situation of the user6 is very unhealthy at the node. Table VIII provides full information on pollutant measurements at each of the stations and pollutant-specific situation and the overall situation of the user at each station.

| Stations | Deakin Uni. | Benn. Reserve | Deakin Burwood Co. | The Settlers Shelter | Unity of Melbourne |
|----------|-------------|---------------|-------------------|----------------------|-------------------|
| NO$_2$ value | 45          | 39.5          | 84.9              | 82.7                 | 0.7               |
| NO$_2$ situation | good        | good          | unhealthy         | unhealthy            | good              |
| O$_3$ value       | 25.6        | 12.1          | 78.9              | 78.3                 | 0.6               |
| O$_3$ situation   | good        | good          | very unhealthy    | very unhealthy       | good              |
| PM$_{2.5}$ value  | 11.8        | 24.1          | 10.8              | 35.1                 | 67.5              |
| PM$_{2.5}$ situation | good        | unhealthy     | unhealthy         | hazardous            | very hazardous    |
| Overall situation | good        | unhealthy     | very unhealthy    | hazardous            | very hazardous    |

Fig. 8 shows the location of stations, measurements for each pollutant and overall situation of a user at the respective area.

In the first two experiments, pinpoints are used to visualize the current situation of a user and data is visualized with colors for the users with normal vision. However, in addition to pinpoints, we implemented a number of other visualization methods such as heat maps, colored air pollution spots maps, pinpoints and pinpoints with indices. Fig. 9 presents the different visualization methods applied for the same set of data.

Finally, we test CAVisAP to differentiate visualization depending on the users’ color vision impairments to provide meaningful information in a readable form. Fig. 10 illustrates the change of color scheme for color-blind users.

The results of the experiment show the importance of adopting sensitivity levels of users to different pollutants as a context. The same pollution levels can affect users diversely depending on their health. This is proven in the first
experiment, where the same pollutant value was unhealthy for the first user and hazardous for the other. Moreover, monitoring a variety of pollutant types enable to avoid exposure. If a user has high sensitivity to particulate matter but neutral to ozone and system reasons situation only considering ozone values, then the user can be exposed to areas with high particulate matter and visualization might still show the area is safe. Lastly, its critically important to consider different color vision impairments of users when providing visualization services. Color-blind users might misinterpret information which considers only users with normal vision. Therefore, the novel approach present in the CAVisAP system enables to provide relevant information taking into account the aforementioned problems.

VII. CONCLUSION

In this paper, a context-aware system CAVisAP for outdoor air pollution visualization was presented. The system provides context-aware visualization of three air pollutants such as nitrogen dioxide (NO₂), ozone (O₃) and particulate matter (PM₂.₅) in the city of Melbourne, Australia. The paper presents an algorithm to define pollutant-specific sensitivity levels of users according to a predefined set of questions. Moreover, context-aware visualization modeling and situation reasoning algorithms are developed. The CAVisAP system is implemented to provide personalized air pollution visualization which takes into account users’ color vision impairments as a context. This is critically important since the misinterpreting of air pollution colors can lead to uncompromising health issues. The developed system was tested for a set of scenarios considering a variety of user profiles with different pollutant sensitivity levels. The experiments justify the importance of considering user profile since the same level of air pollution is proven to be very hazardous for one user while another can feel only a little discomfort. The experiments validate the importance of adopting the user context to provide personalized visualization.

As future work, user experience tests can be designed to identify usable visualization methods showcased in the CAVisAP. Moreover, the system can be enhanced with the integration of air-pollution based routes between two or more locations. Further, context-aware prediction methods can be applied to provide air pollution forecasts.

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