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

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***Abstract*— Recently air pollution became a severe issue in many big cities due to population growth and rapid development of economy and industry. This led to proliferating need to monitor urban air quality in order to avoid personal exposure as well as to make savvy decisions on managing the environment. In the last decades 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 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. However, air pollution does not respect borders. Heavy metals and pollutants are carried by wind, contaminating water and soil far from the origin [2]. Therefore, air pollution is not a problem of solely industrial regions but a global burden which affects all parts of society. World Health Organization (WHO) reports that 92% of the world's population lives in the areas that exceed ambient air quality limits. In addition, the report states that air pollution is the biggest environmental risk to health, being responsible for each ninth deaths per year. Moreover, statistics show that outdoor air pollution alone causes 3 million deaths annually [3].

Human exposure to air pollution may cause different health issues depending on the type of pollutant, duration of exposure and the toxicity level of the pollutant. The WHO developed air quality guidelines to explain in details health effects of various pollutants [4]. The health effects of air pollution can vary from nausea, difficulty in breathing or skin irritation to cancer. The most widespread health effects observed by different investigations include reduced lung functioning, asthma attacks, development of respiratory diseases and premature death [5].

Atmospheric environmental protection, including air quality management, response policies, health impact and risk assessment as well as air pollution modeling would be impossible without quantitative description of air quality with measurable quantities. The aim of the air quality management is to keep the ambient air clean enough so that it is safe for the public health and the environment. In order to assess status of the air, current air quality must be monitored. Public awareness of air pollution can contribute to both reducing emission levels and decreasing exposure. Moreover, the air quality information is required by scientists, regional and national policy-makers and planners to enable them to make savvy decisions on managing the environment. Air quality monitoring provides necessary scientific basis for developing policies, setting objectives and planning enforcement actions [5]. 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 modelling, 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 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 personalized experience. Experiments are conducted for the city of Melbourne, Australia using air pollution data from Environment Protection Authority of Victoria [6] - with control of user profile data to demonstrate feasibility and functionality of the proposed model. The remainder of this paper is organized as follows. Section II provides a background information on Internet of Things and context-aware computing and discusses 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 discussion and conclusions of this study.

II. Background

In the last decades 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 opportunity to get more accurate data in near real-time [7]. However, there are numerous challenges of adopting IoT for environmental issues. According to CISCO's report, there were 10 billion devices connected to the Internet in 2013, while by 2020 it is expected to grow up to 50 billion [8]. This leads to the generation of an enormous amount of data that has to be stored, processed and demonstrated in an efficient and easily interpretable form.

Data generated by billions of devices might not have any value unless it is processed and interpreted. Numerous data collection, modelling and reasoning techniques are evolved to add a 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 a meaningful context information which can characterize the user's situation. Location, time, user and activity can be considered as primary context types. System can be considered as context-aware if it uses context to provide relevant information according to the user's current task [9]. Application of context-aware approach to outdoor air pollution monitoring enable systems to understand user's needs and provide relevant information.

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. There are a number of standards on calculating AQI worldwide. In this research we use Australian standards specified by Australian National Environment Protection Measure for Ambient Air (NEPM) [10]. Methods of calculation can be found in the website of the NEPM. Table I illustrates The AQI levels and gives a brief description of each category.

TABLE I. AUSTRALIAN AQI STANDARDS

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	Aiq quality is unhealthy, and everyone may begin to experience health effects

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 a report in [11] average person spends 80% of their time indoors. Therefore, many of the existing studies focus on indoor air quality monitoring. For example, [12], [13], [14], [15] and [16] present different solutions for indoor air quality monitoring, prediction and control. However, recent statistics from WHO [3] on air pollution illnesses and mortality show that number of deaths caused by outdoor air pollution is more than 3 million. The number roughly is the same as the household pollution mortality rate. Hence numerous works propose systems to monitor and predict ambient air pollution. Studies in [17], [18], [19] demonstrate various solutions for outdoor air quality, while other papers such as [20], [21], [22] and [23] consider both environment types.

B. Physical Air Characteristics

In addition to air pollutants different air quality characteristics can affect pollution levels of environment. For example, air exchange rate inside a room or wind outside enable air movement, consequently, decrease concentration of pollutants of an area. Moreover, [15] considers temperature and humidity to calculate humidex introduced in [24] which is an approach to estimate human discomfort due to heat and humidity levels. From the reviewed literature [12] considers air exchange rate (AER) and [25] takes into account room ventilation to calculate indoor air quality, whereas [17] considers wind speed when measuring outdoor air pollution rate.

C. Air Pollutants

In order to accurately measure air pollution rate, a range of pollutants must be considered. For example, US Environmental Protection Agency (EPA) covers six main pollutants to calculate Air Quality Index (AQI) and sets its limits on human health [26]. European Environment Agency proposes European Air Quality Index which is based on five key pollutants that harm people's health and the environment such as particulate matter ($PM_{2.5}$ and PM_{10}), ground-level ozone (O_3), nitrogen dioxide (NO_2) and sulphur dioxide (SO_2) [27]. [14], [17] and [28] cover majority of the pollutants mentioned in the above standards, while [29] consider 12 pollutants. However, pollutant types are not specified in several studies such as [16], [18] and [30]. Overall, findings from review show that majority of the studies consider carbon oxides or particulate matter which demonstrate significance and widespread nature of the pollutants.

D. Context Awareness

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 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 few consider context-aware approach. Most papers consider basic context information such as current location, time and pollutant type. [28] and [31] provide only location-based information, while [23] considers time. [14], [15] and [16] consider more context information such as environment and user's personal health features, however, all three researches 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 on applying context-aware approach to outdoor air pollution monitoring. Moreover, user's visual perception context such as eyesight impairments, color-blindness and others are not considered for data visualization.

E. Data Acquisition

Variety of data acquisition methods are used in different studies. The most common practice is installment of different gas sensors or sensor nodes with several built-in sensors. For example, in [20] sensor node with 12 built-in sensors is equipped, while authors in [12] and [15] use individual pollutant sensors. [18], [30] and [31] work with historical air pollution datasets and [30] further considers traffic datasets to estimate more accurate pollution rates. Crowd-sensing is another widespread approach to monitor air pollution. For example, authors in [21], [32] and [33] collect data from participants, whereas [22] collects data from both, sensors and crowd. Open-source data, national weather and pollution monitoring centers and internet-connected monitoring stations are other forms of data sources in the literature [17],[23],[30],[34].

F. Data Visualization

Many researches already proven importance of data visualization to understand trends and make decision over a given dataset. For example, in [35] authors use datasets with identical statistical parameters to generate dissimilar graphs and demonstrate importance of graphical representation method. There is no single standard visualization approach for air quality data, therefore, methods vary from study to study. Majority of papers present numeric indices for air quality [12],[17],[20], where several of them illustrate severity of pollution with respective colors (i.e. good-green, bad-red) [13],[36]. Moreover, in [30] authors provide additional meaning by using descriptive words such as "good", "non-critical", "warning", "alert", or "alarm". [23],[32] and [33] visualizes data with pollution heatmaps. [18] and [23] provide pollution-based routes from origin to destination. [14], [19], [28] and [36] 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, user's preferences and vision impairments are not considered when providing visualization services. Even though there is an attempt of applying context-aware approach in the field of data visualization as discussed in the previous sections, there are still open research areas on adopting user context when visualizing environmental data.

IV. CONTEXT-AWARE AIR POLLUTION VISUALIZATION MODEL

Context modeling in this research is based on Context Spaces Theory (CST) introduced in [37]. The main idea of the approach is to represent context as a multidimensional space. The CST provides an abstraction which enables to achieve a coherent context representation. In addition to the aim of comprehensively and insightfully representing context, the theory addresses challenges of reasoning about context in uncertain environments.

A. Context Attributes

In order 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 current location of the user's query for air pollution information.

Time. This attribute represents 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. In order to identify 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 user's personal sensitivity to each pollutant.

Color blindness. This context attribute provides information on user's ability to differentiate colors assigned for AQI levels. In case, if user has color vision deficiency, specific colors should be used in order to provide 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 following five situation spaces according to the users' pollutant sensitivity levels and AQI values. Table II presents the situations spaces of the CAVisAP system.

TABLE II. SITUATION SPACES

S.I[a] / AQI	**Neutral**	**Low**	**Moderate**	**High**	**Extremely high**
0-33	Good	Good	Good	Good	Good
34-66	Good	UH[b]	UH	UH	UH
67-99	UH	UH	VUH	VUH	Hs
100-149	VUH	VUH	VUH	Hs	VHs
>150	Hs	Hs	Hs	VHs	VHs

a. Pollutant sensitivity levels of users

b. UH: Unhealthy, VUH: Very Unhealthy, Hs: Hazardous, VHs: Very Hazardous

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 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.

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

Color-blind safe colors are tested with simulation tool Sim Daltonism [38].

V. IMPLEMENTATION

CAVisAP system architecture comprises of four layers such as Data Acquisition, Data Collection and Storage, 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 collection and storage layer provides a service for aggregation and storage of historic data. Data processing layer is responsible for context information retrieval, situation reasoning, and data sharing. Finally, 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.

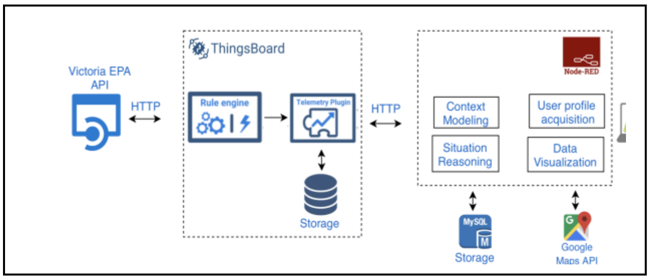

Fig. 1. CAVisAP system architecture

A. Data Acquisition and Storage

Air pollution data for Melbourne is obtained from web service provided by the Environment Protection Authority of Victoria [6]. 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, O_3, NO_2, SO_2, $PM_{2.5}$ and PM_{10}.

The next, all data collected from the above-mentioned source is ingested into ThingsBoard IoT platform. 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 allows to process incoming device data with rule chains based on message content or entity attributes [39]. In the ThingsBoard platform we created virtual devices representing actual stations. Each device adopts attributes such as name, latitude and longitude from a real-world air pollution monitoring station. Moreover, air pollution data obtained from stations is ingested to the respective virtual device. In addition, we created virtual devices with simulated attributes and data to demonstrate situations which were not possible with data obtained via Victoria API. Fig. 2 shows example of virtual devices created in the ThingsBoard.

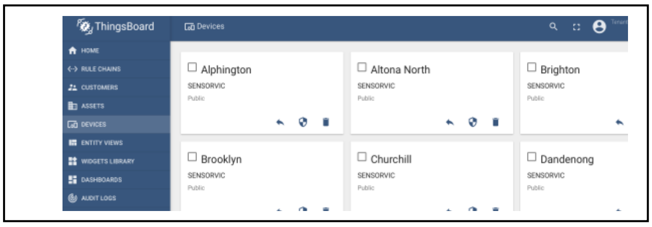

Fig. 2. Virtual devices in ThingsBoard

B. Data Processing

Data processing layer comprises of two parts. First, defining user profile in order to further define user context. Second, situation reasoning based on user context and air pollution data. Data processing layer is implemented in Node.js, which is an open source runtime environment for executing JavaScript code server-side [40]. In order 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 our 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 [41]. The set of questions to define users' pollutant sensitivity levels is developed based on a number of research studies introduced in [42]-[47]. The set contains wide variety of questions related to social status, age, lifestyle and habits of a user. However, the identified sensitivity levels are used as a proof of concept and cannot be utilized as a reference to relate to actual sensitivity of a person to a pollutant. 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 and further used to identify sensitivity level. 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.

```
8: {
    q: "How often do you do physical exercises?",
    a: ["I do not exercise", "Less than once a week",
        "1-2 times a week", "3-5 times a week",
        "More than 5 times a week", "I do not know/Not sure"],
    no2Index: [0,0,0,1,2,0],
    o3Index: [0,0,0,1,2,0],
    pm25Index: [3,2,1,0,0,0]
```

Fig. 3. Example question to identify pollutant sensitivity level

After getting the responses, weights for each pollutant are collected into arrays. Then number of pollutant specific weights are counted. If there is at least one answer with sensitivity weight 4, then pollutant sensitivity level is defined as extremely high. Because, usually weight 4 is assigned to answers which confirm that 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 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. Table IV present full version of the algorithm to define sensitivity level for each pollutant.

TABLE IV. POLLUTANT SENSITIVITY LEVELS CALCULATION

ALGORITHM: Pollutant sensitivity levels calculation

INPUT: responses to the set of questions, pollutant sensitivity weights of each answer (0,1,2,3,4), pollutant sensitivity levels (neutral, low, moderate, high, extremely high), pollutant types (NO_2, O_3, $PM_{2.5}$)

OUTPUT: sensitivity levels to each pollutant

PARAMETERS: pollutant sensitivity weights array

METHOD:
```
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(number of pollutantSensitivityWeight (2) > 5)
        return high;
      else if ( 0< number of pollutantSensitivityWeight (2) <= 5)
        return moderate;
      else {
        if(number of pollutantSensitivityWeight (1) > 7)
          return moderate;
        else if ( 0< number of pollutantSensitivityWeight (1) <= 7)
          return low;
        else return neutral; }}}}
```

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


```
▾object
  userId: "id-f7wthwwn5vj"
  no2sensitivity: "neutral"
  o3sensitivity: "high"
  pm25sensitivity: "high"
  colorBlindness: "true"
  ▾currentLocation: object
    lat: -37.8472505
    lng: 145.1145886
```


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 color-blind person. Therefore, being aware of user context makes it possible to provide critically valuable information to users in a comprehensive for them way.

The next step is to identify user's current situation with regards to the air pollution levels in the nearby places. Users are provided with choice to change 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 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 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. Table V illustrates situation reasoning algorithm based on Australian air quality index standards.

TABLE V. CURRENT SITUATION REASONING ALGORITHM

ALGORITHM: Current situation reasoning based on Australian AQI

INPUT: pollutant AQI indices, user's pollutant sensitivity levels, pollutant types

OUTPUT: overall current situation

PARAMETERS: pollutant specific situation variable

METHOD:
```
for each pollutantType do {
  if (AQIIndex <= 33)
    pollutantSpecificSituation = good;
  else if (33 < AQIIndex <= 66) {
    if (sensitivityLevel==”neutral”)
      pollutantSpecificSituation = good;
    else pollutantSpecificSituation = unhealthy; }
  else if (66 < AQIIndex <= 99) {
    if (sensitivityLevel == (“neutral” || “low”))
      pollutantSpecificSituation = unhealthy;
    else if (sensitivityLevel ==(“moderate” || “high”))
      pollutantSpecificSituation = veryUnhealthy;
    else pollutantSpecificSituation = hazardous; }
  else if (99 < AQIIndex <= 149){
    if (sensitivityLevel = “high”)
      pollutantSpecificSituation = hazardous;
    else if (sensitivityLevel==”extremelyHigh”)
      pollutantSpecificSituation = veryHazardous;
    else pollutantSpecificSituation = veryUnhealthy; }
  else {
    if (sensitivityLevel == (“high” || “extremelyHigh”))
      pollutantSpecificSituation = veryHazardous;
    else pollutantSpecificSituation = hazardous; }}
```

C. Data Visualization

In this study, we use NodeRED for data visualization. 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 [48]. Moreover, we use Google Maps API [49] to present geospatial data and customize maps with our content on air pollution data and user's current situation regarding the measurements. 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. Moreover, according to the values of color-blindness context attribute visualization color hues change. Fig. 5 shows a segment of workflow in NodeRED.

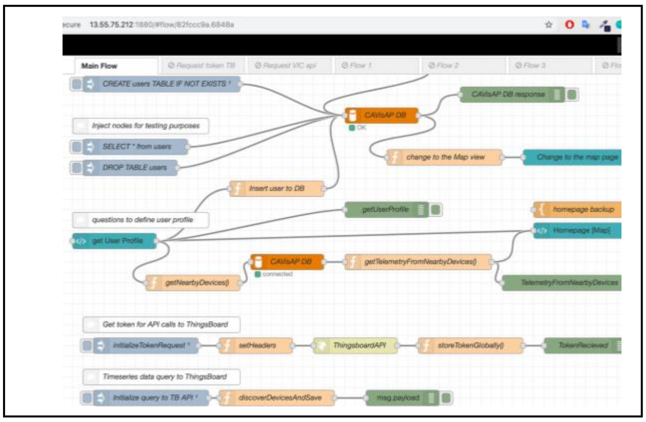

Fig. 5. NodeRED workflow segment

VI. EXPERIMENTS AND RESULTS

In order 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 visualization of the same AQI for users with different sensitivity levels. We create five user profiles with different sensitivity levels to d neutral sensitivity to NO_2 and O_3. Table VI illustrates the user profiles.

TABLE VI. POLLUTANT SENSITIVITY LEVELS OF USERS

Users	**Sensitivity levels**		
	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 VII shows the details on station names and respective $PM_{2.5}$ and AQI values at each station.

TABLE VII. AIR QUALITY INFORMATION OF STATIONS

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 VIII presents situation reasoning for all five users calculated with aforementioned algorithm.

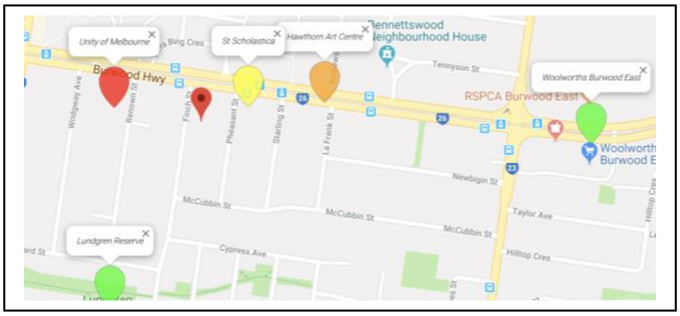

Fig. 6. Locations of stations

TABLE VIII. SITUATION REASONING AT EACH STATION

Users	**Stations**				
	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 visualization of the air pollution data for the first set of experiments. As it can be seen, situation at Woolworth Burwood remains good for all five users, while at Lundgren Reserve its unhealthy for all users which have at least low level of sensitivity to $PM_{2.5}$. Moreover, 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.

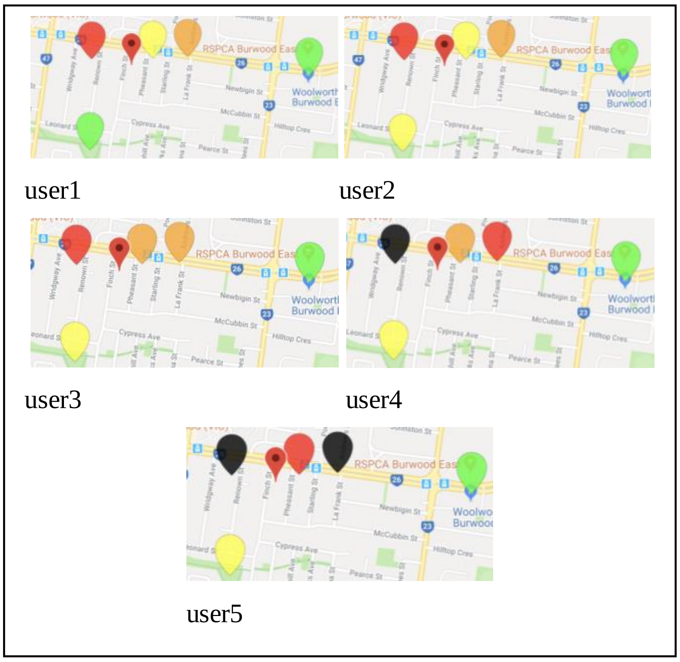

Fig. 7. Visualization results for users with different $PM_{2.5}$ sensitivity levels

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 IX presents the user profile.

TABLE IX. USER SENSITIVITY TO ALL THREE POLLUTANTS

Users	Sensitivity levels		
	NO_2 sensitivity	*O_3 sensitivity*	*$PM_{2.5}$ sensitivity*
user6	neutral	moderate	extremely high

At the second scenario, we consider five stations with different situations depending on pollutant type. For example, at the station Unity of Melbourne station air quality is good regarding NO_2 and O_3 values. However, the level of particulate matter is very hazardous. Hence, 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 very unhealthy ozone level for moderate sensitivity groups. Therefore, situation of the user6 is very unhealthy at the node. Table X provides full information on pollutant measurements at each of the stations and pollutant-specific situation and overall situation of the user at each station.

TABLE X. AIR QUALITY INFORMATION OF STATIONS

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.

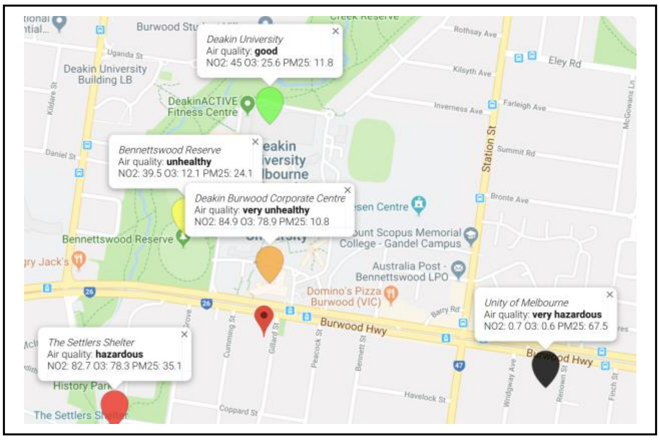

Fig. 8. Air pollution levels and user's situation at each station

In the first two experiments, pinpoints are used to visualize current situation of a user and data is visualized with colors from a normal vision schema. 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.

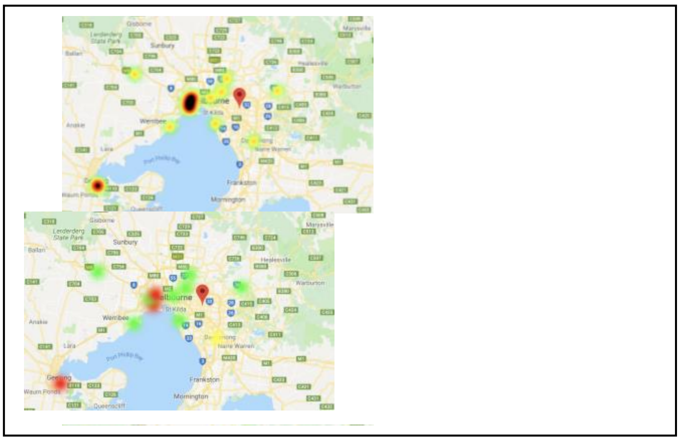

Fig. 9. Same values, different visualization methods

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

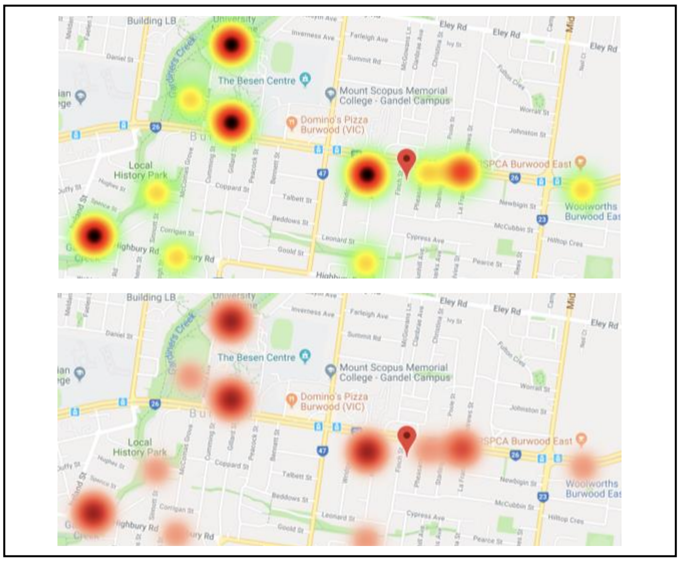

Fig. 10. Illustration of color-blind safe visualization

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 (NO_2), ozone (O_3) and particulate matter ($PM_{2.5}$) in the city of Melbourne, Australia. In addition to primary context as location and time, CAVisAP takes into account users' pollutant sensitivity levels and color vision impairments to provide personalized pollution maps. The developed system was tested for a set of scenarios considering variety of user profiles with different pollutant sensitivity levels. A set of questions was developed to identify users' sensitivity levels to NO_2, O_3 and $PM_{2.5}$. 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. Moreover, CAVisAP attempt to provide a novel approach to visualize air pollution data considering users' color vision impairments. This is critically important, since misinterpreting of air pollution colors can lead to uncompromising health issues.

As a future work, user experience tests can be designed to identify usable visualization methods present in CAVisAP. Moreover, the system can be enhanced with 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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