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Towards an integrated framework for air quality monitoring and exposure estimation—a review

Savina Singla (ID) · **Divya Bansal** · **Archan Misra** ·
Gaurav Raheja

Abstract For the health and safety of the public, it is essential to measure spatiotemporal distribution of air pollution in a region and thus monitor air quality in a fine-grain manner. While most of the sensing-based commercial applications available until today have been using fixed environmental sensors, the use of personal devices such as smartphones, smartwatches, and other wearable devices has not been explored in depth. These kinds of devices have an advantage of being with the user continuously, thus providing an ability to generate accurate and well-distributed spatiotemporal air pollution data. In this paper, we review the studies (especially in the last decade) done by various researchers using different kinds of environmental sensors highlighting related techniques and issues. We also present important studies of measuring impact and emission of air pollution on human beings and also discuss models using which air pollution inhalation can be associated to humans by quantifying personal exposure with the use of human activity detection. The overarching aim of this review is to provide novel and key ideas that have the potential to drive pervasive and individual centric and yet accurate pollution monitoring techniques which can scale up to the future needs.

S. Singla (✉) · D. Bansal
Punjab Engineering College, Chandigarh, India
e-mail: savina.singla@gmail.com

D. Bansal
e-mail: divya@pec.edu.in

A. Misra
Singapore Management University, Singapore, Singapore
e-mail: archanm@smu.edu.sg

G. Raheja
Indian Institute of Technology, Roorkee, India
e-mail: gr.iitroorkee@gmail.com

Introduction

Mobile sensing data, collected from personal devices such as smartphones, smartwatches, and other wearable platforms, is being increasingly used for a variety of applications, in domains such as personal wellness and transportation safety. In the area of health and wellness, the exposure to poor-quality air, containing a variety of harmful contaminants like carbon monoxide, particulate matter, sulfur dioxide, and nitrogen dioxide, has been identified as one of the key health hazards, especially in urban environments. Given the rapid proliferation of mobile devices, as well as the different types of advanced sensors being embedded in those devices, there is naturally high interest in exploring the feasibility of using a mobile sensing-based participatory paradigm to quantitatively define an individual's exposure to environmental pollution

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and air quality. Figure 1, illustrates the overall architecture of the sensor-based monitoring systems. Data is collected from the subjects using sensors, which in turn is transferred to the central server for analysis and visualization. At a high level, such a participatory mobile sensing paradigm contributes to the vision of pervasive, individual-centric pollution monitoring in two distinct ways:

(a) **Distributed pollution sensing**: Mobile devices, often augmented with special-purpose wearable environmental sensors, provide a way to sample the air quality parameters of a city (Wilhelm et al. 2016; Opensense II 2017; SensorsNews 2017). By tagging each sample with the mobile device's time-varying location tag (e.g., using GPS data for outdoor location estimation), the devices effectively provide a fine-grained spatiotemporal sampling of the city's environmental parameters. The key research challenge is to accurately extrapolate this spatiotemporally distributed non-uniform data samples, obtained from hundreds or thousands of heterogeneous devices, to build an accurate, fine-grained map of the true pollution levels across the city.

(b) **Fine-grained personal exposure sensing**: Besides environmental sensing, the sensors on mobile devices also help track physical world context of each individual, not just their location coordinates, but also their activities (such as running, walking, cycling, exercising). This physical context helps quantify the quantity of pollutants inhaled by an individual at different time instants. In particular, it is well known that the quantity of pollutants inhaled is driven not just by the user's location (i.e., the exposure to different pollution levels), but also by the user's activity (as the intensity of such activities affect the inhalation rate, and thus the quantity of contaminants ingested). The key research challenge is to recognize these activities, and then infer the resulting ventilation/inhalation rate, accurately which in turn will help us to measure the impact of poor air quality on health. Another research challenge which emerges from the above research is to overcome the noisy, often uncalibrated readings reported by the embedded heterogeneous sensors.

In this article, we review the existing studies in each of these independent domains and try to find relations between them, in order to come up with better and more valuable outcomes. Further, this paper is divided into five different sections. Types of pollutants and their impacts on human health are discussed in the "Types of environmental pollutants that need
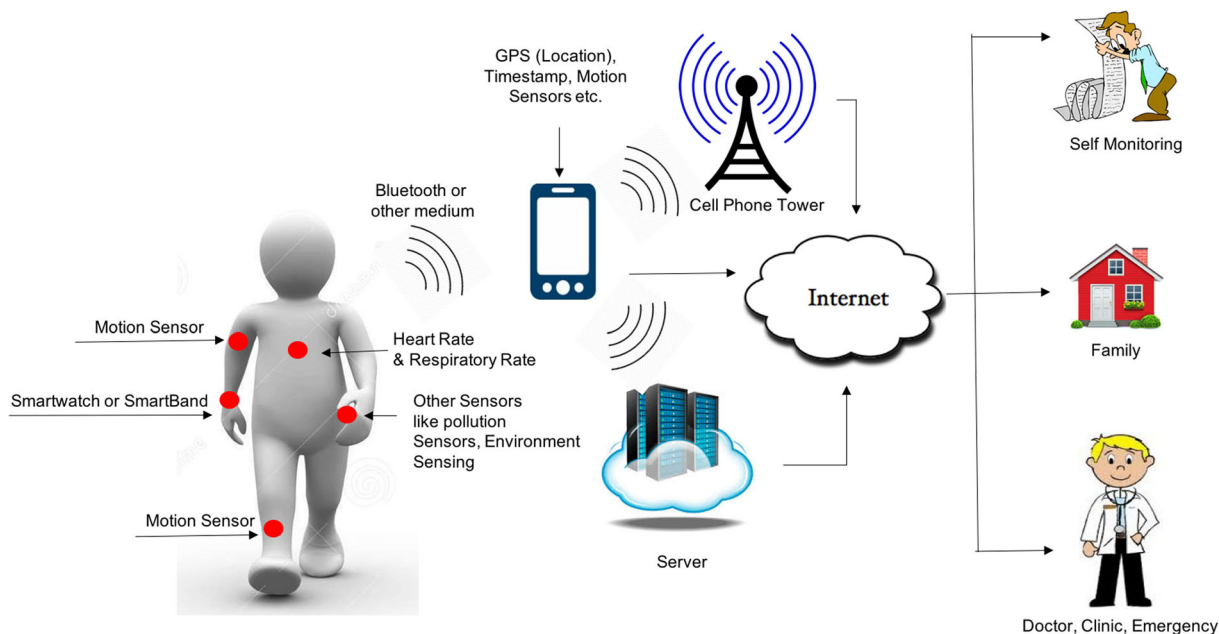
Fig. 1 Illustration of the sensor monitoring system

to be monitored" section. Different types of sensors and methods used for air quality monitoring, impact and exposure of an individual to air pollution, interpolation, and calibration techniques on collected data are discussed in detail in the "Mobile sensing-based pollution monitoring" section. Detailed analysis of activity recognition methods, their evaluation, and their importance in air quality monitoring is presented in the "Quantifying personal exposure" section followed by open problems and research directions in the area which are discussed in the "Open problems and research directions" section. Overall conclusion of the paper is presented in the "Conclusion" section.

Types of environmental pollutants that need to be monitored

Ambient air quality in a given urban scenario is a complex function of urban activity defined by urban land use, design, human density, environmental conditions like temperature variations, wind direction, and changing seasons, and level of real-time urban activity. It is vital to understand the impact of human health on urban population in short-term as well as long-term contexts. Air pollution imposes such a burden on human health and it is estimated that every year, millions of people die prematurely due to it (WHO 2018). Not only limiting to humans, air pollutants are equally harmful for plants and crops (Thomas 1961; Heagle et al. 1973; Kampa and Castanas 2008; Treshow 1984). According to the studies done by Manning and Godzik (2004), Rodriguez et al. (2010), and Klumpp et al. (1994), various plant species like *Alchemilla* sp., *Astrantia major* , *Centuarea nigra*, and *Centauria scabiosa* act as bioindicators for ozone and species like *Tillandsia capillaris* and *Lolium multiflorum* act as bioindicators for $PM_{2.5}$. Therefore, monitoring and controlling air pollution is very important and is also a well-recognized problem now. However, traditionally and even now, the study and analysis on air pollution is done based on the data provided by fixed air monitoring sites mostly established by the government. These analyses are based on the pollution data on city or suburb level and lack finer spatial resolution thereby ignoring the variations in air pollution at a diminutive level, i.e., on different neighborhood streets and roads. Therefore, this data cannot be used to draw any inferences based on an individual level.

Estimating the pollution level on individual basis becomes an important study especially when performed on various sensitive groups like small children, expecting mothers, and asthmatic patients. These estimates lead to a variety of important applications like lifestyle management, health checks, and early warnings.

With the advancing technology, the sensors capable of sensing the ambient air are becoming smaller and smaller that they can now be used as a wearable sensor. By exploiting this feature, several solutions have been proposed by different researchers all over the globe, so as to make this sensing more personal and effective. Variety of handheld sensors are these days available in the market. Classification of existing work based on static sensor network (SSN), community sensor network (CSN), and vehicle sensor network (VSN) has been done by Yi et al. (2015).

Rana et al. (2010) have used the audio sensors of mobile phone to create the noise pollution map. Studies reported by Faulkner et al. (2011) use the smartphone accelerometer to detect earthquakes and hence act as a potential application for disaster management using the sensory abilities of smartphones. We now present state-of-the-art research studies reported in the area of environmental monitoring.

Since different types of pollutants are emitted from different sources and deploying AQM (air quality monitoring) is expensive, it is very important to understand the characteristics of different types of pollutants and their impacts on human health. Understanding the ill effects of various pollutants and the source of their emission is also important because it gives the baseline to the whole study and can help urban planners to plan the cities accordingly. Studies reported by Kampa and Castanas (2008), Folinsbee (1993), Bernstein et al. (2004), and Brunekreef and Holgate (2002) discuss and state the ill effects of these pollutants on the human health. Major air pollutants which have been found as deterrent to human health are as follows:

– Carbon monoxide (CO): It is released when engines burn fossil fuels. It is also emitted from the vehicles, furnaces, and heaters. It makes harder for body parts to get oxygen, which is needed for them to function properly. It also makes people feel dizzy, tired, and have headache. It is very dangerous for the people with heart diseases (Stewart 1975).

- Nitrogen dioxide (NO_2): Power plants and cars are the main source of NO_2. It can give people cough and make them feel shortness of breath. If exposed to it for long periods of time, the chance of getting respiratory diseases increases. It also reacts in the atmosphere to form acid rain, which harms the plants and animals (Dawson and Schenker 1979), (SPEERS and UTELL 1991).

- Sulfur dioxide (SO_2): It mostly comes from burning of coal or oil in power plants. Factories that make chemicals, paper, or fuel are also responsible for emitting it. Like NO_2, SO_2 also forms acid rain when reacted. People who are suffering from diseases like asthma or emphysema are affected by making it difficult for them to breathe. It can also cause irritation in people's throat, nose, and eyes. It makes the environment hazy and makes it difficult to see long distances. It can harm trees, crops, and buildings (Frank 1964), Seaton et al. (1995). Ill effects of SO_2 on plants have been discussed in Thomas (1961)

- Particulate matter (PM): There are two types of PM which are commonly known as $PM_{2.5}$ (coarse particles) and PM_{10} (fine particles). Sources of coarse particles are road dust, construction, etc, whereas those of fine particles are fuels burnt in automobiles and power plants. They are so small that they can enter the lungs while breathing which leads to serious sickness like asthma attacks, respiratory problems, and premature deaths. A study performed by Tecer et al. (2008) reports adverse effects of particulate matter on the prevalence of respiratory diseases in children (Seaton et al. 1995).

- Ozone: Ozone is created indirectly, when nitrogen oxides mix with volatile organic compounds in sunlight. Nitrogen oxides mainly come from burning gasoline, coal, and other fossil fuels. Ozone near the ground can lead to more frequent asthma attacks to asthmatic patients and can cause sore throats, breathing difficulty, and cough. It also leads to premature deaths and hurts plants and crops (McDonnell et al. 1983).

As the main source of CO and NO_2 are vehicles and industries, the city authorities can plan the hospitals and schools away from the industrial areas and crowded places. Vehicle parking in these areas can be planned little far, so that it does not affect the sensitive groups like children and patients. SO_2 is mainly a product of industries, so an industrial area can be planned on outskirts of a city. Similarly, particulate matter can come from different sources and activities like construction, so they can be planned accordingly. But the challenge is to accurately monitor these pollutants in order to make effective policies and planning.

To regulate the pollutants, governments and organizations of different countries have put their limits, in order to understand their concentration and reduce health risks. Pollution regulatory authorities of different countries like the US Environmental Protection Agency (EPA), the World Health Organization (WHO), the Department for Environment Food and Rural Affairs of the UK, the European Commission (EC), Central Pollution Control Board (CPCB) of India, and the Chinese Ministry of Environmental Protection (MEP) have issued different limits for these pollutants which are tabulated in Table 1. Methods and

Table 1 Standards set by different regulatory authorities on common pollutants

Pollutants	CPCB	EPA	WHO	EC
$PM_{2.5}$ (annual mean)	40 μg/m^3	15 μg/m^3 (primary and secondary)	10 μg/m^3	25 μg/m^3
PM_{10} (annual mean)	60 μg/m^3		20 μg/m^3	40 μg/m^3
Carbon monoxide (8-h mean)	2 mg/m^3	9 ppm		10 mg/m^3
Nitrogen dioxide (annual mean)	40 μg/m^3	53 ppb	40 μg/m^3	40 μg/m^3
Sulphur dioxide (24-h mean)	80 μg/m^3	75 ppb (1 h)	20 μg/m^3	125 μg/m^3

India Standard (2017), EPA Standards (2017), WHO Standard (2017), and Europe Standard (2017)

sensors to monitor these pollutants are discussed in further sections of the paper.

Mobile sensing-based pollution monitoring

Traditionally, air pollution has been monitored and quantified by static monitoring stations, deployed at selected locations around a city. While these sensors are often carefully calibrated and usually quite accurate, they only provide a high-level overview of air quality level: they simply cannot be used to study the finer spatial and temporal variation in air quality across city neighborhoods, buildings, or campuses. A significant study done by Santamouris (2013) shows that environmental parameters, such as temperature and pollution, can vary substantially with even modest (a few meters) variation in location. Clearly, mobile sensing-based data can dramatically augment these sparse observations. However, the use of such mobile and portable sensors gives rise to two research challenges: (a) the cheaper embedded sensors on such personal devices are usually less accurate and subject to usage-based artifacts. As a result, there is a need to develop methods to filter out noisy data, i.e., correct the errors in reported data and (b) as the sensing process is driven by underlying human mobility, the sensing reports are non-uniformly generated in both space and time. Hence, there is a need to interpolate the data to accurately infer the "missing data samples."

We first start by discussing the different types of mobile sensors used in the existing studies or are available in the market in the following section.

Types of sensors used in mobile environmental monitoring

Many of the companies like Sensordrone (Sensor-drone 2018) and Variable Senors (Variable inc 2018), Alphasense (Alphasense 2016) are providing such commercial sensors. These are small handheld hardware sensors, which can also be connected to a smartphone via bluetooth as the communication interface. Thus, the ambient data collected from these sensors is transferred to a central data aggregation server using the communication interface of a smartphone. These mobile sensors then provide spatiotemporal environmental readings at a very fine granularity. Table 2 tabulates different sensors used by various research works under review. Brauer et al. (2015) have used the data obtained from satellites to estimate the air pollution. They have simulated the models by Goddard Earth Observing System (GEOS)-chem CTM (Chemical Transport Models). It is applied for a wide

Table 2 Sensors used for ambient air monitoring

Sensors	Study
SHT11 from Sensirion	Aram et al. (2012)
Estimation from satellites	Brauer et al. (2015)
Variable Technologies CO sensor	Devarakonda et al. (2013)
MQ-6 gas sensor	Sirsikar et al. (2015)
Self designed air quality measurement system	
GasMobile	Hasenfratz et al. (2012)
Self designed sensors	Honicky et al. (2008)
Variable Inc Node + Oxa sensors	Hu et al. (2014a)
Variable Inc Node + Oxa sensors and Wahoo heart rate monitor	Hu et al. (2014b)
Sensordrone	Jafari et al. (2015)
OpenSense system: the core of the measurement station is a	Li et al. (2012)
Gumstix embedded computer running the Linux operating system	
Smartphone camera	Liu et al. (2015)
Airveda sensors	Jain et al. (2018)

range of atmospheric composition problems (GEOS-chem 2017). As per the studies reported by Hasenfratz et al. (2012) and Honicky et al. (2008), sensors are ingeniously designed and developed by them in order to attain the pollution data. The camera of the smartphone has been used for capturing environmental images by Liu et al. (2015). To train the model, they use learning-based methods using series of photos and readings from the nearby stationary $PM_{2.5}$ sensor. In order to estimate the haze, they use degradation of the image, which can be observed from decreased image contrast. Linear least square regression is applied on the extracted features to obtain certain coefficients which are required to estimate the concentration of $PM_{2.5}$. USB pluggable ozone sensors for mobile phones have also been developed and used by Hasenfratz et al. (2012) for obtaining richer set of air quality data. A systematic review of portable and low-cost sensors for monitoring benzene and other volatile organic compounds (VOC) has been done by Spinelle et al. (2017). The US EPA also encourages the use of mobile low-cost sensors in order to monitor and cover more of the area (Snyder et al. 2013). They use Air Sensor Toolbox (Airsensortoolbox 2017) for citizen science projects.

It can be observed from Table 2 that portable sensors have been emerging and are being widely used by researchers in various research studies worldwide. Measurement methodology of these sensors is tabulated in Table 3. Detailed analysis and working methodology of portable and mobile sensors can be found in the study conducted by Yi et al. (2015) and Snyder et al. (2013). Companies like Sensordrone, Variableinc, and Airveda provide small portable as well as mobile sensors which are easy to carry and handle. These portable and mobile sensors are creating a larger space in the research area, where the environmental monitoring at a minute level is becoming possible. However, this new method of monitoring air quality opens up several research issues and challenges to be addressed which are discussed in the later parts of this paper.

Calibrating these low-cost sensors against the accurate methods is certainly needed in order to attain accurate solution (discussed in the "Review of calibration techniques of environmental sensors" section). Certain

Table 3 Measurement methods of existing mobile and portable sensors (Yi et al. 2015; Snyder et al. 2013)

Pollutant	Measurement method
$PM_{2.5}$, PM_{10}	Beta attenuation
	Light scattering
	Light obscuration
Carbon monoxide (CO)	IR absorption with gas filter
	Correlation wheel
	Electrochemical sensor
	Solid-state sensor
	Metal oxide semiconductor (MOS)
Nitrogen dioxide (NO_2)	Cavity-attenuated phase shift spectroscopy
	Electrochemical sensor
	Solid-state sensor
	MOS
Ozone (O_3)	Chemiluminescence detection
	Electrochemical sensor
	Solid-state sensor
	UV absorption
Sulphur dioxide (SO_2)	UV fluorescence
	Electrochemical sensor
	Solid-state sensor

Table 4 National ambient air quality standards for measuring air pollutants in different countries

Pollutants	Methods of measurement		
	India (CPCBIndia 2017)	Europe (EuroSensors 2017)	USA (EPASensors 2017)
$PM_{2.5}$, PM_{10}	Gravimetric	Gravimetric	Gravimetric
	TEOM (tapered element oscillating microbalance)	TEOM	
	Beta ray attenuation	Beta ray attenuation	Beta ray attenuation
Carbon monoxide (CO)	Non-dispersive infra red (NDIR) spectroscopy	NDIR	NDIR
Nitrogen dioxide (NO_2)	Modified Jacob and Hochheiser (MJH)	–	–
	Chemiluminescence	–	–
Sulphur dioxide (SO_2)	Improved West and Gaeke (IWG)	–	–
	Ultraviolet fluorescence	–	–

recommendations on what methods to use for measuring different pollutants are made by various agencies tabulated in Table 4. Detailed working of these methods can be found in CPCBIndia (2017).

Monitoring air quality and impacts of pollution

Importance of monitoring the air pollutants has been explained in the previous sections. As can be inferred from Table 5, the studies reviewed in this paper suggest some possible solutions to monitor one or more of the discussed pollutants and help in understanding their distribution at a finer level. Various types of air pollution monitoring systems are discussed and reviewed by Khot and Chitre (2017). Also, the methods used for estimating the inhalation of pollutants and monitoring air quality are discussed by Kaur et al. (2017a). To predict the industrial pollution by

Table 5 Major pollutants under study in different research works

Environmental factors		Study
Pollutants	Other factors	
✗	Temperature and humidity	Aram et al. (2012)
$PM_{2.5}$, Ozone	✗	Brauer et al. (2015)
CO	✗	Devarakonda et al. (2013)
NO_2	✗	Dewulf et al. (2016)
CO_2, NO_2, SO_2	Temperature	Sirsikar et al. (2015)
Ozone	Temperature, Humidity	Hasenfratz et al. (2012)
CO, NO_X, $PM_{2.5}$	Temperature, Accelerometer	Honicky et al. (2008)
CO	Temperature, Humidity	Hu et al. (2014a)
CO	✗	Hu et al. (2014b)
CO	Temperature, humidity, pressure	Jafari et al. (2015)
CO, PM, Ozone	Temperature, humidity	Li et al. (2012)
$PM_{2.5}$	✗	Liu et al. (2015)
$PM_{2.5}$, Carbon emissions	Temperature, relative humidity	Mun et al. (2009)
NO_2, $PM_{2.5}$	GPS	Ouidir et al. (2015)
$PM_{2.5}$, PM_{10}	GPS	Jain et al. (2018)

nonlinear auto regressive model (NARX)-based artificial neural network (ANN) is presented by Broderick et al. (2015). Carbon monoxide is found to be monitored in most of the studies (Devarakonda et al. 2013; Honicky et al. 2008; Hu et al. 2014a; Jafari et al. 2015; Li et al. 2012) followed by nitrogen dioxide in Dewulf et al. (2016), Honicky et al. (2008), and Ouidir et al. (2015) and sulphur dioxide in Sirsikar et al. (2015). Monitoring of particulate matter and ozone is done in Brauer et al. (2015), Hasenfratz et al. (2012), Li et al. (2012), Liu et al. (2015), Mun et al. (2009), and Ouidir et al. (2015). It is not mandatory that these pollutants are present only in the outdoor environments or the areas having more vehicular traffic, but they have also been prevalent in indoor environments as well. Studies reported by Lee and Chang (2000) were conducted in classrooms of a school in Hong Kong and experimental findings reported that level of particulate matter and carbon dioxide exceeded by 1000 μl/l and 1000 μg/m^3 respectively in indoor environment which indicated poor air quality and inadequate ventilation. A study conducted in Tokyo and Beijing (Ando et al. 1996) also reports that suspended particulate matter indoors was observed to be high as compared to that of outdoors. Major sources of indoor air pollution are found while performing certain activities such as smoking, frying, and smoky cooking as reported by Wallace et al. (2003). It has been observed that the concentration of particulate matter in houses primarily increases at meal times. Also, an idea of a route recommendation system is proposed in Singla et al. (2016) and Singla (2018).

Wen et al. (2013) have studied the trends of CO on a street in Taipei City. They deployed 44 sensor nodes, 40 transmitter nodes, and 4 gateway nodes in this study. To estimate human exposure, sensors were deployed at 1.5 m on the lampposts and traffic signs. They could find four CO concentration peaks throughout the day and also tried to provide street level insights into real-time monitoring. Six wireless multi sensor miniature nodes have been deployed by Moltchanov et al. (2015) in three urban sites which were about 150 m apart. Their network was able to capture spatiotemporal pollution data at a very fine resolution.

This makes clear that the fixed monitoring stations deployed by the government are inadequate in air quality monitoring and need more rigorous and intensive monitoring to actually estimate an individual person's exposure to air pollution and understand its impact on his/her health.

From the review of studies discussed in this as well as previous sections, it has been inferred that there is no shortage of environmental and sensor data to measure, and the challenge is what to do with all of the data.

A lot can be achieved with the collected environmental data and can be used to solve many problems related to lifestyle management based on various demographic groups. So, pollution data can be translated into two empirically verified metrics: *Impact* and *Exposure*.

Impact is the contribution made by an individual to air pollution, i.e., the impact of human activities on an environment. Normally, the impact is calculated when the person is detected to be in a vehicular state, as the vehicular pollution is one of the biggest causes of air pollution (Mordukhovich et al. 2016). *Exposure* to an air pollution is considered as the inhalation of polluted air. According to Ott (1982), exposure is when a pollutant comes into contact with physical boundary of a person. The following section reports existing studies which are focused on estimating impact and exposure of humans to pollution data.

Impact and emission of air pollution

To fully understand the exposure of an individual to the air pollution, there is a need to *estimate the emission*. Emission is normally observed when a person is commuting in a vehicle. Activity recognition plays an important role here to detect the vehicular mode. A study done by Zhang et al. (2016) estimates the vehicle emission under different traffic conditions. Motor Vehicle Emission Simulators (MOVES) (Moves 2016), COPERT (Copert 2016) are some of the models which estimate the emissions from vehicles. Rakha et al. (2003) compare the various emission models like MOBILE5a, MOBILE6, and VT-MICRO and have proposed a comprehensive modal emissions model (CMEM). These emission models have been frequently used for estimating vehicle emissions. MOVES is the latest emission model and estimates CO_2 based on the consumption estimation of fuel (Zhang et al. 2016). E-mission is another vehicle emission model developed by Shankari et al. (2015). Personal Environmental Impact Report (PIER) authored by Mun et al. (2009) estimates the carbon dioxide emissions when the activity is classified as driving.

Variations in exposure due to human activity

Urban-human impact studies shall be required to understand the degree to which a particular activity or use may be considered sensitive to air pollution, which is guided by the following factors (Spirn and Whiston 1986),viz:

– **Age and health of users**: Young children, the elderly, and people suffering from respiratory and cardiovascular diseases are normally vulnerable to air pollution.
– **Duration for which an activity is performed**: The longer an individual remains in a particular place, the more is the potential exposure to air pollution.
– **Frequency of using a place**: More frequently, the more a person uses the place, the greater is the potential cumulative exposure to air pollution.
– **Intensity of using a place**: If a place is used with high intensity, a greater number of individuals are exposed to air pollution.
– **Voluntary vs. involuntary use**: Necessary activities like using a bus stop, place of work, and schoolyard cannot be avoided and almost become mandatory in our daily lives.

Exposure, directly or indirectly, refers to the pollutants inhaled by an individual. So calculating the inhalation can give better estimation of exposure. Respiratory minute volume (RMV) is the inhaled volume of air into a person's lungs per minute. An algorithm has been proposed by Valli et al. (2013) to calculate the RMV from heart rate. A study done by Young et al. (2013) also calculates the RMV. The inhalation rate of a person varies with the human activity performed. The more vigorous the activity is performed, the higher is the inhalation. Therefore, it is important to first detect the activity performed by an individual, while estimating his/her exposure to air pollution. This brings the importance of activity recognition. Lots of work on human activity recognition using smartphone sensors have been done as discussed in the "Quantifying personal exposure" section. These methods can also be used for online activity recognition to correctly estimate the inhalation rate. Table 6 highlights different studies focusing on impact and exposure to air pollution considering the impact of human activity performed. Various classifiers like ZeroR, Naive Bayes, BayesNet, LibSVM, MLP, JRip, and J48 have

Table 6 Studies focusing on impact and exposure

Study	Impact	Exposure	Consideration of human activity
Mun et al. (2009)	✓	✓	✗
De Nazelle et al. (2012)		✓	✓
De Nazelle et al. (2012)	✗	✓	✓
Predić et al. (2013)	✗	✓	✓
Hu et al. (2014a)	✗	✓	✗
Hu et al. (2014b)	✗	✓	✓
Ouidir et al. (2015)	✗	✓	✗
Broderick et al. (2015)	✗	✓	✓
Dewulf et al. (2016)	✗	✓	✗
Zhang et al. (2016)	✓	✗	✗
Kaur et al. (2017b)	✗	✓	✓

been used by Hu et al. (2014a) to find the association between activity, location, and dosage. Another study reported by Hu et al. (2014b) estimates the maximum inhaled dosage while jogging, lesser while bicycling, and least while driving. Kaur et al. (2017b) have estimated the exposure of an individual to air pollution in different vehicular modes and while performing variety of activities . Their results show that the inhalation dosage increased by 78% for CO (carbon monoxide) and 28.41% for $PM_{2.5}$ (particulate matter with diameter less than 2.5μm), when a person switches his/her activity from walking to running. The PALM project for Environmental Protection Agency (EPA) (Broderick et al. 2015) investigates the activities and locations that contribute to the personal exposure. Panis et al. (2010) have compared exposure of cyclists and car passengers in Belgium. According to the authors, the main factors that affect exposure of cyclists to air pollution are found to be: (i) more and deep inhalation due to vigorous activity and (ii) longer time to complete the trip. Now that it has been found that use of mobile sensors is extremely important to find an individual's exposure to ambient air pollution and its impact on his or her health, it becomes very obvious that these mobile sensors are often heterogeneous w.r.t make/model/type of technology used. However, this throws another important challenge of calibrating these different types of sensors. In the next sections, we discuss the research studies focused around calibration of sensors.

Review of calibration techniques of environmental sensors

Despite their fast emergence, wearable and portable sensors are a nascent technology, which require in depth understanding for effective utilization.

Calibration of crowdsourced sensor data is an important step as the data is received from various sources and heterogeneous hardware. The importance of same is highlighted by Singla and Misra (2016) where the authors have crowdsourced barometric data and calibrated to improve the indoor location accuracy. As compared to the fixed air monitoring stations, the mobile handheld sensing units are not so accurate, and also quality of these sensors deteriorate over time affecting the accuracy primarily due to the accumulation of dust particles. So these sensors need to be calibrated with high-end-fixed air quality monitors which are otherwise expensive in order to ensure higher levels of accuracy from mobile sensors. Various research groups have performed calibration of the handheld sensors. Data from $PM_{2.5}$ sensor has been calibrated by Brauer et al. (2015) through the developed calibration models. N-SMARTS and commonSense projects by Honicky et al. (2008) also address the questions, as how to automatically calibrate the sensors w.r.t. other sensors (mobile or fixed). The models used are Gaussian process based.

To calibrate the traditional gas sensors, neural networks-based methods have been used by Kamionka et al. (2006). In these studies, real gas concentration has been compared with the one sensed by the traditional sensor in order to make it more accurate. Talampas and Low (2012) have used the maximum likelihood approach to calibrate the low-cost mobile sensors with the highly accurate fixed pollution sensors. The mobile sensors used in this work are mounted on vehicles thereby making vehicular sensor network which are capable of communicating to each other forming adhoc networks. Calibration of low-cost portable particle sensor is done with Alphasense OPC-N2 optical air quality monitoring sensor and Dylos DC1100 Pro Air Quality Monitor using linear compensation by Hojaiji et al. (2017). Tsujita et al. (2004) have compared the results in various conditions varying the temperature and humidity level.

So calibration is often done using two common methods. One is to calibrate in the laboratory using different gas mixtures and second is by placing the sensor next to high-quality reference station. The second one looks more feasible and convenient because the sensitivity analysis of both the sensors can be done in different environments and climatic conditions without the requirement of any laboratory setup. It is also beneficial because the environment while calibrating and actual deployment remains similar without any major difference.

Spatiotemporal interpolation of environmental data

Spatiotemporal interpolation of data collected from sensors needs to be done to be able to construct new data points within the range of known data points. This is required to estimate the spatial distribution of pollution with sufficient accuracy. A study in this direction has been conducted in Japan in which regression Kriging was applied (Araki et al. 2015). The performance was accessed using root mean square error (RMSE) and R^2, which was calculated by applying leave out one cross validation. Kriging has been applied in the New York City for estimating the spatial pattern of intraurban pollution variation by Matte et al. (2013). Evaluation of interpolation techniques like inverse distance weighted (IDW) and Kriging is presented by Jha et al. (2011), where the study has been conducted in Port Blair India on various pollutants like suspended particulate matter (SPM), sulphur dioxide (SO_2), and nitrogen dioxide (NO_2). Kim et al. (2014) have also carried out ordinary Kriging for spatial interpolation with monitored air quality in Korean cities.

It is observed that Kriging helds to be well suited for spatiotemporal data and is used in most of the studies.

Mobile sensors-based air pollution monitoring systems

It is now evident from the review of existing studies that there are numerous possibilities of having large number of applications of the environment monitoring. Jafari et al. (2015) propose a wide range of applications from civil to military. Their work can be exploited by fire fighters and in smart buildings to optimize the usage of various resources.

Aram et al. (2012) have proposed an approach which is useful for monitoring climatic conditions in small spaces such as laboratories and home rooms, which can trigger alarms in certain severe conditions.

Marker maps and heat maps of the city have been used by Devarakonda et al. (2013) to help users gain better understanding of the city pollution level at a minute level. Opensense (Aberer et al. 2010) aims to study the feasibility of installing sensors on public transport and cabs, taking advantage of their regular commute cycles distributed over the entire city. Pollution sensing network has also been tested on buses by Al-Ali et al. (2010). Air Quality Egg (Air Quality Egg 2016) has also introduced a personal pollution sensing system. The study conducted in University of California by Solomon et al. (2001) highlights the health hazards on school children, due to the exposure to diesel pollutants found by monitoring the school bus. An interesting study by Doraiswamy et al. (2005) has been done to estimate the concentration of air pollutants inside and outside the truck cabs.

Another study has been done by Ouidir et al. (2015), where the exposure to air pollution, both indoors and outdoors, is estimated for 40 pregnant women in Grenoble. A detailed study has been done to find the effects of pollution in all the three trimesters of pregnancy. PALM Broderick et al. (2015) developed a modeling technique for the evaluation of personal exposure, indoors and outdoors.

After an extensive review of these studies, it has been concluded that it is very important to consider and estimate the distribution of pollution, which in turn results in accurately estimating the human exposures. Fine-grained pollution data collected over time is a key to understand the impact and exposure to ambient air pollution. Mobile sensors play an important role in achieving the same. Calibrating low-cost mobile sensors and finding out methods and efficient models (capable to integrate mobile sensors with fixed infrastructure) can give this research a completely new direction. For modeling the inhalation patterns, the activity performed by an individual plays an important role. Various activity recognition techniques have been reviewed and discussed in the next section. These methods can be integrated in the already presented systems for achieving better accuracy.

Looking at the future directions and potential applications, there seems to be immense opportunities covering out which can extremely penetrate civic authorities and urban planners. Cities should be planned accordingly taking into account the sources of air pollution. Buildings which comprise of sensitive groups like schools, hospitals, and old age centers should be planned where the pollution is likely to be less, for example, away from the industrial area and the areas with dense traffic. Incentivization to citizens and organizations who encourage the use of public infrastructure such as buses and trains at non peak hours can be introduced.

Evaluation

Both advantages and disadvantages are tagged with these types of mobile sensors-based participatory systems.

Advantages

1. Such systems are cost-efficient.
2. Very high and diminutive coverage of the city.
3. More personalized as coupled with individuals.
4. Crowd management and studies possible as metadata can be achieved from smartphones used by such systems.
5. Increased mobility.
6. Fault tolerance (if one sensor gets faulty, it will not effect the system)

Disadvantages

1. Low accuracy.
2. Constraints on computational power, weight, and size of sensors.
3. Can lead to compromised privacy of individuals
4. Effective calibration techniques required and calibration to be done time to time.

Quantifying personal exposure

There are various physical activities performed by an individual in a daily life. An individual's daily schedule comprises some daily physical activities like walking, running, sitting, climbing up and down the stairs, gyming, vaccuming, reading a book, brushing, eating, and drinking. The ability to recognize these activities automatically through sensors has led to a contribution of various new applications such as fitness, healthcare, and old age care. In this section, we discuss the methods and techniques used which can be used to recognize the physical activities performed by a person in detail. This gives an opportunity to integrate such solutions with air quality monitoring systems in

Table 7 Classification of activities

Activity class	Activities
Locomotive activities	Walking, standing, climbing stairs up, climbing stairs down, running, jogging, GAIT analysis, etc.
Gestures	Eating with spoon, brushing, switching button, opening door, drinking, chewing, swallowing, etc.

order to have personalized inhalation models used to determine impact of pollution on individual's health.

Presently, wearable motion sensors were used to recognize the user activities. But these days, with the increasing availability of various inertial sensors in smartphones and smartwatches, the solution area has started revolving around them. As the mobile phones earlier were limited with resources, computation power, and battery, the classification and recognition was done centrally. Smartphones are becoming self-sufficient in terms of computing power and resources, so the researchers have shifted their focus towards providing the online classification-based solutions on local devices. Various techniques and research done in the area of online activity recognition have been well described by Shoaib et al. (2015). Evolution of technology for estimating personal exposure to air pollution is discussed by Larkin and Hystad (2017).

Work in relating activity/breathing rate to exposure impact

Different studies focusing on impact and exposure to air pollution considering the human activity performed are tabulated in Table 6. Various classifiers like ZeroR, Naive Bayes, BayesNet, LibSVM, MLP, JRip, and J48 are used by Hu et al. (2014a) to find the association between activity, location, and dosage. Another study done by Hu et al. (2014b) estimates the maximum inhaled dosage while jogging, lesser while bicycling, and least while driving. The PALM project of Environmental Protection Agency (EPA) (Broderick et al. 2015) investigates the activities and locations that contribute to the personal exposure. To better understand the interaction between physical activity and exposure to air pollution, Greenwald et al. (2016) have tried to quantify the change of ventilation rate due to activity . They found a two-predictor model using heart rate and breathing rate of a person. But in this work, only walking and running of school students are considered. Authors have used chest strap to collect the heart rate of the subjects. Inhalation dosage was calculated for two students while playing soccer in the playground. They estimated different inhalation dosages for sprinter and soccer player based on their demographics and heart rate. Larkin and Hystad (2017) have reviewed various research works in the area of pollution monitoring and modeling and how they can be transformed to estimate the health impacts. ExposureSense Predić et al. (2013) uses ozone (O_3) pluggable sensors to collect mobile participatory data through smartphones and estimate human exposure to pollution by monitoring daily activities of the people.

Work in physical activity context monitoring

To quantify an individual's exposure, the activity being performed during exposure becomes a very important factor. These activities have been classified into two categories for the review purpose: (i) locomotive activities and (ii) gestures. Locomotive activities comprise of the activities which lead to any motion of the body. Normally, these activities are performed by the lower part of the human body whereas the gestures are expressions performed by the upper body like the hands and face which can be seen in Table 7. More

Table 8 Sensors used for activity recognition

Activity class	Smartphone	Smartwatch	Others
Locomotive activities	Accelerometer, gyroscope, magnetometer, GPS	Accelerometer	Inertial sensors on the calf and leg
Gestures	Accelerometer, gyroscope, magnetometer	Accelerometer, gyroscope	Inertial sensors on arms, ear microphone, stethoscope, electromyogram (EMG)

Table 9 Research done in locomotive activity recognition

Activities detected	Sensors used	Features	Accuracy	Reference
Dancing, climbing stairs down, climbing stairs up, slow-walk, running, fast walk	Smartphone sensors: triaxial accelerometer in the android phone Smartwatch sensors: NA other sensors: NA	Time dom: Mean along z-axis, MinMax, STD and RMS for A_m, APF (Average Peak Frequency) along x-axis, y-axis and z-axis, VarAPF, STD along x-axis, y-axis and z-axis, RMS along x-axis, y-axis and z-axis, Correlation between z-axis and y-axis, and MinMax along x-axis, y-axis and z-axis Freq Dom: NA	91.15%	Bayat et al. (2014)
Walking, jogging, climbing stairs, sitting, and standing	Smartphone sensors: accelerometer Smartwatch sensors: NA Other sensors: NA	Time Dom: Average, Stdev (each axis), average absolute difference, average resultant acceleration, time between peaks, binned distribution Freq Dom: NA	91.7% through Multilayer Perceptron	Kwapisz et al. (2011)
Standing, walking, running, stairs up, stairs down, vaccuming, brushing, situps	Smartphone sensors: NA Smartwatch sensors: other Sensors: accelerometer, which can transfer data to phone via bluetooth	Time Dom: Mean, Stdev, correlation Freq Dom: Energy	Through plurality voting close to 99%	Ravi et al. (2005)
Running, walking, biking, standing and sitting	Smartphone sensors: accelerometer, magnetometer, gyroscope Smartwatch sensors: NA other Sensors: NA	Time Dom: mean, variance and Stdev from sum square of three acceleration components and auto correlation based features Freq Dom: FFT	With linear acceleration: 93%, and with Earth's coordinates: 97%	Ustev et al. (2013)
Running, volleyball, handball, basketball, futsal	Smartphone sensors: accelerometer Smartwatch sensors: NA Other Sensors: NA	Time Dom: average acceleration, standard deviation, minimum and maximum for each axis; average acceleration magnitude (norm of the acceleration vector), minimum and maximum magnitude for all three axes Freq Dom: NA	–	(Costa et al. 2016)
Walking, jogging, sitting, lying, standing, walking upstairs and walking downstairs	Smartphone sensors: sccelerometer Smartwatch sensors: NA Other sensors: NA	61 time-domain features	96.68% with Random Forest, Window size 5, sampling rate 80	Ama et al. (2016)
Idle, sitting, standing, walking, going up the stairs, going down the stairs, running and cycling	Smartphone sensors: accelerometer Smartwatch sensors: NA Other sensors: NA	Both frequency and time domain features are used	82.40% and 91.22% for the J48 and the SVM	Bisio et al. (2014)

Table 9 (continued)

Activities detected	Sensors used	Features	Accuracy	Reference
Stationary, walking, running, bicycling, ascending stairs, descending stairs, driving	Smartphone sensors: accelerometer Smartwatch sensors: NA Other sensors: NA	Time dom: raw values of three axes, and acceleration magnitude Freq dom: NA	F score: 0.9967 for cross validation	Wang et al. (2015)
Walking, running, standing, sitting, lying, walking upstairs and walking downstairs	Smartphone sensors: accelerometer Smartwatch sensors: NA Other sensors: NA	Features are self extracted as deep neural networks are used		Zhang et al. (2015)

F.D Features: Frequency Domain Features, T.D Features: Time Domain Features

vigorous are these activities during the exposure (to air pollution), and more is the impact on health (Table 8).

1. **Locomotive activities:** As discussed above, the locomotive activities are the activities which lead to the motion of body and are normally performed by the lower parts. These include walking, jogging, running, and climbing stairs up and down. A lot of research is being done on detecting these types of activities automatically by using different types of sensors. Table 9 highlights the work done in detecting locomotive activities by various people in different parts of the world.

   Accelerometer of smartphone has been used extensively to detect activities like walking, jogging, ascending stairs up, descending stairs down, and sitting (Kwapisz et al. 2011; Costa et al. 2016; Ama et al. 2016; Bisio et al. 2014; Wang et al. 2015; Zhang et al. 2015).

2. **Gestures:** Gestures are mainly performed by upper parts of the body. Automatic recognition systems which can recognize the gestures are being created on a competitive scale. Table 10 highlights the work done in gesture recognition using sensors. Wearable devices like smartwatches and smartbands equipped with sensors like accelerometer, gyroscopes, and magnetometers are heavily used for recognizing such activities. Vigorous activities performed by upper body parts like gyming, weight lifting, and exercises using shoulders can be recognized with the help of gesture recognition techniques.

   Table 8 tabulates the sensors which have been used in existing research studies to detect different types of activities discussed above.

These kinds of techniques have also given rise to several other important applications like (i) automatic diet monitoring (Amft et al. 2005; Amft and Tröster 2008, 2009; Sen et al. 2015), (ii) supermarket-based solutions (Radhakrishnan et al. 2016), (iii) lifestyle management (Sen et al. 2016; Wiese et al. 2013), and (iv) daily activity tracking.

Open problems and research directions

We performed an extensive review of research studies in the field of air pollution monitoring and activity recognition using different types of sensors. We tried

Table 10 Research done in gesture recognition

Activities detected	Sensors used	Features	Accuracy	Reference
Arm gestures: cutlery, spoon, with hands, drinking	Smartphone sensors: NA; Smartwatch sensors: NA; Other sensors: Inertial sensors on arm	Time dom: segment length, number of motion segments, begin and end of lower arm rotation, rate of turn of lower arm rotation and pitch orientations; Freq dom: NA	87% to 94%	Amft et al. (2005)
Intake gestures, chewing, and swallowing	Smartphone sensors: NA; Smartwatch sensors: NA; Other sensors: commercial motion sensors (www.xsens.com) in a jacket	Time dom: temporal features from arm acceleration sensors; Freq dom: NA	94%	Amft and Tröster (2009)
Arm movements, chewing and swallowing	Smartphone sensors: NA; Smartwatch sensors: NA; Other sensors: Inertial sensors (Manufacturer: XSens, model: MTi): acceleration sensors, gyroscopes (rate of turn) and compass sensors (magnetic field), Ear microphone, stethoscope microphone, electromyogram (EMG)	T.D features were used; Freq dom: NA	Movement: 75 to 82%, Chewing recognition: 85 to 87%, Swallowing recognition: 75%	Amft and Tröster (2008)
Picking and identification of items from a supermarket	Smartphone sensors: NA; Smatwatch sensors: accelerometer, gyroscope and camera of a smartwatch. Infrastructure sensors: BLE beacons	Time Dom: Mean, Magnitude, Variance and CoVariance; Freq Dom: Energy, FFT, Entropy	Picking gesture: 94%, Shelf detection: 85%, which item: 61%	Radhakrishnan et al. (2016)
Arm gestures	Smartphone sensors: NA; Smartwatch sensors: NA; Other sensors: Inertial sensors on lower and upper arms	Time Dom: Pitch and roll angles of lower and upper arms. Derivative and cumulative sum of the acceleration signal and rate of turn from lower arm sensor; Freq Dom: NA	97.4%	Junker et al. (2008)
27 upper body postures like rotation of trunk bending, lifting shoulders, arm postures etc.	Smartphone sensors: NA; Smartwatch sensors: NA; Other sensors: Thermoplastic elastomer strain sensor was used for measuring strain in the clothing	Time Dom: Mean sensor value; Freq Dom: NA	84% for an all-user classification and 65% for an inde- pendent user	Mattmann et al. (2007)
Where do people prefer keeping phones, throughout the day: front or back trouser pocket, jacket or shirt pocket, bag, table, car, in hand etc.	Smartphone sensors: accelerometer, light & proximity, capacitive sensing; Smartwatch sensors: NA; Other sensors: NA	Time Dom: Mean, Variance, RMS, Interquartile range 25%, 50%, 75% quartiles, The sum of detail coefficients across 5 wavelet levels; Freq Dom: NA	Combination of accelerometer and light proximity sensor achieved accuracy of 85% for In Bag, In pocket, out or in Hand	Wiese et al. (2013)

Table 10 (continued)

Activities detected	Sensors used	Accuracy	Features	Reference
Detecting playing foosball, break determination, role in the game	Smartphone sensors: NA Smartwatch sensors: accelerometer and gyroscope data Other sensors: NA	95%	Time Dom: Mean, variance, covariance Freq Dom: Energy, Entropy	Sen et al. (2016)
Eating with hand, eating using spoon, eating with chopsticks, estimating number of hand to mouth actions	Smartphone sensors: NA Smartwatch sensors: accelerometer and gyroscope Other sensors: NA	Person-independent models-97%, for identifying eating vs. non-eating,spoon vs. chopstick vs. hands: 85.51%. 90.74% for person-specific models	Time Dom: Accel & Gyro mean, Accel & gyro variance, accel & gyro covariance, accel and gyro correlation, duration of gesture Freq Dom: NA	Sen et al. (2015)
Which door was used, had person entered or left the room, how many people entered the room, who used the door	Smartphone sensors: accelerometer Smartwatch sensors: accelerometer Other sensors: Door-mounted Raspberry Pi, Estimote (BLE) Beacons	person transited a door: 100%, detecting switch press cases: 82.1%, multiple gestures: 91.7%	Frequency and Time domain features were used	Vigneshwaran et al. (2015)

Time dom: time domain features, Freq dom: frequency domain Features

to join the strings between these two distinct research areas and came out with strong relationship between them. We try to propose an integrated system, where these distinct research areas can be made to work cohesively in order to achieve a better system.

We identified several gaps and challenges which have been stated below:

1. **Joint estimation models for calibration and interpolation of data:** Separate work has been done on calibrating low-cost sensors and estimating the missing pollution data via several interpolation techniques. Joint frameworks need to be developed in order to achieve the fully integrated system which uses potential of low-cost mobile sensors and provide data with finer granularity.

2. **Better planning and sensing for improved coverage:** It has been found that site selection for placement of sensors has not been done formally. Better models and parameters can be defined on how to make such selection. Such studies can help the governments and administrations to do better planning and hence make correct decisions w.r.t scientific outcomes from investments being made and drafting policies.

3. **In-depth study on exposure and impact:** To accurately estimate the individual's exposure and impact, activity recognition needs to be considered. There are several open problems identified in this domain too. We found that it is difficult to compare results of all the studies as they have been performed on different experimental setups. As can be observed from state-of-the-art studies, each study is found to be using different datasets, different classifiers, and different methods. We observe that most of the studies done in the domain of air pollution monitoring lack scientific evaluation. It is shown that studies in which multiple sensors have been integrated, individual contribution of the sensors has not been evaluated in terms of resource consumption.

Many research studies do not consider important metrics like sampling rate, size of dataset, duration of training, and other performance evaluation metrics which form an important aspect and need high consideration. This severely affects the accuracy and efficiency of systems. It is also important to test systems on uniform experimental setups. This helps in correct evaluation of the system.

4. **Improved routing algorithms for exposure minimization:** Mobile sensors for AQM are deployed at a much wider scale. This large-scale finer data can be very useful for finding air quality-friendly routes which are not only based on expected commute time but also consider air quality as a metric. In deploying such like applications, integration of routing algorithms, air quality monitoring systems along with calibration and interpolation, becomes a major challenge. Designing such systems will be a very useful contribution to the current navigation systems which are only based on traffic flow and time. It will be a new era of navigation systems where the users will be able to adapt the green and healthy routes.

5. **A step to create standardized datasets:** As of now, there is no standardized dataset on air pollution and activity recognition, to the best of our knowledge. Researchers collect their own data to come up with results and models. In order to evaluate and validate these models with each other, some standardized datasets are needed. This problem can be solved, if the researchers make their data available to others working in the same field.

6. **Data processing challenges:** Complex and powerful data processing approaches are required for the estimation of personal air pollution exposures, modeling of air pollution concentrations, and characterization of the contextual characteristics relevant to air pollution and health research as data is received through the integration of smartphone and air monitoring data streams.

7. **Association between exposure estimation and epidemiological research:** This gives an opportunity for a multi-disciplinary research in order to come out with new preventive measures using the collaboration of exposure estimation and epidemiology. Currently, the environment is not considered as a major factor or even a factor while treating patients for various diseases.

Based on the discussions and open challenges, we propose three modules to be integrated in the upcoming personalized air quality monitoring systems which can be seen in Fig. 2. In order to estimate personal exposure of an individual, it is advisable to make use of mobile sensors as they have an ability to cover large city space giving an advantage of mobility. Calibration of such sensors w.r.t high-end-fixed sensors is vital in order to attain accuracy in results. This is very important as such applications also focus on sensitive groups like small children and patients with cardiovascular and respiratory problems. As already discussed, that in order to quantify personal exposure, activity performed by a person is a crucial factor to be considered. So appropriate activity recognition models can be built or used for the same.

Conclusion

In this paper, we have reviewed the existing studies in monitoring air pollution and physical activity recognition using sensors. We studied several ways of using environmental data, which lead to personalized sensing with which various critical applications like urban lifestyle management, early warnings to sensitive groups like children, pregnant women, and patients with respiratory diseases can be implemented. Wearable devices/sensors are being developed at breathtaking speed. The range of physical attributes and context aware sensing that such sensors can monitor accurately and efficiently, in real time, is continually expanding. In this study, we have also presented empirically verifiable metrics like impact and exposure to air pollution of an individual, which

Fig. 2 Major components of proposed integrated system
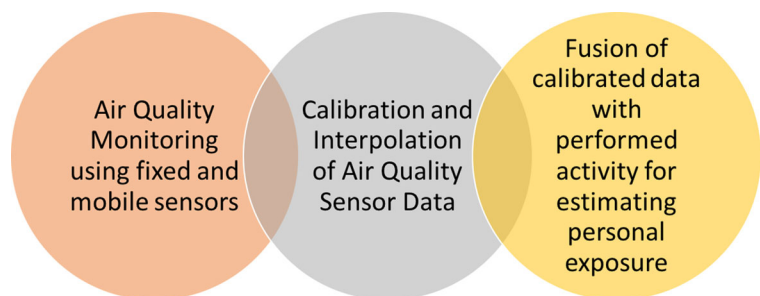
can help in personal realization and aid in recommending changes in our day-to-day activities. We have also presented the correlations and models which can map the effect of the physical activities performed by a person to degree of inhalation dosage of air pollution. We observed that recognition of physical activities is an important module in personalized air monitoring systems. In this paper, we also review in detail the research done in physical activity recognition. Through this study, we have presented potential use of smart sensors and technologies which can help transform the urban landscape from infrastructure to environment and use of citizen centric mobile applications, which can give personal recommendations based upon personal health, demographics, and air pollution. Thus, we presented vision and motivations for use of different kinds of environmental sensors, application domains with new approaches in defining them, crowdsensing realization and challenges, open challenges, and future trends in crowdsensing environmental monitoring. The overarching goal is to develop technical solutions leading to Plug n Play sensors/devices, which can be deployed in any environment in an interoperable framework. Moreover, we have also emphasized on the use of mobile sensors in contrast to fixed air monitors in order to increase the spatial coverage of the cities both indoors and outdoors.

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