# Image-Based Air Quality Estimation*

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**Abstract.** In this paper, we attempt to estimate the outdoor air quality only using images. To address this problem, we mainly collect an available database of high quality outdoor images. We hope this database will encourage further research on image based air quality estimation. Moreover, we perform comprehensive experiments based on this database. We use different hand-crafted features to analyze the appearance variances of outdoor images in different air quality conditions. Results show that the accuracy of meteorological features is much better than that of traditional hand-crafted features. Moreover, in meteorological features, the extinction coefficient indicating the degree of light intensity attenuated by particles performs best with the accuracy of 64.

**Keywords:** Air Quality Estimation · Image Database · Hand-Crafted Features.

## 1 Introduction

The China economy has grown at a fantastic speed recently. The fast development in economy greatly increases the stress on the environment protection. Air pollution is a serious environmental issue that is attracting increasing attention globally. Particulate matters like PM2.5, PM10, and NO2, represent air pollutants that can be inhaled via nasal passages to the throat and even the lungs. Long-term exposure to air pollutants increase the incidence of associated disease in humans. Therefore, it is important to awake the whole society by the air quality estimation to work together in controlling the air pollution.

## 2 Related Work

To estimate fine-grained, city-wide air quality with limited monitoring stations, there has been much existing literature from several research fields.

Some researchers employ theoretical meteorological emissions models [11] [15] for pollutant discharge simulation [35] [16] [3]. [5] proposed a CMAQ model to simulate PM2.5 formation and its response to precursor emission reductions, which could be used to design effective emissions control strategies for regulatory applications. [26] proposed a WRF-CHEM model to simulate the meteorological model and air quality,

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which is a fully coupled online model that enables air quality simulations at the same time as the meteorological model runs, improving its potential for operational forecasts. However, the simulation processes suffer from unreliable pollutant emission data and incomplete theoretical foundations, which leads to low estimation accuracy.

Some researchers adopt statistical methods in a data-driven manner. Artificial neural networks(ANNs) [4] [7], multiple linear regression [17], and support vector regression [23] [27] [12] are commonly used for air quality prediction. Considering the high spatial correlations between different air quality stations, spatiotemporal prediction models have been considered, like the spatiotemporal artificial neural network (STANN) [22], the spatiotemporal support vector regression (STSVR) models [8] and the spatiotemporal stacked autoencoder model [19].

Recently, many studies have focused on air quality estimation via spatiotemporal (ST) heterogeneous urban big data, which refers to the data sets containing spatial, temporal, and category information [34] [6] [13] [9]. The basic assumption is that air quality is considerably influenced by these urban dynamics (e.g., wind, vehicular traffic, and point of interest (POI)). By analyzing the temporal dependency and spatial correlation between urban dynamics data, such as meteorology and traffic, air quality at locations which are not covered by monitoring stations can be estimated. However, These works achieve good results at the cost of time consumption on the complex algorithms. Moreover, the massive sensing data used in these works are difficult to obtain.

With the development of computer vision, use of the outdoor camera is of great interest. Despite the remarkable value, only a few studies have focused on air quality estimation based on image data. Z Zhang et al. constructed an image database of two view sites, and extract several image features as the robust representation for air quality prediction. By using machine learning methods, they learned an adaptive classifier for air quality estimation [33] [32]. H Q Wang et al. chose a view site to collect scene images by a camera. They analyzed a relationship between the concentration of PM2.5 and the degradation of observed images [30]. C. B. Liu et. al built a database of outdoor images available for Beijing, Shanghai and Phoenix. They fused image features and other relevant data, such as the position of the sun, date, time, geographic information and weather conditions, to predict PM2.5 [20]. Y. B. Zhang et. al proposed a haze image database and record the related weather and air quality information at a view site in Hefei [31]. Based on this database, they proposed a novel no-reference image quality assessment (IQA) method for haze images.

## 3 Our Database

In this paper, we present a database of high quality images in different outdoor scenes, captured regularly for a period of 5 years. The database is called Visual Air Quality Index Database(VAQI-1).

VAQI-1 contains 7649 images in total, which come from 85 different view sites in 26 cities in China. The distribution of view cities is shown in Figure 1. VAQI-1 is a comprehensive collection of images under a wide variety of air quality. We adopt the air quality index (AQI) as the ground truth data. AQI is a guideline for reporting air quality, and is divided into six levels indicating the increasing air pollutant concentration (in

| AQI values | Air Pollution level | Colors | Descriptions |
|---|---|---|---|
| 0-50 | I | Green | No air pollution |
| 51-100 | II | Yellow | Air quality is good while a few contaminants exist |
| 101-150 | III | Orange | Concentrations of contaminants increase. |
| 151-200 | IV | Red | Slight irritations may occur. |
| 201-300 | V | Purple | Irritations further deteriorates. |
| 301-500 | VI | Maroon | There may be strong irritations and symptoms. |

**Table 1.** AQI values, Air pollution levels, colors and Descriptions.


**Fig. 1.** Distribution of view cities in China

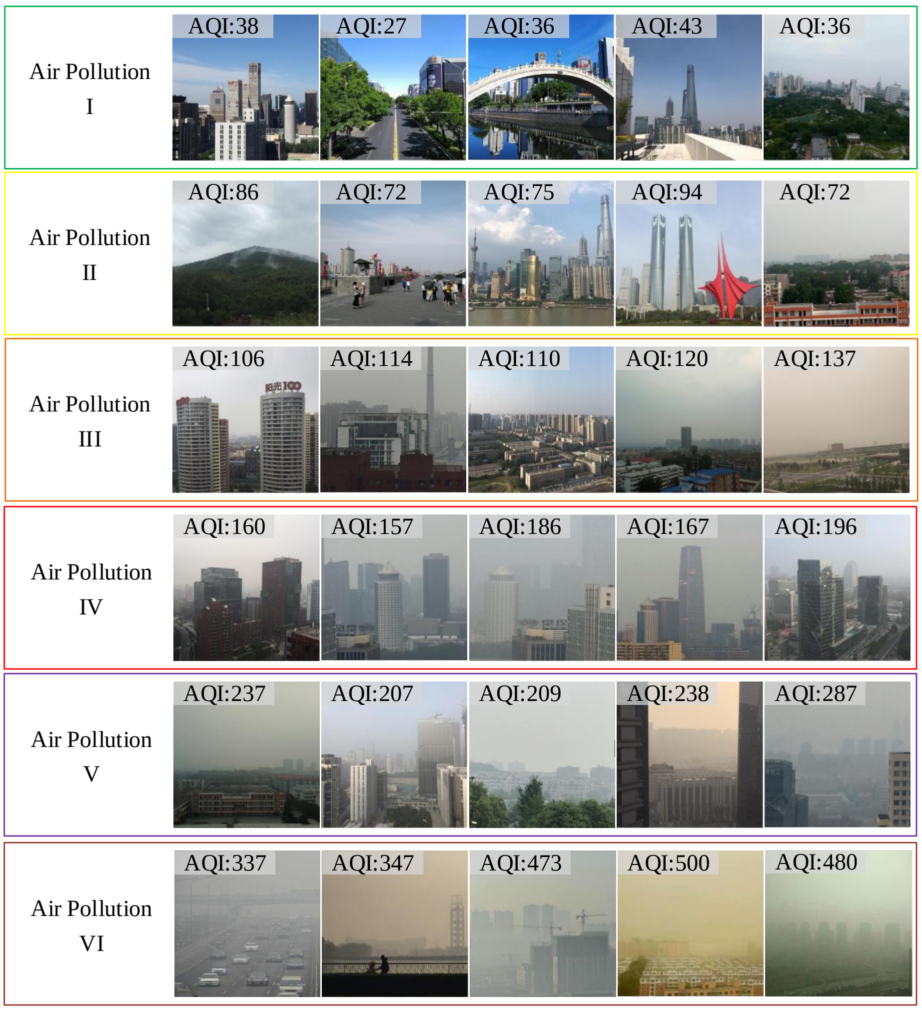


**Fig. 2.** Example scene images of VAQI-1

| Air Quality Category | Number of Outdoor Images |
|---|---|
| Excellent | 2219 |
| Good | 2031 |
| Lightly Polluted | 1161 |
| Moderately Polluted | 706 |
| Heavily Polluted | 831 |
| Severely Polluted | 701 |

**Table 2.** Statistic numbers of outdoor images in VAQI-1.

Table 1). The statistic numbers of VAQI at six air pollution levels are shown in Table 2. Figure 2 shows example outdoor images at different air pollution levels.

### 3.1 Collection and Annotation

Images of VAQI come from two sources. The first one is an environmental protection project, named Yi Mu Liao Ran [2]. Zou Yi, an organizer of this project, takes an identical photo of a specific site every day by using a smart phone camera and records the corresponding AQI values. He selects the view sites near air quality monitoring stations, which ensures the the accuracy of AQI values. With the increase of this project's influence, people from other cities start to follow him. They use smart phone cameras to take photos of specific sites, and send their photos along with AQI values to this project. There have been 5315 outdoor images from 31 view sites in 17 cities. This project has become the main source of VAQI.

The second one is MJ weather [1], which is a free weather information query software. It offers a public platform where people can upload real-time images taken by smart phone cameras along with the location and time of photo taking. The corresponding AQI value is obtained from the nearest air quality monitoring station. We select images with the time strictly coinciding with the update time of the nearest monitoring station. We select 9 major cities with serious air pollution. There have been 2334 outdoor images from 54 view sites in these cities, which enlarges the quantity and enriches the site diversity of VAQI.

### 3.2 Appearance

Outdoor scene appearance is greatly affected by characteristics of atmosphere pollutants like PM10, SO2, NO2 and O3. The characteristics include species, size and concentration. Figure 3 shows the example view site appearances with different AQI values in VAQI-1. With the increase of concentrations on large-scale atmosphere pollutants, the air quality is getting worse, which leads to variances of image features like contrast, transmission, saturation. These features are the main references to air quality estimation.


**Fig. 3.** Example view site appearances with different AQI values

Water droplets in the air also have an influence on scene appearance, like fog scenes. Appearances of fog is similar with haze. However, unlike the atmosphere pollutants, concentration on water droplets does not affect the air quality. The AQI values of foggy images are always less than 50. Figure 4 shows a comparison of fog and haze appearances. As can be seen, the color of fog is more vivid than haze, and the fog has clearer boundaries. Despite such differences, there is no effective method to distinguish fog and haze based on scene images, which makes the image based air quality estimation more challenging.

### 3.3 Diversity

1)*Site Diversity*: In real life, varieties of air quality occur in any type of sites (e.g., highway, city, farm, nature scene and so on). With the aim to estimate the exact air quality anywhere, we collect outdoor images from almost all types of sites, which provides a wide estimating range of view sites. However, appearances of different sites at the same AQI will have a huge distinction, which also pushes a limit of visual estimation abilities for both human and computers.
2)*Visual Angle Diversity*: The visual angle is the angle a viewed object subtends at the camera, which includes high angle, flat angle and low angle. The high-angle photography technology is utilized in general outdoor surveillance, which employs the camera look down on a distant viewed object from a high angle. However, there are a lot of outdoor images taken from flat angle and low angle in real life. In general, images from


**Fig. 4.** Example scene appearances of fog and haze with AQI values. [red box] foggy scene appearances. [green box] haze scene appearances.

low angle weaken the visual effects of scene imaging, which will affect the visual analysis of air quality(see red box in Figure 5). Similar, short-distance images also show the incomplete atmosphere information of scenes(see green box in Figure 5). VAQI-1 contains a certain number of such images, which not only enriches the visual angle diversity, but also increases the difficulty of air quality estimation.

We compare VAQI-1 with existing outdoor air quality databases (see Table 3). As can be seen, VAQI-1 expands both the database size and the number of view sites. Only VAQI-1 is publicly available. Moreover, we will constantly update and maintain VAQI-1 for a long term with the aim to encourage further research on image based on air quality estimation.

## 4 Image Based Air Quality Estimation

In this section, we attempt to estimate the air quality based on the VAQI-1. Note that the scene appearances with adjacent AQI values are almost the same, which brings difficulty to AQI estimation based on images. Moreover, the diversity of scene and visual angle further increases the estimation difficulty. According to the air pollution level, we divide VAQI-1 into six classes, and then the air quality estimation becomes a six-class classification of air pollution levels. We randomly select half images from each class as the training set and the rest as testing set.

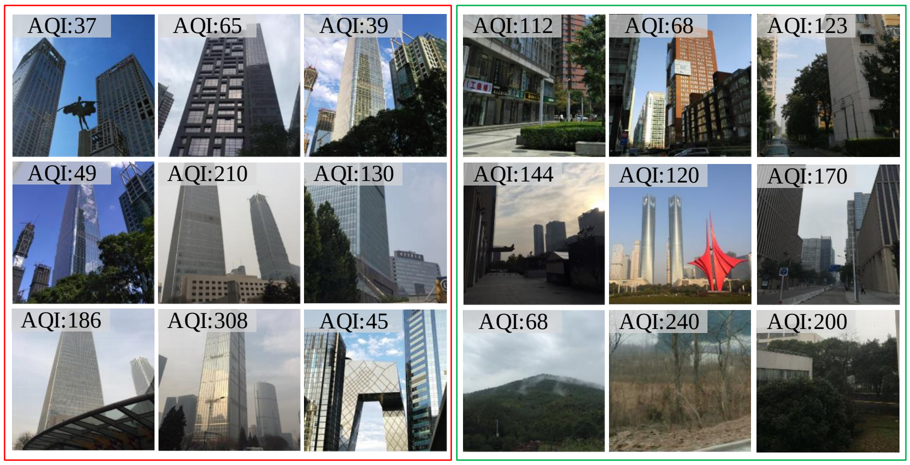


**Fig. 5.** Example images of low angle and near distance in VAQI-1. [red box] images of low angle. [green box] images of near distance.

| Database | Number of view sites | Number of Outdoor Images | Collection Period |
|---|---|---|---|
| OAQIS in [33] | 2 | 2000 | 2014 |
| Database in [30] | 1 | $<$500 | 2013-2014 |
| Database in [31] | 1 | 287 | 2014 |
| Database in [20] | 3 | 6587 | 2014-2016 |
| VAQI-1 | 75 | 7649 | 2014-Now |

**Table 3.** Statistics of databases for image-based air quality estimation.

In traditional image classification tasks, the mainly used hand-crafted features are SIFT [10], HOG [29], LBP [29] and color histogram. We attempt to use these features for air quality estimation. Moreover, by analyzing the visual and spectral clues related to the air quality, we also extract several meteorological features:

1)*Medium transmission*: Medium transmission indicates the degree of light intensity attenuated because of the particulate matter scattering. Based on He et al. [14], we compute the dark channel values of each image, and combine the scene imaging model to calculate medium transmission.

2)*Extinction Coefficient*: Extinction coefficient indicates the scattering degree of the particles in the atmosphere. We compute the value of extinction coefficient based on [18] [25].

3)*Contrast*: Contrast indicates the atmospheric clarity. Outdoor images captured in clear and haze days exhibit different global and local contrast. We compute the contrast according to Root Mean Square (RMS) [24].

4)*Sky Color*: Sky is the most important cue for weather labeling. A clear sky is blue as air molecules scatter blue light more than other light. Pollution particles scatter long-wavelength light, which makes sky look gray or yellow. We detect the sky region in an image with the method suggested in [21] [28]. Then, we extract A and B channels in the LAB color space of the sky region to form a feature vector.

We employ these hand-crafted features and utilize LIBSVM to evaluate their performance based on VAQI-1(see Table 3). As can be seen, the accuracy of SIFT, HOG, LBP and color histogram, for air quality estimation is quite low, which shows that the traditional hand-crafted features can not describe the air quality. On the other hand, the accuracy of meteorological features is much better than that of traditional hand-crafted features. However, the sky color is easily effected by the presence of clouds, as the clouds are made of tiny water droplets, making sky look gray or white. Although medium transmission and contrast perform better than sky color, these two features are determined by both the atmospheric clarity and the distance between the objects and the visual sensors, which can not accurately indicate the air quality like extinction coefficient. Extinction coefficient performs best with the accuracy 64%, which shows that this feature gives the best description of air quality.

## 5 Conclusion

In this paper, we attempt to solve a challenging problem: How to estimate outdoor air quality only using outdoor images? The absence of public database is a barrier to solve this problem. Therefore, we build an available database of high quality outdoor images in different view sites, which is labeled by AQI values. To the best of our knowledge, this database is currently the largest for image based air quality estimation. Based on this database, we perform comprehensive experiments by using different hand-crafted features including the traditional features and meteorological features respectively to analyze the appearance variances of outdoor images in different air quality conditions. The results show that the accuracy of meteorological features is much better than that of traditional hand-crafted features. Moreover, in meteorological features, the extinction

| Num | Feature | Accuracy |
|---|---|---|
| 1 | SIFT | 0.06 |
| 2 | HOG | 0.15 |
| 3 | LBP | 0.19 |
| 4 | Color Histogram | 0.20 |
| 5 | Sky Color | 0.45 |
| 6 | Contrast | 0.52 |
| 7 | Medium Transmission | 0.57 |
| 8 | Extinction Coefficient | 0.64 |

**Table 4.** The accuracy of air pollution level classification with different hand-crafted features.

coefficient indicating the degree of light intensity attenuated by particles performs best with the accuracy of 64%.

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