Photo-Based Monitoring of Particulate Matter in the Campus: A New Strategy for Student Health

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Abstract. It is imperative for the students’ future health to ensure the students in good physical levels. Recent years have witnessed the increasingly serious harm to student health caused by the continually growing concentration of Particulate Matters (PMs). Consequently, the task of preventing and controlling PM concentrations in the campus is eagerly required. A well-designed model for the monitoring of PM (as the basis for PM prevention and control) has posed a big challenge. Prior works have revealed that photo-based methods are available for the monitoring of PM. Towards validating the effectiveness of existing methods for PM monitoring in the campus, we construct a novel dataset that involves 1,500 photos collected in the Beijing University of Technology. Results confirm that state-of-the-art methods are far from ideal for the monitoring of PM in the campus. To solve the aforesaid issue, this paper further proposes a novel photo-based PM monitoring model by using the weighted average method solved by LASSO regression to fuse the above methods’ outputs tested to infer the PM values. Results demonstrate the superiority of our proposed model as compared to state-of-the-art methods on the large-scale AQPDBJUT dataset.

1. Introduction

Recent years have witnessed the extreme growth of Particulate Matter (PM), leading to an increasing amount of atmospheric environment pollution [1]. PM has become one of the most important factors which affect people’s health. It is worth noting that high-concentration PM does potential and permanent harm to student health [2, 3]. Feizabad et al. [2] found that the concentration of PM shows a positive association with vitamin D deficiency and a negative association with bone turnover, which indicates that the bones of students who live in a high-concentration PM area for a long time grow much more slowly than their peers. Gauderman et al. [3] showed that the high-concentration PM is associated with the impairment of lung function between the ages of 10 and 18. As seen, it is urgent to control PM concentration through the real-time PM monitoring data, towards ensuring student health. Relevant researches have received wide concerns from the public during the past few years [4-12].

To create a good living environment for students, we studied the characteristics of PM monitoring in the campus. Combined with prior studies, it was found that there is a correlation between PM...
concentration and photos [11, 13]. For a future investigation, we establish a new dataset that consists of 1,500 photos taken in the Beijing University of Technology. We called it the AQPDBJUT dataset. The performance of nine state-of-the-art [14, 15] are examined. Experiments show that their performances are not well. To this end, we further propose a new photo-based monitoring model which applies the weighted average method solved based on the LASSO regression to integrate the outputs of those testing state-of-the-art methods (including contrast, blurriness and natural scene statistics).

2. Dataset
The AQPDBJUT dataset is composed of a total number of 1,500 photos of resolution 4,032 \( \times \) 3,024. Different from the existing datasets, the photos in the AQPDBJUT dataset were just taken in the Beijing University of Technology (BJUT) as shown in figure 1. The equipment used is Canon EOS 500D, a single-lens reflex camera as shown in figure 2. In this dataset, the photos were captured in different seasons and times over the past three years. It has the characteristics of strong coverage, high definition, etc. Specifically, these photos contain relatively limited scenes, mainly including teaching buildings, playgrounds, trails, and so forth, around student life trajectory. We appropriately increased the number of photos in the locations which is the high-frequency sites for student’s outdoor life. This makes the AQPDBJUT dataset more suitable for PM monitoring in the campus.

A professional PM monitoring device called ‘XHAQSN-808’ has been equipped in the campus of Beijing University of Technology. Its detailed parameters are illustrated in figure 3. Base on that device, the more accurate and real-time monitoring data can be obtained to assign the photos. So, the photos in the AQPDBJUT dataset can better reflect the situation of students exposed to high-concentrations PM. According to the statistics of our monitoring device, the real-time monitoring of PM concentration in the AQPDBJUT dataset span up to 0-350 \( \mu g/m^3 \).

![Typical photos in the AQPDBJUT dataset](image)

**Figure 1.** Typical photos in the AQPDBJUT dataset: (a) Science building; (b) Olympic stadium-badminton hall; (c) College of economic and management; (d) Back of playground.
Figure 2. The configuration of Canon EOS 500D single-lens reflex camera.

Figure 3. Sensor-based real-time PM monitoring equipment ‘XHAQSN-808’.

3. Methodology

We propose a photo-based PM monitoring model. To specify, we first extract nine features from a given photo, which are the outputs of nine state-of-the-art or state-of-the-art photo quality models. Those photo quality models include NIQMC [16], BIQME [15], FISH [17], FISHBB [17], ARISM [18], NIQE [19], ASIQE [20], PPC [14], and GSWD [13]. Then, we combine those above nine features with weighted average method. The nine weights used in the weighted average method are resolved with the LASSO regression. Such regression makes some weights tend to be zero. The expectation of using such regression is not only for finding weights, but also for reducing dimensionality of features (i.e. removing redundant features). The loss function of LASSO regression is computed by

\[ J(\beta) = \frac{1}{n} \sum_{i=1}^{n} (y_i - X_i \beta)^2 + \lambda \| \beta \|_1 = \text{ESS}(\beta) + \lambda \sum_{j=1}^{p} |\beta_j| \]  

(1)

where \( \lambda \| \beta \|_1 \) is the penalty item; \( \text{ESS}(\beta) \) represents the error sum of squares, as expressed as follows

\[ \text{ESS}(\beta) = \sum_{i=1}^{n} \left( y_i - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 \]  

(2)

Then, we take the derivative on \( \beta_j \) in the target function, and controlling for the other \( p-1 \) parameters unchanged.
\begin{equation}
\beta_j = \begin{cases} 
(m_j - \frac{\lambda}{2}/n_j), & \text{if } m_j > \frac{\lambda}{2} \\
0, & \text{if } m_j \in [-\frac{\lambda}{2}, \frac{\lambda}{2}] \\
(m_j + \frac{\lambda}{2}/n_j), & \text{if } m_j < \frac{\lambda}{2} 
\end{cases}
\end{equation}

where \( \beta_j \) and \( m_j \) represent the \( j \)-th component of the \( \beta \).

4. Experiment

We calculated the performance of the proposed model and nine state-of-the-art or state-of-the-art models on the AQPDBJUT dataset. We choose three typical criteria to evaluate the model's monitoring performance, including the Root Mean Square Error (RMSE), the Normalized Mean Gross Error (NMGE), and the error-sensitive Peak Signal to Noise Ratio (PSNR). A good model is expected to obtain low values in RMSE and NMGE, but high value in PSNR. The result of the above ten models are shown in table 1. It is not difficult to find from the table that the model we proposed has obtained the best performance. Compared with the second-place GSWD model and the third-place FISHBB model, our model has achieved a gain of 0.426% and 3.82% in the PM\(_{10}\) concentration. In the PM\(_{2.5}\) concentration, the gains of our model are 1.13% and 6.87% as compared with the second-place FISHBB model and the third-place FISH model, respectively. This means that the proposed model can effectively decrease the weight of some features which are less relevant to PM. Thus, our model can increase the accuracy of the final regression and better monitor the PM concentration in the university campus.

| Model  | PM\(_{10}\) RMSE | PM\(_{10}\) NMGE | PM\(_{10}\) PSNR |
|--------|------------------|------------------|------------------|
| NIQMC  | 79.294           | 0.9201           | 10.146           |
| BIQME  | 82.810           | 0.9907           | 9.7691           |
| FISH   | 75.195           | 0.8269           | 10.607           |
| FISHBB | 69.732           | **0.7069**       | 11.262           |
| ARISM  | 81.147           | 0.9581           | 9.9454           |
| NIQE   | 80.400           | 0.9447           | 10.026           |
| ASIQE  | 82.664           | 0.9880           | 9.7845           |
| PPC    | 135.78           | 1.8529           | 5.4739           |
| GSWD   | 66.609           | 0.7525           | 11.660           |
| Prop.  | **66.225**       | 0.7374           | **11.710**       |

| Model  | PM\(_{2.5}\) RMSE | PM\(_{2.5}\) NMGE | PM\(_{2.5}\) PSNR |
|--------|------------------|------------------|------------------|
| NIQMC  | 53.658           | 0.8812           | 13.538           |
| BIQME  | 57.023           | 0.9862           | 13.009           |
| FISH   | 49.997           | 0.7446           | 14.151           |
| FISHBB | 45.219           | 0.6305           | 15.024           |
| ARISM  | 77.133           | 0.9604           | 10.386           |
| NIQE   | 54.666           | 0.9178           | 13.376           |
| ASIQE  | 56.880           | 0.9821           | 13.031           |
| PPC    | 150.96           | 3.1456           | 4.5530           |
| GSWD   | 68.646           | 1.1204           | 11.398           |
| Prop.  | **44.334**       | **0.7254**       | **15.196**       |
5. Conclusion
With the rapid development of economic, more and more attention has been concentrated on student’s health. However, at present, the monitoring system of PM concentration in the campus is still lower, which seriously affects the following governance and prevention. Experiment shows that the performance of nine state-of-the-art methods is not ideal. In order to facilitate PM monitoring, we first established a new dataset called AQPDBJUT, in which all the photos were captured in the Beijing University of Technology. To solve the aforesaid issue, this paper further proposes a novel photo-based PM monitoring model by using the weighted average method solved by LASSO regression to fuse the above methods’ outputs tested to infer the PM values. Through this simple monitoring model, the campus information network can timely obtain the real-time changes of PM, and timely make the corresponding prevention and control, which providing a new solution for the campus air pollution.

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