AQPDBJUT Dataset: Picture-Based PM Monitoring in the Campus of BJUT

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Abstract. Ensuring the students in good physical levels is imperative for their future health. In recent years, the continually growing concentration of Particulate Matter (PM) has done increasingly serious harm to student health. Hence, it is highly required to prevent and control PM concentrations in the campus. As the source of PM prevention and control, developing a good model for PM monitoring is extremely urgent and has posed a big challenge. It has been found in prior works that photo-based methods are available for PM monitoring. To verify the effectiveness of existing PM monitoring methods in the campus, we establish a new dataset which includes 1,500 photos collected in the Beijing University of Technology. Experiments show that stated-of-the-art methods are far from ideal for PM monitoring in the campus.

1. Introduction

Recent years have witnessed the extreme growth of Particulate Matter (PM), leading to an increasing amount of atmospheric environment pollution \cite{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 \cite{2,3}. In \cite{2}, Feizabad \textit{et al.} 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. In \cite{3}, Gauderman \textit{et al.} 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 \cite{4-9}.

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
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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.

a correlation between PM concentration and photos [10]-[12]. 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 [11]-[18] are examined. Experiments show that their performances are not well.

2. Dataset

The AQPDBJUT dataset is composed of a total number of 1,500 photos of resolution 4,032×3,024. Different from the existing datasets, the photos in the AQPDBJUT dataset were just taken in the Beijing University of Technology (BJUT). The equipment used is Canon EOS 500D, a single-lens reflex camera as shown in Fig. 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 are the high-frequency sites for student’s outdoor life. This makes the AQPDBJUT dataset more suitable for PM monitoring in the campus.
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Figure 2. The configuration of Canon EOS 500D single-lens reflex camera.

| Model of Camera          | Canon EOS 500D/Canon Rebel TL/Canon Kiss X3 |
|--------------------------|---------------------------------------------|
| The Camera Type          | Canon EOS DSLR                               |
| Photosensitive Element   | CMOS 22.3×14.9 mm                            |
| Pixel                    | 1.510 megapixel 4,752 x 3,168 pixels (jpeg)  |
| Lens System              | Canon EF ring lens, Canon EF-S ring lens     |
| SAFOX VIII                | TTL-CT-SIR, CMOS Inductor                    |
| Focus Mode               | One-Shot, Predictive AI Servo, Switching Auto Focus |

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

| Instrument Model | XHAQSN-808 |
|------------------|------------|
| Monitoring Parameter of XHAQSN-808 | PM2.5, PM10, SO2, NO2, CO, O3, temperature, humidity |
| Temporal Resolution | 10S         |
| Power Supply      | 220V, 12V   |
| Boundary Dimension | 220×220×300 |
| Work Environment  | T(-20~60)°C, RH(15%~95%) |
| Communication Mode | GPRS, WiFi, Bluetooth |
| Battery           | Lead-acid battery |
| Working Hours     | 240h        |
| Weight            | 2.4Kg       |
| Storage Environment | 0°C~50°C, <90%RH |

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 Fig. 2. Based 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 spans up to 0-350 $\mu g/m^3$.

3. Experiment

We calculated the performance of nine 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). The photos quality methods include NIQMC [17], BIQME [18], FISH [14], FISHBB [14], ARISM [13], NIQE [16], ASIQE [15], PPPC [11], and GSWD [12]. 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 will be presented in the next section.
Table 1. Comparison of PM$_{2.5}$ concentrations between nine state-of-the-art methods on the AQPDBJUT dataset.

| PM$_{2.5}$ | RMSE  | NMGE  | 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|
| PPPC     | 150.96| 3.1456| 4.5530|
| GSWD     | 68.646| 1.1204| 11.398|

models are shown in Table 1. It is not difficult to find from the table that the model FISHBB has obtained the best performance in the PM$_{2.5}$ concentration.

4. Conclusion

With the rapid development of economic, more and more attention has been concentrated on students health. However, at present, the monitoring system of PM concentration in the campus is still lower, which seriously affects the following governance and prevention. 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. Then, we selected nine state-of-the-art models to make an experiment. Experiment shows that nine state-of-the-art methods are not perfect in the AQPDBJUT dataset and cannot accurately monitor the PM concentration in the campus.

5. Reference

[1] H. Zhang, S. Wang, J. Hao, X. Wang, S. Wang, F. Chai, and M. Li, “Air pollution and control action in Beijing,” Journal of Cleaner Production, vol. 122, pp. 1519-1527, Jan. 2016.
[2] E. Feizabad, A. Hossein-nezhad, Z. Maghbooli, M. Ramezani, R. Hashemian, and S. Moattari, “Impact of air pollution on vitamin D deficiency and bone health in adolescents,” Archives of Osteoporosis, Apr. 2017.
[3] W. J. Gauderman, E. Avol, F. Gilliland, H. Vora, D. Thomas, K. Berhane, R. McConnell, N. Kuenzli, F. Lurmann, E. Rappaport, H. Margolis, D. Bates, and J. Peters, “The effect of air pollution on lung development from 10 to 18 years of age,” The New England Journal of Medicine, Set. 2004.
[4] K. Gu, J. Qiao, and W. Lin, “Recurrent air quality predictor based on meteorology- and pollution-related factors,” IEEE Trans. Industrial Informatics, vol. 14, no. 9, pp. 3946-3955, Sept. 2018.
[5] K. Gu, Z. Xia, and J. Qiao, “Stacked selective ensemble for PM$_{2.5}$ forecast,” IEEE Trans. Instrumentation and Measurement, vol. 69, no. 3, pp. 660-671, Mar. 2020.
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[6] M. Liu, K. Gu, and J. Qiao, “Convolutional neural network for smoke image super-resolution,” *Proceedings of the 2nd International Conference on Computer Science and Application Engineering*, Oct. 2018.

[7] K. Gu, Z. Xia, J. Qiao, and W. Lin, “Deep dual-channel neural network for image-based smoke detection,” *IEEE Trans. Multimedia*, vol. 22, no. 2, pp. 311-323, Feb. 2020.

[8] K. Gu, S. Wang, G. Zhai, W. Lin, X. Yang, and W. Zhang, “Analysis of distortion distribution for pooling in image quality prediction,” *IEEE Trans. Broadcasting*, vol. 62, no. 2, pp. 446-456, Jun. 2016.

[9] K. Gu, L. Li, H. Lu, X. Min, and W. Lin, “A fast reliable image quality predictor by fusing micro- and macro-structures,” *IEEE Trans. Industrial Electronics*, vol. 64, no. 5, pp. 3903-3912, May 2017.

[10] C. Liu, F. Tsow, Y. Zou, and N. Tao, “Particle pollution estimation based on image analysis,” *PloS one*, vol. 11, no. 2, pp. e0145955, 2016.

[11] K. Gu, J. Qiao, and X. Li, “Highly efficient picture-based prediction of PM2.5 concentration,” *IEEE Trans. Industrial Electronics*, vol. 66, no. 4, pp. 3176-3184, Apr. 2019.

[12] G. Yue, K. Gu, and J. Qiao, “Effective and efficient photo-based PM$_{2.5}$ concentration estimation,” *IEEE Trans. Instrumentation and Measurement*, vol. 68, no. 10, pp. 3962-3971, Oct. 2019.

[13] K. Gu, G. Zhai, W. Lin, X. Yang, and W. Zhang, “No-reference image sharpness assessment in autoregressive parameter space,” *IEEE Trans. Image Processing*, vol. 24, no. 10, pp. 3218-3231, Oct. 2015.

[14] P. V. Vu and D. M. Chandler, “A fast wavelet-based algorithm for global and local image sharpness estimation,” *IEEE Signal Processing Letters*, vol. 19, no. 7, pp. 423-426, Jul. 2012.

[15] K. Gu, J. Zhou, J. Qiao, G. Zhai, W. Lin, and A. C. Bovik, “No-reference quality assessment of screen content pictures,” *IEEE Trans. Image Process.*, vol. 26, no. 8, pp. 4005-4018, Aug. 2017.

[16] A. Mittal, R. Soundararajan, and A. C. Bovik, “Making a ‘completely blind’ image quality analyzer,” *IEEE Signal Processing Letters*, vol. 20, no. 3, pp. 209-212, Mar. 2013.

[17] K. Gu, W. Lin, G. Zhai, X. Yang, W. Zhang, and C. W. Chen, “No-reference quality metric of contrast-distorted images based on information maximization,” *IEEE Trans. Cybernetics*, vol. 47, no. 12, pp. 4559-4565, Dec. 2017.

[18] K. Gu, D. Tao, J. Qiao, and W. Lin, “Learning a no-reference quality assessment model of enhanced images with big data,” *IEEE Trans. Neural Networks and Learning Systems*, vol. 29, no. 4, pp. 1301-1313, Apr. 2018.