A robust photo-based PM$_{2.5}$ monitoring method by combining linear and non-linear learning

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Abstract
Good health is pursued by people all over the world. However, the continual industrialisation has led to more and more atmospheric contamination, and PM$_{2.5}$ has caused serious harm to our life safety and living environment. Without increasing the cost of sustainable industrial production, more and more attention has been paid to the related researches on improving PM$_{2.5}$ monitoring, prevention and control level. Therefore, it is extremely urgent to establish a robust PM$_{2.5}$ monitoring model that can adapt to a variety of scenarios, not only in local places like campuses but also in wide area like city. Existing work has proven that PM$_{2.5}$ monitoring can be achieved by means of photos. But experiments show that the stated-of-the-art methods are far from ideal for PM$_{2.5}$ monitoring when the author tested the performance in two public datasets. To solve the aforesaid issue, this paper ulteriorly proposes a novel photo-based PM$_{2.5}$ monitoring model, which fuses the results of existing methods by firstly using the weighted average based on the least absolute shrinkage and selection operator regression for learning the basic linear component, secondly using the support vector regression for learning the non-linear residual component, and finally incorporating the above two outputs to infer the final PM$_{2.5}$ concentration.

The main contributions and innovations of this paper are embodied in: (1) the innovative use of image quality assessment model to extract 9 features for PM$_{2.5}$ monitoring, (2) separately extract macro information and micro information from PM$_{2.5}$ pictures, (3) two newly-established large-scaled datasets are applied to verify the effectiveness and robustness of the proposed PM$_{2.5}$ monitoring model. Experiments show that on the latest PM$_{2.5}$ datasets (local and wide), the proposed model has achieved high performance and demonstrated strong robustness.

1 INTRODUCTION

Environment contamination has received more attention along with the industrialization and economic globalisation. In all of the environment contaminations, atmospheric pollution is observed the most easily by ordinary people. It may be the reason that such cases tend to be the hottest baidu or Google search in recent years, when PM$_{2.5}$ pollution levels were literally off the charts [1–5]. A lot of researches have indicated that high-concentration PM does potential and permanent harm to our bodies [6–12]. [6] showed that PMs, including PM$_{2.5}$, are one of the most critical reasons causing lung cancer. In [7], Feizabad et al. gave the finding that the concentration of PM has a positive association with vitamin D deficiency and a negative association with bone turnover, which explained that students living in a high-concentration PM area for a long time grow much more slowly than their peers. In [8], Gauderman et al. showed that the high-concentration PM may be associated with the injury of lung function of juveniles between the ages of 10 and 18. In [9], outdoor air pollution, including ozone and fine particulate matter PM$_{2.5}$, may negatively impact human health and be rated to take charge of 5% to 10% of the total annual premature mortality in the contiguous United States. In [10], the exposure to high-level of PM$_{2.5}$ perhaps illustrates the disproportional risk
of T2D concerning obesity in Asian populations. In [17], PM$_{2.5}$ in ambient air pollution may motivate the innate immune system in chronic allergic disease. During the past few years, researchers have given wide concerns about environment contaminations especially PM$_{2.5}$ [13–22].

Existing researches on PM$_{2.5}$ are mainly in three aspects. (1) The first type is the danger of PM$_{2.5}$, as stated above. (2) The second type is the cause analysis of PM$_{2.5}$ [23–26]. In [23], the correlation of PM$_{2.5}$ and PM$_{10}$ pollution was explored by combining with the spatial location and industrial allocation of the study area, and it was revealed that they were significantly correlated and maybe came from the same type pollution sources. In [24], Liu analyzed a heavy air pollution episode from November 6th to 10th in Shenyang, in which the highest hourly PM$_{2.5}$ concentration was 1326 μg/m$^3$, creating a new record in Shenyang. By combining with HYSPLIT backward trajectory model, Liu employed data of various pollutants concentration and meteorological observation, and explored that the human factor, the meteorological condition, the pressure field during the haze episode, and straw burning for large range had a certain impact on regional pollution. In [25], C. S. Liang et al. reviewed source appointment, including the composition and sources of PM$_{2.5}$ in different countries in the six inhabitable continents based on the best available results. Besides, the authors summarised PM$_{2.5}$ pollution countermeasures by policy, planning, technology and ideology. In [26], the results showed that during winter-time (November through February in the next year) PM$_{2.5}$ concentrations exceeding the 24h National Air Quality Standard (35 μg/m$^3$) occurred under calm wind, extremely low temperature (≤ 20°C) and moisture (water-vapour pressure < 2 hPa) multi-day surface-inversion conditions that trap the pollutants in the breathing level and inhibit transport of polluted air out of Fairbanks. (3) The third type is the forecast of PM$_{2.5}$ [27, 28]. In [29], Q. W et al adopted prediction model based on the neural network optimised by artificial bee colony algorithm effectively improved the accuracy of PM$_{2.5}$ prediction. In [30], H. D. He et al. predicted PM$_{2.5}$ concentration based on the impact of measurements of the known air pollutants and meteorological data on the unknown PM$_{2.5}$ concentration over the following 48h. In [27], the authors investigated the potential of satellite-derived products to improve PM$_{2.5}$ estimates across Metro Manila. In [29], Q. W et al adopted prediction model based on the neural network optimised by artificial bee colony algorithm effectively improved the accuracy of PM$_{2.5}$ prediction. In [30], H. D. He et al. predicted PM$_{2.5}$ concentration based on the similarity in air quality monitoring network. In [32], X. Y. Ni helped to realize the correlation analysis and short-term prediction of PM$_{2.5}$ concentrations in Beijing, China, by using multi-source data mining.

However, the exact cause of PM$_{2.5}$ is complex, and the main source production is the daily power generation industry production of automobile exhaust emissions after the process of combustion and emissions of residues, containing heavy metals and other toxic substances on the basis of public information. Also, the prediction of PM$_{2.5}$ is difficult due to the complex causes. So, in this paper, importantly, the author focuses on PM$_{2.5}$ monitoring to take emergency plan against air pollution timely, which has been taken seriously by more and more countries, like China.

In February 2012, the State Council of China agreed to release newly revised “environmental and air quality standards”, in which the monitoring index of PM$_{2.5}$ was newly added. The author reviewed the monitoring methods for PM$_{2.5}$, indicating sensor-based method and photo-based method. However, in sensor-based method, there are some typical disadvantages. Sensors are seriously affected by temperature, with slow response speed, and with narrow coverage, which do not apply in wide range even in some large-scaled local area. Photo-based methods in prior works have showed the availability and convenience for PM monitoring [33–38]. Currently, there are two datasets with huge amounts of photographs. The first one is local, called the AQPDJUT dataset which includes 1500 photos collected in Beijing University of Technology [35]. The second one is in wide range, called the AQPDJUT dataset which includes 1500 photos collected in Beijing City. These photos were obtained in different places and in different times with a wide coverage of photo scenes [36]. However, on these datasets, the nine state-of-the-art [37–44], which are detailed in Section 3, were tested to show poor performances. Given that, the author comes up with a robust photo-based monitoring model in view of good performance and even on different kinds of datasets. To be specific, in the proposed model, based on the results of existing methods, the author firstly uses the weighted average based on LASSO regression for learning the basic linear component, secondly applies the support vector regression (SVR) for learning the non-linear residual component, and finally incorporates the above two outputs to infer the PM$_{2.5}$ concentration.

Compared with the previous works, the main advantages and innovations of this paper are embodied in taking the lead in introducing 7 state-of-the-art image quality assessment models and 2 popular PM monitoring models into a robust photo-based PM$_{2.5}$ monitoring method, and integrating the advantages of different learning methods such as linear and non-linear learning in extracting relevant features. At last the author uses the two newly-proposed large-scale AQPDJUT and AQPDJUT datasets to verify the improvement of PM$_{2.5}$ monitoring accuracy and robustness. The author provides three main contributions and one application prospect of this paper as follows:

1) The author applies 7 image quality assessment models and two PM monitoring models to extract 9 features for PM$_{2.5}$ monitoring, and introduce image quality assessment models into PM$_{2.5}$ monitoring tasks innovatively;
2) The author employs linear regression and non-linear regression to extract macro information and micro information to integrate different photo features, and the author integrates two learning methods in the regression process and get a better performance;
3) Two newly-established large-scaled datasets are used to verify the effectiveness and robustness of the PM$_{2.5}$ monitoring model;
4) Different from the previous work, the author focuses on the robustness of the algorithm which will be greatly improved while the premise of the improvement of accuracy by 0.01%. At the same time, this paper takes the results of different
advanced models which can effectively avoid the disadvantages of falling into the local optimal solution.

Besides the first part of introduction, the other part of this paper is framed as follows. In Section 2, the author introduces the two datasets in detail. Section 3 gives the specific content of the method. In Section 4, the author sets out the nine state-of-art performance measures and compare the proposed algorithm with these methods on the AQPDBJUT and AQPDCITY datasets. In the end, general conclusions and future work are given in Section 5.

2 | DATASET

The author works on two datasets, including the AQPDBJUT dataset [35] and the AQPDCITY dataset [36].

2.1 | The AQPDBJUT dataset

Unlike the existing datasets, the photos in the AQPDBJUT dataset, as illustrated in Figure 3, were collected in a local place of Beijing University of Technology (BJUT) merely. The AQPDBJUT dataset is consisted of 1500 photos with the characteristics of strong coverage, high definition (4032 × 3024) etc. Further, the photos were taken by the equipment of Canon EOS 500D (shown in Figure 1), which is a single-lens reflex camera. And these photos were taken in the different seasons and times. Specifically, the photos in the dataset comprises relatively limited scenes, mainly including teaching buildings, trails, playgrounds and so forth, around student life trajectory. To make the AQPDBJUT dataset more suitable for PM$_{2.5}$ monitoring and fit for local places, the number of photos taken for high-frequency sites for student’s outdoor life was increased properly. The author got the true values of PM$_{2.5}$ at that time by a professional but expensive PM$_{2.5}$ monitoring device called “XHAQSN-808”. This equipment has been located in the campus of Beijing University of Technology. Its specific parameters are illustrated in Figure 2. Based on that device, each photo corresponds to its accurate and real-time monitoring true PM$_{2.5}$ value, which ranges from 0 to 350 μg/m$^3$ in the AQPDBJUT dataset. The importance will be attached to the situation of students exposed to high-level PM$_{2.5}$.

2.2 | The AQPDCITY dataset

Another 1500 photos (with a wide range of resolutions from 500 × 261 to 978 × 550) were captured at different times, in different places, in various environment and weather conditions to form the AQPDCITY dataset, as showed in Figure 4. Further, these photos are taken by common devices like the smartphone and a single-lens reflex camera etc. In pictures of the AQPDCITY dataset, there are various scenarios, including street scenes, buildings, squares, parks etc, which can better mirror the wide distribution in the city. The PM$_{2.5}$ concentration spaned from 0 to 634 μg/m$^3$.

3 | METHODOLOGY

To accurately extract the information in the picture as much as possible, a novel algorithm is proposed to obtain the value of PM$_{2.5}$. Based on the results of related existing methods, the author firstly uses the weighted average based on LASSO regression for learning the basic linear component, secondly applies the SVR for learning the non-linear residual component, and finally incorporates the above two outputs to infer the PM$_{2.5}$ concentration. For the reader’s convenience, Figure 5 and

| Instrument Model | XHAQSN-808 |
|------------------|------------|
| Monitoring Parameter | PM$_{2.5}$, PM$_{10}$, SO$_{2}$, NO$_{2}$, CO, O$_{3}$, temperature, humidity |
| Temporal Resolution | 10s |
| Power Supply | 220V, 12V |
| Boundary Dimension | 220×220×300 |
| Work Environment | T(-20°-60°), RH(15%-95%) |
| Communication Mode | GPRS, WIFI, Bluetooth |
| Battery | Lead-acid battery |
| Working Hours | 248h |
| Weight | 2.4Kg |
| Storage Environment | 0°C–50°C, <90%RH |

ALGORITHM 1 Framework of the proposed photo-based PM$_{2.5}$ monitoring method by combining linear and non-linear learning

Input: A series of photos and their associated PM$_{2.5}$ labels
1: Extracting features from seven related image quality assessment models and two monitoring models, as shown in Figure 5
2: Combining nine features by basic linear component, lasso-based weighted average, as shown in Figure 5
3: Learning the residual component between the original images and the linear-learning result by non-linear learning method as shown in Figure 5
4: Estimating the overall monitoring score by combining the basic linear component and non-linear residual component, as shown in Figure 5

Output: The estimated PM$_{2.5}$ concentration
FIGURE 3  Example photos with different scenes in the AQPDBJUT dataset: (a–c) Buildings; (d–f) Scenic spots

FIGURE 4  Example photos with different scenes in the AQPDCITY dataset: (a–c) Buildings; (d–f) Scenic spots
Algorithm 1 are presented to illustrate the method proposed by us as an example.

### 3.1 Feature extraction

First, nine features were extracted from nine related photo quality models, including NIQMC [43], BIQME [44], FISH [39], FISHBB [39], ARISM [41], NIQE [40], ASIQE [42], PPCP [37], and GSWD [38]. These models are picture-based. To better illustrate the relationship of the above image quality metrics, these metrics are introduced as follows:

- In [43], the model of NIQMC for blind image quality assessment was designed, by generating an overall quality estimation of a contrast-distorted image by properly combining local and global considerations.
- In [44], a new reference-free model of BIQME was developed and a robust image enhancement framework based on quality optimisation was built.
- In [39], a pair of simple and effective wavelet-based algorithms of FISH and FISHBB was proposed to estimate global and local image sharpness.
- In [41], through the analysis of AR model parameters, the model of ARISM was built. First, the difference of energy and contrast of local estimated AR coefficients was calculated point by point, then the image sharpness was quantified with percentile pool to predict the overall score.
- In [40], the perception blind image quality assessment model of NIQE was designed to predict the quality of distorted images with as little or no prior knowledge of their distortion as possible.
- In [42], the new novel blind/no-reference model of ASIQE was presented to obtain the perceived quality of pictures of screen content in large data learning, in which four features that described image complexity, screen content statistics, global brightness quality, and detail clarity were extracted.
- In [37], a new picture-based predictor of PPCP, was designed to estimate PM$_{2.5}$ concentration in real time using images collected by mobile phones or cameras.

- In [38], an effective and efficient photo-based method for the air quality estimation in the case of PM$_{2.5}$, called GSWD, was designed. The authors extracted two categories of features (including the gradient similarity and distribution shape of pixel values in the saturation map) by observing the photo appearances captured under different PM$_{2.5}$ concentrations.

### 3.2 Basic linear component with LASSO-based weighted average

Then, those above nine features with weighted average method are combined. 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

$$L(\beta) = \frac{1}{m} \sum_{i=1}^{m} (Y_i - X\beta)^2 + \epsilon \|\beta\|_1 = E(\beta) + \epsilon_1(\beta)$$

where $Y$ is the target vector; $X$ is the sampled matrix; $m$ is the number of sample; $\epsilon_1(\beta)$ is the penalty item; $E(\beta)$ represents the error sum of squares, expressed as follows

$$E(\beta) = \sum_{j=1}^{m} \left( \sum_{i=1}^{q} \alpha_j x_{ij} \right)^2.$$  

(2)

Then, the author takes the derivative on $\alpha_j$ in the target function, controlling the other $q-1$ parameters unchanged.

$$\alpha_j = \begin{cases} 
\left( n_j - \frac{\epsilon}{2} / m_j \right), & \text{if } n_j > \frac{\epsilon}{2} \\
0, & \text{if } n_j \in \left[-\frac{\epsilon}{2}, \frac{\epsilon}{2}\right] \\
\left( n_j + \frac{\epsilon}{2} / m_j \right), & \text{if } n_j < -\frac{\epsilon}{2} 
\end{cases}$$

(3)

where $\alpha_j$ and $n_j$ represent the $j$th component of the $\alpha$.
3.3 | Non-linear residual component with support vector regression

The SVR is applied to integrated those above nine features with a nonlinear mapping to derive the residual component between the basic linear component and the PM$_{2.5}$ concentration true value [38], defined as follows:

$$\min_h \left(\frac{1}{2}\|h\|^2 + \varepsilon \sum_{j=1}^n (\ell_j + \ell_j') \right)$$

subject to

$$f_j - h^\top \Theta(e_j) + d_j \leq \psi_j + \ell_j'$$

$$f_j - h^\top \Theta(e_j) + d_j \leq \psi_j + \ell_j'$$

$$\ell_j, \ell_j' \geq 0, j = 1, 2, \ldots, n$$

where $\ell_j$ and $\ell_j'$ represent a group of slack variables; $\psi_j$ is the scope of error tolerance; $h$ represents a positive regularization term, which can adjust the flatness of the function $f$ and the error tolerance limits $\psi_j$. In order to get an equation which is more convenient to calculate, the author rewrites Equation (4) by Lagrangian multiplier method, and after careful simplification and arrangement, the equation can be described as:

$$f^{(i)} = \sum_{j=1}^n (g_j^* - g_j) \chi(e_j, e_j') + \tilde{d}$$

where $\tilde{d} = f_i^* - \eta - \sum_{j=1}^n (g_j^* - g_j) e_j^* e_j$; $\chi(e_j, e_j') = \Theta(e_j)^\top \Theta(e_j)$. In the next part, through some comparative experiments, it is easy to know that the proposed model has a wide range of coverage and a strong robustness in PM$_{2.5}$ monitoring.

3.4 | Overall quality measure

The overall monitoring score can be estimated by straightforwardly combining the basic linear component and non-linear residual component as follows:

$$\text{Final Score} = L(\alpha) + f^{(i)}.$$  

For the convenience of readers, the author provides the flowchart in Figure 5.

4 | EXPERIMENT

The author calculated the performance of the proposed model and nine state-of-the-art models on the AQPDBJUT and AQPDCITY datasets. Three typical criteria are chosen 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). Among the aforesaid three evaluation criteria, a good model is expected to achieve low value in RMSE and NMGE, and high value in PSNR. The RMSE is computed by:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{j=1}^n (y_j - \delta_j)^2}$$

where $y_j$ and $\delta_j$ separately represent the model’s estimated PM$_{2.5}$ values and its corresponding groundtruth value of the jth sample; $n$ is the number of samples. The second criterion of the normalized mean gross error (NMGE) indicates the mean error regardless of it is over or under estimation, defined as follows:

$$\text{NMGE} = \frac{\sum_{j=1}^n |y_j - \delta_j|}{\sum_{j=1}^n \delta_j}.$$  

The last one is the error-sensitive peak signal to noise ratio (PSNR), which is calculated by:

$$\text{PSNR} = 10 \log_{10} \left(\frac{(2^l - 1)^2}{\frac{1}{n} \sum_{j=1}^n (y_j - \delta_j)^2}\right).$$

A good model is expected to obtain low values in RMSE and NMGE, but high value in PSNR. During the comparisons, the author elaborately selects nine state-of-the-art models, and the research points of the above methods mainly include photo contrast, bluriness estimation, the distance between a given photo and a natural scene statistics (NSS) model and PM$_{2.5}$ concentration monitoring method. Compared with the above-mentioned models, the author first uses 9 image quality assessment models to monitor PM$_{2.5}$ concentration, and combines linear learning by lasso-based weighted average and non-linear learning by support vector regression. Then, the author computes the performance of the PM$_{2.5}$ monitoring model and nine state-of-the-art models on the AQPDCITY and AQPDBJUT datasets respectively, to testify the accuracy and robustness of the proposed model.

And the results of the above ten models on the two datasets are shown in Table 1 and Table 2. It is not difficult to find from the table that the proposed model has obtained the best performance in both datasets. The author first analyses the results in Table 1. On the dataset of AQPDBJUT, compared with the second-place FISHBB model, the proposed model has gained 11.03%, 7.69%, 6.76% respectively in RMSE, NMGE, PSNR. Further, the RSME, NMGE, PSNR gains between the proposed model and the third-place FISH model grow up to about 19.5%, 21.8%, 13.3%. As listed in the Table 1, the experiment results of PSNR in the ten methods are shown as: Prop. > FISHBB > FISH > NIQMC > NIQE > ASIQE > BIQME > GSWD > ARISM > PPC. Then, on the AQPDCITY dataset, similarly, compared with the second-place GSWD model, the proposed model has gained 0.02%, 18.25%, 0.02% respectively in RSME, NMGE, PSNR. Further, the RSME, NMGE, PSNR
TABLE 1 Comparison of PM$_{2.5}$ concentrations between the model and 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 | 10.586 |
| 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 |
| Prop       | 40.233 | 0.5820 | 16.039 |

TABLE 2 Comparison of PM$_{2.5}$ concentrations between the model and nine state-of-the-art methods on the AQPDCITY dataset

| PM$_{2.5}$ | RMSE  | NMGE  | PSNR  |
|------------|--------|--------|--------|
| NIQMC      | 125.46 | 0.9411 | 6.1610 |
| BIQME      | 128.32 | 0.9933 | 5.9648 |
| FISH       | 120.94 | 0.8655 | 6.4793 |
| FISHBB     | 117.29 | 0.8248 | 6.7458 |
| ARISM      | 126.79 | 0.9660 | 6.0691 |
| NIQE       | 126.36 | 0.9590 | 6.0985 |
| ASIQE      | 128.17 | 0.9099 | 5.9748 |
| PPPC       | 99.304 | 3.8388 | 8.1915 |
| GSWD       | 91.233 | 1.7599 | 8.9277 |
| Prop       | 91.212 | 0.6212 | 8.9297 |

The performance of the proposed model is verified by being compared with many state-of-the-art image quality assessment models. Next, the author further discusses the contributions the author has made in this paper, systematically. First, the author showed that the integration of image quality assessment methods leads to achieving excellent performance and boosting the robustness capability. Second, as compared with models which solely use linear learning or non-linear learning, the proposed model can obtain better performance and robustness during experiment on the open datasets.

5 | CONCLUSION

With the rapid development of the economy, the air quality problem (especially PM$_{2.5}$) has become so prominent that more and more attention has been concentrated on it. The performances of monitoring PM$_{2.5}$, through nine state-of-the-art methods, are barely satisfactory, which will seriously damage enhancing the capacity for emergency management. To change this, a method fusing linear learning for main features and non-linear learning for residual parts is proposed to infer the final PM$_{2.5}$ score. In this paper, the author demonstrates that linear learning by lasso-based weighted average can effectively extract the macroscopic information of the photo, while non-linear learning by support vector regression can extract the microscopic information of the photo effectively. Experiments show that, the influence of the scene and content in the above-mentioned data can be gradually alleviated, and it leads to the steadily improving performances of the state-of-the-art methods. In addition, through the devised monitoring model, the real-time changes of PM$_{2.5}$ not only in local places like campuses but also in wide places like cities, can be timely obtained. And then, the corresponding control can be made out to prevent air pollution. Experimental results in the AQPDBJUT and AQPDCITY datasets show that the proposed model outperforms several state-of-the-art models and ranks the first place in the PM$_{2.5}$ monitoring task.

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