PACS 64.60.A+82.70.R
УДК 530.182, 510.42

SENSING AIR POLLUTION FIELD STRUCTURE IN THE INDUSTRIAL CITY'S ATMOSPHERE: MYCROS TECHNOLOGY "GEOMATH"

A. V. Glushkov, V. N. Khokhlov, Yu. Ya. Bunyakova,
G. P. Prepelitsa and I. A. Tsenenko

Institute of Applied mathematics OSEU, P.O.Box 108, Odessa-9, 65009, Ukraine
E-mail: glushkov@paco.net

Abstract

SENSING AIR POLLUTION FIELD STRUCTURE IN THE INDUSTRIAL CITY'S ATMOSPHERE: MYCROS TECHNOLOGY "GEOMATH"

A. V. Glushkov, V. N. Khokhlov, Yu. Ya. Bunyakova, G. P. Prepelitsa and I. A. Tsenenko

It is carried out the mycros computer data processing technology for sensing the air pollution field structure in the industrial city's atmosphere, based on the using empirical data and the joint multifractal and wavelet analysis PC programs complex "GeoMath". The correct data about dusty air pollution field structure in the Odessa's atmosphere and their detailed analysis are presented.

Key words: mycros computer technology "GeoMath", correlation dimension method, sensing the air pollution field structure.

Резюме

ДЕТЕКТУВАННЯ СТРУКТУРИ ПОЛЯ ЗАБРУДНЕННЯ ПОВІТРЯ У АТМОСФЕРІ ПРОМИСЛОВОГО МІСТА: МІКРОС ТЕХНОЛОГІЯ "GEOMATH"

О. В. Глушков, В. М. Хохлов, Ю. Я. Бунякова, Г. П. Препелица, І. О. Цененко

Розроблено мікрос технологію обробки данних і детектування структури поля забруднення повітря в атмосфері промислового міста, яка базується на використанні данних емпірічних спостережень і ПК комплексу програм мультіфрактального та вейвлет аналізу "GeoMath". Наведені надійні дані по аерозольному пилу в атмосфері м.Одеса та їх докладний аналіз.

Ключові слова: мікрос технологія "GeoMath", метод кореляційної розмірності, детектування структури поля забруднення повітря.

Резюме

ДЕТЕКТИРОВАНИЕ СТРУКТУРЫ ПОЛЯ ЗАГРЯЗНЕНИЯ ВОЗДУХА В АТМОСФЕРЕ ПРОМЫШЛЕННОГО ГОРОДА: МИКРОС ТЕХНОЛОГИЯ "GEOMATH"

А. В. Глушков, В. Н. Хохлов, Ю. Я. Бунякова, Г. П. Препелица, И. А. Цененко

Разработана микрос технология обработки данных и детектирования структуры поля загрязнения воздуха в атмосфере промышленного города, базирующаяся на использовании данных эмпирических наблюдений и ПК комплексе программ мультифрактального и вэйвлет анализа "GeoMath". Представлены надежные данные по аэрозольным взвесям в атмосфере г.Одессы и их детальный анализ.

Ключевые слова: микрос технология "GeoMath", метод корреляционной размерности, детектирование структуры поля загрязнения воздуха.

1. Introduction

Carrying out new, advanced sensors and mycrosystems technologies in the modern atmosphere and environmental physics is related to one of the most important problems (c.f.[1-18]). Above them one may turn attention to a problem for sensing air pollution field structure in atmosphere in general and atmosphere of industrial cities in particular (c.f.[1-7,15,18,19]).

A great number of different experimental methods are used in studying the atmosphere pollution. Besides standard physical-chemical analysis, in last years a great interest attracts using laser emission analysis schemes. They are based on using different linear and non-linear optical phenomena. In particular, an effect of the low threshold laser clamp on the solid ingredients of the disperse medium [1,2].

This effect is technically realized in real atmosphere on the distances of hundred meters from emitter. As emitters the pulsed laser (CO_2, HF, DF etc.) are used. Generating the optical emission spectra, electric and magnetic pulses and also acoustical emission follows the distant laser clamp.

In ref. [3] it has been developed a new scheme theoretical schemes for sensing temporal and spatial structure of the air pollution fields in the industrial city's atmosphere and the preliminary data regarding the Odessa atmosphere were presented. At first on the basis of the correlation dimension approach to empirical data there have been discovered the effects of stochasticity and fractal features in the dusty air pollution field structure.

Here we present an advanced mycros data processing technology for sensing air pollution field structure in atmosphere, based on the using empirical observation data and the joint multifractal and wavelet analysis PC programs complex "GeoMath" [16]. Absolutely correct data about dusty air pollution field structure in the Odessa's atmosphere and their detailed analysis are presented.

2. Initial empirical data

Most continuous regular measurements of dust in Odessa industrial zone are carried out once a day since the 1976. The procedure of measurement is following. The 3000 liters of air are pumped during the 20 minutes through the filter. A difference between the mass of filter after using and that before using is expressed in mg/m^3. The filter is uniform stratum of electrostatically-charged ultrathin perchlorovinyl fibers with average diameter of 2 μm, which is applied on gauze back. The filtration effectiveness for particles 0.34 μm in diameter amounts to 99%.

In this paper, we use the time series of measurements from January 1, 1976 to December 31, 2002, i.e. the length of sample is 9862 daily data (taken from ref.[19] and refs. there). To investigate the existence of stochasticity (chaos) at the different time scales, the original time series was averaged to derive the weekly, semi-monthly and monthly datasets (lengths of sample are 1408, 648 and 324, respectively) in addition to the daily one.

Table 1 summarizes some statistics for the analyzed datasets. One can be noted that both the skewness and the kurtosis for all datasets are not equal to zero and enlarge with decreasing time interval. Figure 1 shows the monthly dataset for the period under consideration. The decrease of dust concentration observed since the late 1980s is caused by shrinkage of industrial activity.

Table 1

Statistics of dusty air datasets with different time resolution
(sample period: January 1, 1976—December 31, 2002)

	daily data	weekly data	semi-monthly data	Monthly data
Number of data point	9862	1408	648	324
Mean, mg/m³	0.549	0.549	0.549	0.549
Standard deviation, mg/m³	0.822	0.537	0.451	0.396
Maximum value, mg/m³	3.5	2.9	2.8	2.5
Minimum value, mg/m³	0.2	0.3	0.4	0.55
Skewness	1.780	1.711	1.653	1.609
Kurtosis	2.728	2.701	2.622	2.608

Note: The mean, standard deviation, maximum value, and minimum value are in mg/m³.

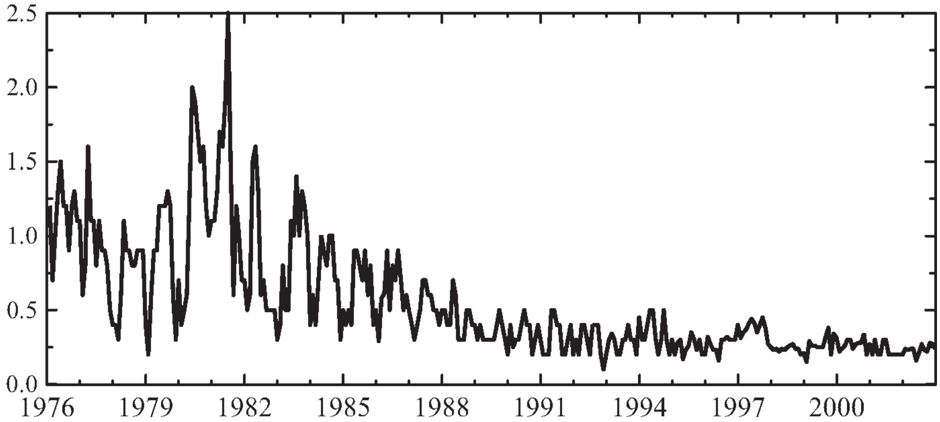

Figure 1. The variation of the monthly air pollution dusty component series at the Odessa city
(X-axis is the year, Y-axis is the dust concentration in mg/m³)

3. PC programs complex "GeoMath":

3.1 Method of correlation integral

The joint multifractal and wavelet analysis PC programs complex "GeoMath" [16] allows determining different statistical and dynamical characteristics of studied syste.m. In particular, one could define the multifractal dimension spectrum, using as a direct calculation as other approaches (wavelet analysis, method of correlation integral) [4,5,11,12]. The correlation dimension method uses the correlation integral (or function) to distinguish chaotic and stochastic systems. The Grassberger-Procaccia algorithm [5] employed in the present study for estimating the correlation dimension of the dusty air pollution series, uses the concept of phase-space reconstruction. For a scalar time series $X i$, where $i = 1, 2, ..., N$, the phase-space can be reconstructed using the method of delays given by

$$Y_j = (X_j, X_{j+t}, X_{j+2t}, ..., X_{j+(m-1)t}) \qquad (1)$$

where $j = 1, 2, ..., N-(m-1)t/Dt$; m is the dimension of the vector Yj , also called the embedding dimension; and t is a delay time. For an m-dimensional phase-space, the correlation function C(r) is:

$$C(r) = \lim_{N\to\infty} \frac{2}{N(N-1)} \sum_{i,j} H(r - |Y_i - Y_j|) \qquad (2)$$

Here H is the Heaviside step function, with $H(u) = 1$ for $u > 0$, and $H(u) = 0$ for $u \le 0$, where $u = r-|Y_i-Yj|$; r is the radius of sphere centred on Y_i or Y_j and $1<i<j<N$. If the time series is characterized by an attractor (a geometric object which characterizes the long-term behavior of a system in the phase-space) then, for positive values of r, the correlation function $C(r)$ is related to the radius r by: $C(r) \sim ar^n$, where a is constant and n is the correlation exponent or the slope of the $log\, C(r)$ versus $log\, r$ plot given by

$$\nu = \lim_{r_i \sim 0, N \sim A} \frac{\log C(r)}{\log r} \qquad (3)$$

The slope is generally estimated by a least-squares fit of a straight line over a certain range of r, called the scaling region. The presence/absence of chaos can be identified using the correlation exponent versus embedding dimension plot. If the correlation exponent saturates and the saturation value is low, then the system is generally considered to exhibit low-dimensional chaos. The saturation value of the correlation exponent is defined as the correlation dimension of the attractor. The nearest integer above the saturation value provides the minimum number of variables necessary to model the dynamics of the attractor. On the other hand, if the correlation exponent increases without bound with increase in the embedding dimension, the system under investigation is generally considered as stochastic. The reliability of the Grassberger-Procaccia algorithm for estimating the attractor dimension is still under investigation. A key question is what is the size of the data required to compute the dimension? Ramsey and Yuan (c.f.refs.[12,19]) concluded that for small sample sizes dimension could be estimated with upward bias for attractors and with downward bias for random noise as the embedding dimension is increased. Havstad and Ehlers (c.f.refs.[12,19]) used a variant of the nearest neighbor dimension algorithm to compute the dimension of only 200 points but obtained an underestimation of the dimension by 11 percents. Jayawardena and Lai (c.f.refs.[12,19]) suggested that only a few thousands of data points are adequate, whereas Kurths and Herzel used only 640 points in analyzing solar time series. Sivakumar et al. used runoff sample sizes from 365 to 10958 points and showed that correlation dimensions have low variability for all cases. For hydrological time series they also concluded that the correlation dimension might have been overestimated (possibly due to the presence of noise in the data) rather than underestimated (due to the small data size).

3.2 Surrogate data

The method of surrogate data (see, e.g. [19]) is an approach that makes use of the substitute data generated in accordance to the probabilistic structure underlying the original data. This means that the surrogate data possess some of the properties, such as the mean, the standard deviation, the cumulative distribution function, the power spectrum, etc., but are otherwise postulated as random, generated according to a specific null hypothesis. Here, the null hypothesis consists of a candidate linear process, and the goal is to reject the hypothesis that the original data have come from a linear stochastic process. The rejection of the null hypothesis can be made based on some discriminating statistics, in particular the correlation dimension. If this statistics obtained for the surrogate data are significantly different from those of the original time series, then the null hypothesis can be rejected, and original time series may be considered to have come from a nonlinear process. One reasonable statistics suggested by Theiler et al. (c.f.refs.[12,19]) is obtained as follows.

Let Q_{orig} denote the statistic computed for the original time series and Q_{si} for the ith surrogate series generated under the null hypothesis. Let μ_s and σ_s denote, respectively, the mean and standard deviation of the distribution of Q_s. Then the measure of significance S is given by

$$S = \frac{\left|Q_{org} - \mu_s\right|}{\sigma_s}. \tag{4}$$

An S value of ~2 cannot be considered very significant, whereas an S value of ~10 is highly significant [19]. The error on the significance value ΔS is estimated by

$$\Delta S = \sqrt{(1+2\sigma_s^2)/n}$$

where n is the number of surrogate data sets. One on the possibilities that can be used for specifying null hypothesis and generating surrogate data is the linearly autocorrelated Gaussian noise. Details on the specification of null hypothesis and surrogate data generation are also provided by Theiler et al. (c.f.refs.[12,19]).

4. Results and discussion

Here we present the results of the advanced applying correlation dimension method to an analysis of the Odessa atmosphere aerosol (dusty) air pollution data and sensing the effects of stochasticity and fractal features in the air pollution field structure. As a first step, the present study investigates the dusty air pollution variability series of different (temporal) scales. Data of four different temporal scales, i.e. daily, 1-week, 0,5-month, and 1-month, over a period of about 20 years observed at the Odessa city (c.f.[3,19]) are analyzed (independently) to investigate the existence of stochasticity (chaos).

The underlying assumption is that the individual behavior of the dynamics of the processes at these scales provides important information about the dynamics of the overall dusty air pollution transformation between these scales. More specifically, if the dusty air pollution variability processes at different scales exhibit chaotic behavior, then the dynamics of the transformation between them may also be chaotic. The correlation functions and the exponents are computed for the four series. The delay time, t, for the phase-space reconstruction is computed using the auto correlation function method and is taken as the lag time at which the auto correlation function first crosses the zero line.

Figure 2 shows the relationship between the correlation exponent values and the embedding dimension values for different data sets. For all the series, the correlation exponent value increases with the embedding dimension up to a certain dimension, beyond which it is saturated; this is an indication of the existence of deterministic dynamics. Saturation of the correlation exponents is observed for all data sets and amounts to the 2.72, 3.42, 4.15, and 5.92.

Also, Fig. 2 shows that relationship for the 30 realization of surrogate datasets, and no saturations are observed in this case. The S values for some embedding dimensions are presented in Table 2. The finite correlation dimensions obtained for the four series indicate that they all exhibit chaotic behaviour. The presence of chaos at each of these four scales suggests that the dynamics of transformation of the air pollution dusty component between these scales may also exhibit chaotic behaviour.

Table 2

Significance values, S, for datasets with different time resolution (sample period: January 1, 1976—December 31, 2002) and some embedding dimensions, m.

	m=2	m=4	m=6	m=8	m=9	m=10	m=11	m=12
Daily	12.3	25.7	41.4	50.6	48.1	47.0	45.6	42.1
Weekly	11.8	20.3	28.4	39.6	45.2	48.3	47.6	44.2
Semi-monthly	12.6	15.6	20.3	28.4	33.7	39.0	44.5	41.9
Monthly	12.1	16.2	22.7	26.1	30.0	32.1	35.2	38.9

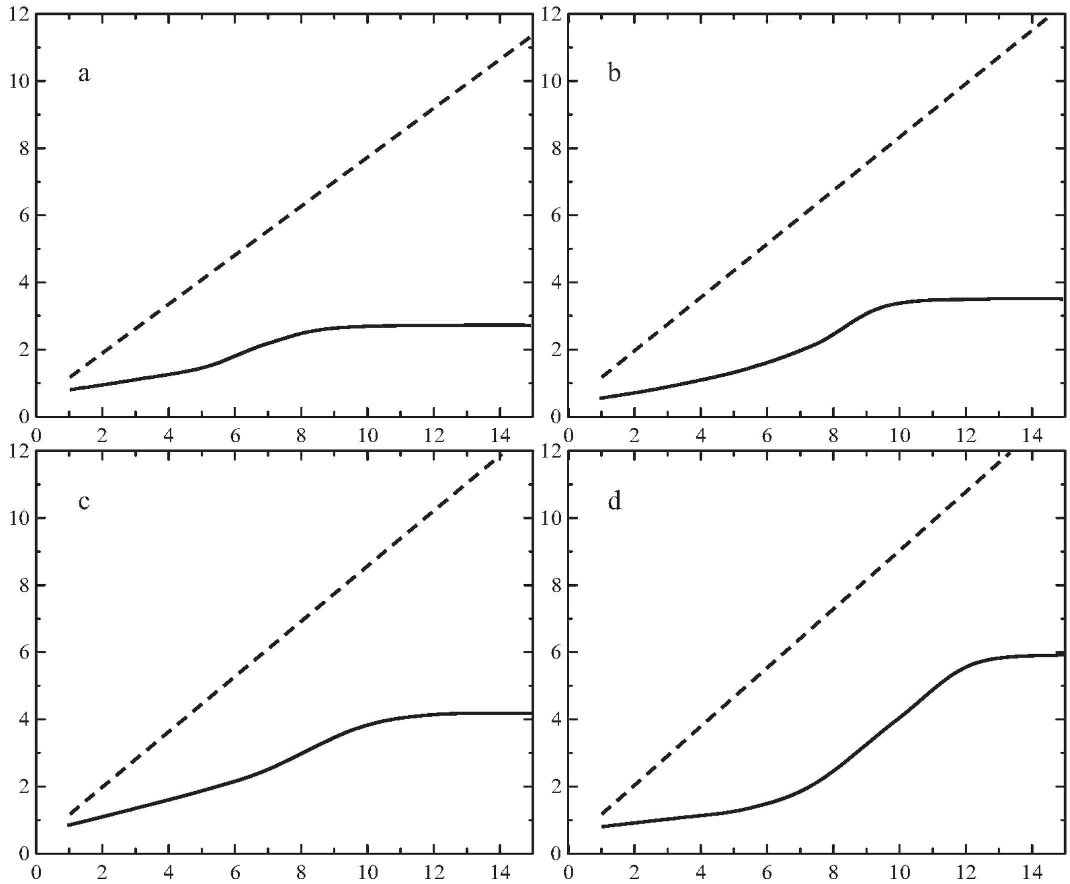

Figure 2. Relationship between correlation dimension and embedding dimension for (a) daily, (b) weekly, (c) semi-monthly, and (d) monthly time series. X-axis is the embedding dimension, Y-axis is the correlation dimension; solid lines relate to the dust concentration, dashed lines relate to surrogate data.

This, in turn, may imply the applicability (or suitability) of a chaotic approach for transformation of the air pollution dusty component data from one scale to another. Discovered features allow making conclusion about fractal properties of the dusty air pollution component series. It should be noted that the obtained information about dynamics and structure of the dusty air pollution component may be very useful and important under searching optimal laser emission spectrum analysis methodises [18]. So, the mycros data processing technology for sensing the air pollution field structure in the industrial city's atmosphere, based on the using empirical data and the joint multifractal and wavelet analysis PC programs complex "GeoMath", can be considered as quite powerful and effective tool in studying such complex systems as considered one.

Acknowledgements. We are grateful to Prof. N.S.Loboda, P.Burlando, D.Schertzer, S.Lovejoy, Dr. P.Molnar, L.Dowse for useful discussion. We acknowledge also the useful critical comments of the refferees.

References

1. Zuev V.E., Zemlyanov A.A., Kopytin Yu.D., Nonlinear Optics of Atmosphere. — L., 1989.
2. Emets E.P., Novoselova A.E., Poluektov P.P., In situ determination of fractal dimension of the aerosol particles// Usp.Phys.Nauk. — 1994. — Vol.164,N9. — P.959-967.
3. Glushkov A.V., Bunyakova Yu.Ya., Khokhlov V.N., Prepelitsa G.P., Tsenenko I.A.,Sensing air pollution field structure in the industrial city's atmosphere: stochasticity and effects of chaos// Sensor Electr. and Microsyst. Techn. — 2005. — N1. — P.80-84.
4. Mandelbrot B.B., Fractal Geometry of Nature. — N. — Y., W.H. Freeman, 1982.
5. Grassberger, P. and Procaccia, I., 1983. Measuring the strangeness of strange attractors//. Physica D. — 1983. — Vol.9. — P.189–208.
6. Havstad, J.W. and Ehlers, C.L., 1989. Attractor dimension of nonstationary dynamical systems from small data sets//Phys. Rev. A. — 1989. — Vol.39. — P.845–853.
7. Berndtsson, R., Jinno, K., Kawamura, A., Olsson, J., Xu, S., Dynamical systems theory applied to long-term temperature &precipitation time series// Trends in Hydrol. — 1994. — Vol.1. — P.291–297.
8. Barnston A.G., Livezey R.E. Classification, seasonality and persistence of low-frequency atmospheric circulation patterns // Mon. Wea. Rev. — 1987. — Vol. 115. — P. 1083-1126.
9. Morlet J., Arens G., Fourgeau E., Giard D. Wave propagation and sampling theory// Geophys. — 1982. — Vol. 47. — P. 203-236.
10. Nason G., von Sachs R., Kroisand G. Wavelet processes and adaptive estimation of the evolutionary wavelet spectrum // J. Royal Stat. Soc. — 2000. — Vol. B-62. — P. 271-292.
11. Loboda N.S. , Stochastic statistical modelling of the irrigation and man-made effects on hydrological systems and water resources// Environm. Inf.Arch. — 2003. — Vol.1. — P.267-273.
12. Glushkov A.V., Khokhlov V.N., Tsenenko I.A. Atmospheric teleconnection patterns and eddy kinetic energy content: wavelet analysis// Nonlin. Proc.in Geophys. — 2004. — V.11,N3. — P.285-293
13. Glushkov A.V., Khokhlov V., Loboda N., Ponomarenko E., Computer Modelling Global Cycle of Carbon Dioxide in System:Atmosphere-Ocean// Environm. Inf.Arch. — 2003. — Vol.1-P.125-130.
14. Glushkov A.V., Khokhlov V.N., Prepelitsa G.,Tsenenko I., Temporal changing of atmosphere methane content: an influence of the NAO// Optics of atm. and ocean. — 2004. — Vol.4. — C.593-598.
15. Glushkov A.V., Khokhlov V.N., Bunyakova Yu.Ya., Renorm-group approach to studying spectrum of the turbulence in atmosphere// Meteor.Climat.Hydrol. — 2004. — №48. — C.286-292.
16. Glushkov A.V., Khokhlov V.N., Svinarenko A.A., Bunyakova Yu.Ya., Prepelitsa G.P., Wavelet analysis and sensing the total ozone content in the earth atmosphere: mycros technology "Geomath"//Sensor Electr. and Microsys.Tech. — 2005. — N3. — P.43-50
17. Glushkov A.V., Bunyakova Yu.Ya., Prepelitsa G.P., Solonko T.V., Sensing air pollution field structure in the industrial city's atmosphere by image recognition method: neural networks modelling//Sensor Electr. and Microsyst.Techn. — 2005. — N2. — P.24-28.
18. Bunyakova Yu.Ya.,Glushkov A.V. Laser emission analysis of the fractal dusty atmosphere parameters// Preprint of the I.I.Mechnikov Odessa Nat.Univ., NIIF., N4. — Odessa, 2004.
19. Bunyakova Yu.Ya. Estimate of influence of the anthropogeneous pressing on air basin of industrial city// PhD Thesis. — Odessa, 2005.