Statistical and Fractal Analysis of Particle Data from Two-Dimensional Video Disdrometer

Statistical and Fractal Analysis of Particle Data from Two-Dimensional Video Disdrometer

(二次元ビデオディスドロメータからの粒子データの統計とフラクタル解析)

GAVRILOV SERGEY

Graduate School of Natural Science and Technology

Kanazawa University

Abstract

Due to the diversity of terrain, rainfall and snowfall phenomena take on different forms depending on location. The amount and type of precipitation may change quite rapidly over a short period of time.

As heavy snowfall may cause severe damage, it is a significant issue to be able to monitor precipitation continuously for decreasing the potential damage as well as obtaining a better meteorological understanding of orographic snowfall. Especially, it is important to understand the snowfall formation mechanism with different types of solid precipitation such as snowflake and graupel.

This thesis aims to solve the problem of improving the accuracy of that kind of studies implementing a new approach to enhance the results. In this study, we conducted feature analysis and classification of particle data from Two-Dimensional Video Disdrometer (2DVD) through the combined use of various statistical methods including supervised and unsupervised machine learning. We developed a new system with 2DVD for observing and estimating various particles. Although the 2DVD takes binary image with lower resolution than Charge-coupled device video camera, combination of up-to-date classifier and features including fractal-related ones enabled the system to outperform the accuracy achieved in our previous study and similar state-of-the-art works.

1 Introduction

1.1 Meteorology and weather monitoring

Modern meteorological weather monitoring consists of a large variety of approaches and techniques, using both remote (radars, lidars) and ground-based observation equipment and methods.

For the purpose of remote measuring the precipitation intensity on a wide area, a popular facility is a *polarimetric radar*. This device is commonly used to obtain the cloud microphysical parameters. While polarimetric radars operate on large-scale, a device named *disdrometer* is additionally used for the ground-based observation of precipitation at a spot. It is a relatively-small instrument which can measure the size and falling velocity of a particle. Based on the fact that rain and graupel have different distribution of size and falling velocity, it is possible to discriminate them using a disdrometer. However, if two particles have similar size and falling velocity, it is impossible to discriminate them by a disdrometer. In this sense, the observation of precipitation using a polarimetric radar and/or a disdrometer is not sufficient for accurately estimating the amount of precipitation consisting of various types.

1.2 Two-dimensional video disdrometer

A two-dimensional video disdrometer (hereafter 2DVD) is an optical device developed for measuring solid precipitation characteristics on ground. The instrument is manufactured by Joanneum Research of Austria. 2DVD measures volume, diameter, shape, and velocity of every individual particle. From this data, one can estimate particle size distribution, precipitation rate, and other related variables.

1.3 Types of solid precipitation

While liquid precipitation consists of raindrops only, solid precipitation may be split into a variety of classes, depending on the particle parameters. These parameters are influenced by various factors such as snow formation processes and macro physical conditions.

This study is intended to make difference only between hydrometeors of 2 basic classes: *snow* and *graupel*. Nevertheless it makes use of 3 intermediate classes which are artificial in the sense that are derived by manual annotation in difficult to classify cases.

A graupel is round-shaped as an approximate ellipse, and in contrast, a snowflake has a complex shape. As to the size of a particle, graupels are relatively smaller than snowflakes. These features meet intuitive criteria in human’s discrimination of snowflake and graupel. The latter feature was frequently used in previous studies since it is easier to observe.

2 Snow classification methods review

We consider the following 2 papers to be the closest and most recent works in the field of snow classification:

1. Nurzynska, K., Kubo, M. and Muramoto, K. (2010) 2D Feature Space for Snow Particle Classification into Snowflake and Graupel. IEICE Transactions on Information and Systems, E93-D, 12, 3344-3351.

2. Grazioli, J., Tuia, D., Monhart, S., Schneebeli, M., Raupach, T. and Berne, A. (2014) Hydrometeor classification from two-dimensional video disdrometer data. Atmospheric Measurement Techniques, 7, 2869-2882.

First one is the previous work of the Bioinformatics Laboratory of Kanazawa University. Instead of 2DVD, it uses grayscale images taken by CCD video camera. Using rich information of high-resolution grayscale image, it achieved high accuracy of particle-by-particle classification into snowflake and graupel.

However, since it requires large space like a room, portability and applicability are low. In addition, it is a hand-made facility and not easy to use.

The authors of the second paper used 2DVD to determine the dominant type of precipitation observed in a time interval. Conversely saying, it does not perform particle-by-particle classification.

3 Materials and Methods

3.1 System and Condition of Observation

2DVD is an optical device developed for measuring precipitation drop size, shape, and velocity field. The sensor unit consists of two orthogonal and synchronized line-scan cameras and a bright light source in front of each of them. While precipitation particles fall between the cameras and light sources (an area of 10cm ×10cm) their shapes are recorded as shadows are being projected. We have ob-served snowfall event from 1250 JST to 1300 JST in January 26, 2011 at Kanazawa University. The data of 16,010 snow particles were recorded by the 2DVD. The air temperature was about 0˚C through the event duration.

3.2. Preparation of Data for Analysis and Classification

Particle Images and Basic Features

Since 2DVD scans two line images at once from two orthogonally oriented cameras (A and B), two different images are obtained for each particle.

A graupel is round-shaped as an approximate ellipse, and in contrast, a snow-flake has a complex shape. As to the size of a particle, graupel are relatively smaller than snowflakes. These features meet intuitive criteria in human’s discrimination of snowflake and graupel. The latter feature was frequently used in previous studies since it is easier to observe.

In addition to shape and size, it is possible to obtain various features of a particle by using 2DVD. The list of features used in this study is shown in Table 1.

Feature type	Feature name
Camera-independent features	equivolumetric_diameter[mm], volume[mm^3], vertical_fall_velocity[m/s], height_of_one_line[mm]
Camera-specific features	height[mm]_A, height[mm]_B, number_of_lines_A, number_of_lines_B, pixelwidth[mm]_A, pixelwidth[mm]_B, width[pixel]_A, width[pixel]_B, height[pixel]_A, height[pixel]_B, total_pixels_A, total_pixels_B, area[mm^2]_A, area[mm^2]_B, perimeter[mm]_A, perimeter[mm]_B, box_count_1_A, box_count_1_B, box_count_2_A, box_count_2_B, box_count_4_A, box_count_4_B, box_count_8_A, box_count_8_B, fractal_1_2_A, fractal_1_2_B, fractal_2_4_A, fractal_2_4_B, fractal_1_4_A, fractal_1_4_B, fractal_4_8_A, fractal_4_8_B, fractal_2_8_A, fractal_2_8_B
Camera-independent features(max and min) converted from camera-specific features (A and B)	height[mm]_max, height[mm]_min, number_of_lines_max, number_of_lines_min, pixelwidth[mm]_max, pixelwidth[mm]_min, width[pixel]_max, width[pixel]_min, height[pixel]_max, height[pixel]_min, total_pixels_max, total_pixels_min, area[mm^2]_max, area[mm^2]_min, perimeter[mm]_max, perimeter[mm]_min, box_count_1_max, box_count_1_min, box_count_2_max, box_count_2_min, box_count_4_max, box_count_4_min, box_count_8_max, box_count_8_min, fractal_1_2_max, fractal_1_2_min, fractal_2_4_max, fractal_2_4_min, fractal_1_4_max, fractal_1_4_min, fractal_4_8_max, fractal_4_8_min, fractal_2_8_max, fractal_2_8_min
Other features(not used in analysis and classification)	time

Table 1. Features for Analysis and Classification.

The 2DVD software computes the volume and equivolumetric diameter based on three-dimensional shape reconstructed from two orthogonal projections. The particle shadows in the upper light sheet are matched with particle shadows in the lower sheet, and the software obtains the vertical fall velocity and height quantization (height_of_one_line) from the falling time through the planes separated 6.2mm vertically at the line-scan rate of 34.1 kHz.The number of lines scanned by each camera is the height of the particle. The light sheet of 10 cm is mapped onto 512 pixels in the line-scan camera, and the horizontal resolution of pixel (pixelwidth) is about 0.2 mm.The longest scan line is the particle width. The area of each particle was computed by multiplying total number of pixels (total_pixels), height_of_one_line and pixelwidth. We got the boundary of particle shape and computed the particle perimeter.

Camera-specific features are important since they contain various information obtained by 2DVD. However, it is not sufficient to use them directly in the analysis and classification. When we use machine learning algorithms, the same type of features obtained by cameras A and B (e.g. perimeter[mm]_A and perimeter[mm]_B) are also treated as simply different and independent ones. To overcome this problem, we added extra features that are the result of integrating camera-specific features by calculating maximum and minimum values. For example, if perimeter[mm]_A> perimeter[mm]_B, then perimeter[mm]_max = perimeter[mm]_A and perimeter[mm]_min = perimeter[mm]_B. In a sense, it is a sorting operation of values from two cameras and if a feature is mainly characterized by large (small) values of it, the integrated feature of its maximum (minimum) will have strong power in the analysis and classification of particles.

Fractal-related Features

Perimeter is a feature that reflects two different characteristics of particle, that is, size and complexity of shape. In this study, we introduced fractal-related features also related to complexity of shape.

Fractal geometry provides a mathematical model for many complex objects with property of self-similarity found in nature. Fractal dimension is a useful feature for shape classification. The snowflake formation modeled by fractal dimension, was proposed for improvement estimates of snowfall retrieval by radar remote sensing. This study uses the box-counting method, which is one of the frequently used techniques to estimate the fractal dimension also known as Minkowski dimension. First, the smallest number of box shaped elements covering the particle boundary is counted (Figure 1). Next, the obtained amount of covering elements is log-log plotted versus the reciprocal of the element size (Figure 2). Finally, the box dimension estimate is taken from the monotonically rising linear slope.

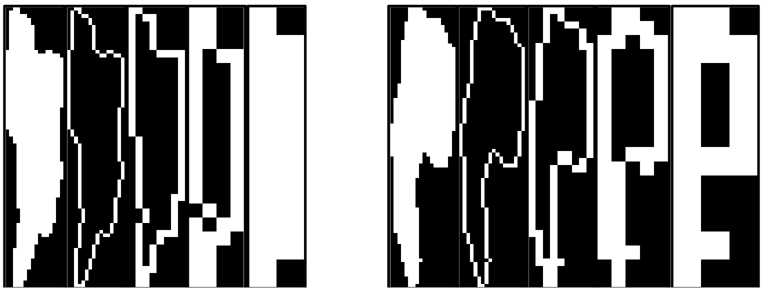

Figure 1. Example of covering results from the box-counting method. (a) Snowflake by camera A; raw image by 2DVD (leftmost), boundary covered by boxes of size 1, 2, 4, and 8. (b) Snowflake by camera B.

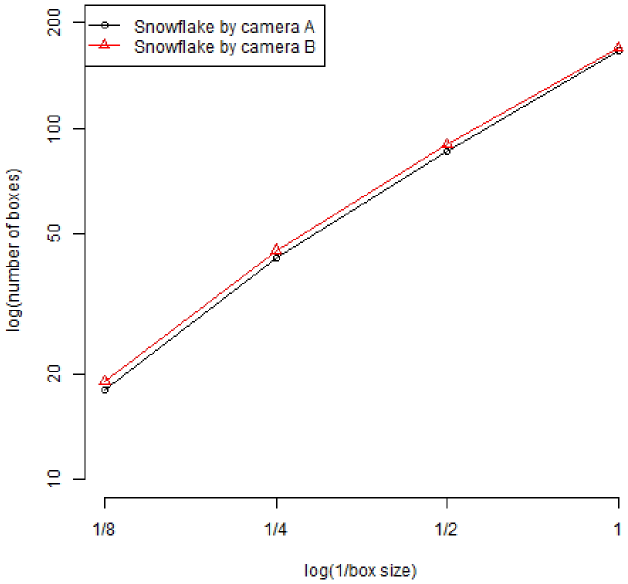

Figure 2. The log-log plot of the box-counting method.

Human Annotation

Total number of particles in our dataset is 16,010, that is, it consists of 16,010 feature vectors with the features listed in Table 1. To conduct meaningful analysis and evaluation of classification performance, we randomly sampled 1,600 feature vectors and annotated them manually. Before annotation, five categories were prepared: snowflake, snowflake-like, intermediate, graupel-like, and graupel. Additionally, if one of two images for a particle matched one of the following rules,it was automatically annotated as warning and filtered out before random sampling since it can be regarded as outlier or erroneous data.

• equivolumetric_diameter[mm] is less than 0.2.

• vertical_fall_velocity[m/s] is greater than 4.

• width[pixel] / height[pixel] is less than 1/3 or greater than 3.

• The horizontal position of the particle in the raw image is left-end and over 50% of left edge of the particle image is occupied by black pixel (i.e. it is strongly suspected that the particle passed by the left end of a camera and whole image of it was not taken by 2DVD).

The numbers of annotated samples are shown in Table 2. According to these annotations, the datasets shown in Table 3 are used for analysis and classification.

Annotation	The number of particles
snowflake	559
snowflake-like	111
intermediate	39
graupel-like	144
graupel	747
warning	2,118
not annotated	12,292

Table 2.The number of samples after annotation.

Dataset	Annotation	The number of particles
whole	snowflake, snowflake-like, intermediate, graupel-like, graupel, warning, not annotated	16,010
no-warning	snowflake, snowflake-like, intermediate, graupel-like, graupel, not annotated	13,892
warning-only	warning	2,118
5-classes	snowflake, snowflake-like, intermediate, graupel-like, graupel	1,600
2-classes	snowflake, graupel	1,306

Table 3.Datasets according to annotation.

3.3. Algorithms

Normalization

A feature vector consists of two or more feature values for features. However, it is problematic to use the original values for machine learning because in general, value distribution can differ from feature to feature. Therefore, it is popular to normalize the original values of feature vectors so that all the features have the same aver-age and variance. In this study, we normalized our dataset with average = 0 and variance = 1 for each feature before the analysis and classification.

Pearson's Correlation Coefficient

To see the direct and pair wise relationship between every pair of features, we calculated Pearson's correlation coefficient. If its value is near to 1, two features are quite similar. It is one of the most basic feature analysis methods. In addition, it is known that, removing one of two similar and redundant features may lead to better performance of classification, regression, clustering, etc.

Principal Component Analysis (PCA)

Among various unsupervised learning algorithms, PCA might be the most popular one. Based on the calculation of features' linear combination that maximizes the variance, PCA converts the original feature space into the space of principal components (PCs). After PCA, all the PCs are ordered as PC1, PC2, … and it is believed that PC1 is the strongest feature for characterizing the feature vectors, PC2 is secondly strong, and so on. Due to this effect of PCA, it is broadly used for different purposes. As the basic analysis of original features, coefficient of each feature in the linear combination formula for some important PCs like PC1 is evaluated. In this study, it may reflect the importance of the feature to characterize and classify snowflakes and graupel.

Support Vector Machine (SVM)

Due to its applicability and high-performance, SVM is one of the most popular machine learning algorithms today. Among various variants and implementations of SVM, we used ksvm function implemented in kernlab package for R. Regarding the choice of kernel, the default one (Radial Basis Function kernel, also known as Gaussian kernel) was adopted. A hyper-parameter "sigma" for this kernel is being automatically optimized by ksvm.

Cross-Validation

To evaluate the performance of predicting the class label (i.e. snowflake or graupel) of unseen samples (i.e. unseen particles), it is popular to conduct cross-validation. In this study, we adopted 10-fold cross-validation that randomly divides given dataset into 10 and perform learning and prediction 10 times by changing 10% of data-set for test (rest of 90% is used for training). One problem about this kind of cross-validation is that the evaluated performance is affected by the result of random division and different performances are achieved in every evaluation. To solve this problem, we repeated 10-fold cross-validation 100 times and averaged the accuracy.

4 Experimental Results and Discussion

4.1 Feature analysis by Pearson's correlation coefficient results may be summarized as follows:

• Box-count features (i.e. features about the number of boxes) are highly similar to each other. In contrast, fractal features are dissimilar to each other.

• Some of other features are similar to each other (i.e. height and perimeter features). It indicates that redundant features like box-count may exist also in these other features.

• About the difference between camera-specific features and camera-independent features calculated from them, fractal features showed clear difference. In other words, calculation of max and min was meaningful at least for fractals.

4.2 Feature analysis by PCA results may be summarized as follows:

• PC1s of these datasets are similar to each other (Figure 3). Most of the important features in PC1 are occupied by box-count features (Table 4).

• PC2 of the dataset “whole” is quite dissimilar to others and the difference is caused by the inclusion of “warning-only”. In other words, after filtering errors, PC2 is more or less the same in each dataset. About top 10 features of PC1 of “warning-only” (Table 4), it is convincing that most of them are occupied by size-related features (height, perimeter, area, etc.) because many of the particles in this dataset were removed from “whole” dataset due to their strange size. About PC2s of the datasets “no-warning”, “5-classes”, and “2-classes”, some of the fractal features occupy top 4 important features.

• PC3s of the datasets “5-classes” and “2-classes” are quite dissimilar (correlation between them is -0.97). Since in “2-classes”, ambiguous particles annotated as “snowflake-like”, “inter-mediate”, or “graupel-like” are removed from “5-classes”, it can be interpreted that PC3 of “5-classes” is highly affected by the characteristics of such ambiguous particles.

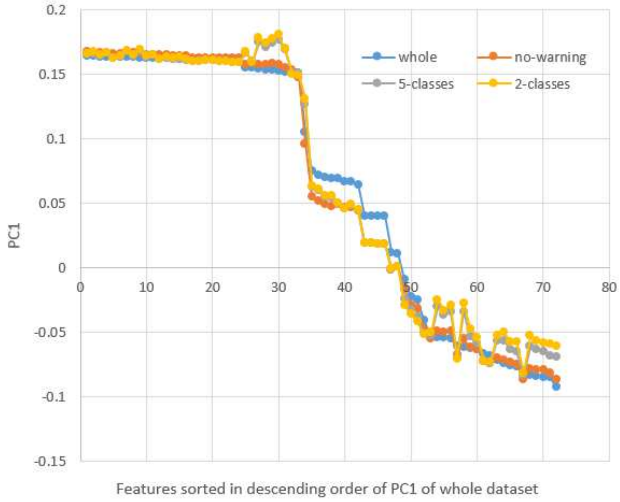

Figure 3. PC1 of the datasets except “warning-only”.

rank	whole	no-warning	5-classes	2-classes	warning-only
1	box_count_4_min	box_count_4_min	total_pixels_B	total_pixels_B	height[mm]_min
2	box_count_8_max	box_count_8_min	total_pixels_max	total_pixels_max	height[mm]_B
3	box_count_4_max	box_count_8_max	total_pixels_min	total_pixels_min	height[mm]_max
4	box_count_4_B	box_count_8_B	total_pixels_A	total_pixels_A	height[mm]_A
5	box_count_4_A	box_count_4_B	width[pixel]_B	width[pixel]_B	perimeter[mm]_min
6	box_count_2_min	box_count_4_max	box_count_8_B	box_count_8_B	perimeter[mm]_B
7	box_count_8_min	box_count_8_A	box_count_8_min	box_count_8_min	perimeter[mm]_A
8	box_count_8_A	box_count_2_min	box_count_4_B	width[pixel]_max	perimeter[mm]_max
9	box_count_8_B	box_count_4_A	width[pixel]_max	box_count_8_max	area[mm2]_max
10	box_count_2_max	box_count_2_B	box_count_8_max	box_count_4_B	area[mm2]_min
10	box_count_2_max	box_count_2_B	box_count_8_max	box_count_4_B	area[mm2]_min

Table 4. Top 10 features in descending order of PC1 values.

4.3 Particle classification by SVM

First, we evaluated the accuracy of prediction with “2-classes” dataset and all 72 features. The average error of prediction (i.e. 1 - average accuracy) was 0.08263. After converting the 72 features into 72 PCs by PCA, the average error decreased to 0.07191.

Since so many redundant features exist in the 72 features, reduction of feature set by feature selection might decrease the average error of prediction. To choose the representative feature in each group, 72 evaluations were performed using only one specific feature in each evaluation. As a result, 14 representative features with the lowest average errors in their groups were selected. Among them, box_count_2_max achieved the best performance (0.1055) as a single feature. It is also notable that the suffixes “_max” and “_min” frequently appear instead of “_A” and “_B”. It indicates that the conversion of camera specific features to camera-independent ones contributed to achieve better classification performance.

Starting from the feature set with all of these 14 features, feature selection by backward elimination was performed. As a baseline performance before the 1st iteration, the average error 0.0543 achieved by the feature set with all of these 14 features was used (Table 5).

In this study, four features were removed through 1st to 4th iterations, and the process of backward elimination stopped since 5th iteration could not achieve any improvement. Using the remaining 10 features, the average error 0.0461 was achieved and it was the best performance of classification in this study . Unlike the analysis in section 4.2, this result revealed that fractal features could not contribute to the best performance. In other words, they might be useful for more detailed characterization of various particles, not for just classifying snowflakes and graupel. In contrast, a box-count feature (box_count_2_max) was so important as to the classification by only one feature achieved average error 0.1055 that is nearly 90% accuracy. It is an interesting finding that, although a box-count feature is a by-product of fractal calculation, it is significantly important in the classification of snowflakes and graupel.

feature	prediction by single feature	1st iteration	2nd iteration	3rd iteration	4th iteration	5th iteration
box_count_2_max	0.1055	0.0599	0.0543	0.0481	0.0493	0.0463
total_pixels_max	0.1198	0.0577	0.0538	0.0485	**0.0461**	removed
number_of_lines_min	0.1222	0.0549	0.0511	0.0485	0.0480	0.0466
height[pixel]_min	0.1224	0.0548	0.0513	0.0481	0.0480	0.0467
perimeter[mm]_max	0.1274	0.0683	0.0665	0.0626	0.0654	0.0653
width[pixel]_max	0.1405	0.0564	0.0509	0.0471	0.0479	0.0476
area[mm2]_max	0.1886	0.0602	0.0574	0.0495	0.0526	0.0522
height[mm]_min	0.1913	0.0546	0.0531	**0.0465**	removed	removed
equivolumetric_diameter[mm]	0.2026	0.0652	0.0622	0.0556	0.0561	0.0573
volume[mm3]	0.2045	0.0567	0.0506	0.0481	0.0486	0.0469
fractal_2_8_min	0.2069	0.0520	**0.0484**	removed	removed	removed
pixelwidth[mm]_max	0.2434	**0.0517**	removed	removed	removed	removed
height_of_one_line[mm]	0.3449	0.0557	0.0529	0.0509	0.0504	0.0513
vertical_fall_velocity[m/s]	0.4261	0.0556	0.0522	0.0503	0.0499	0.0503

Table 5. Average errors (i.e. 1 – average accuracy) in the predictions by single feature and multiple features with backward elimination. If the elimination of a feature decreased (increased) the average error of prediction, it is shown in red (blue) color.The least average error in each column is shown in bold face.

5 Conclusion and Future Works

5.1 Dissertation summary

In this study, we tried not only to (i) outperform the accuracy of the existing analogous classification methods, but to (ii) explicitly use the fractal features derived from particle shape and (iii) estimate the value of each feature in the contribution to classification. That was a nontrivial task due to the described study area problems. Moreover, it had been challenging as recent researches show significant advance in adjacent domains.

We conducted feature analysis and classification of particle data from 2DVD through the combined use of various statistical methods including supervised and unsupervised machine learning. Experimental results revealed that fractal and box-count features are useful for the characterization and classification of snowflakes and graupel. The average accuracy of particle-by-particle classification was around 95.4%, which has not been achieved by previous studies.

From this result, it can be said that we could develop a system for automatically monitoring solid precipitation with practically sufficient accuracy of discriminating snowflakes and graupel. Additionally, we demonstrated that combining acquisition time information with the results of classification on large amount of particles, it becomes possible to conduct time-series analysis of amount and type of particles, which contributes to elucidate the mechanism of orographic snowfall (phenomena).

5.2 Future works

In this study, we mainly focused on two types of particles (i.e. snowflake and graupel). As an extension of this study, conducting human annotation with not only two types but also other detailed types of particles (e.g. dendrite-like, aggregate-like, melting-snow-like, and other depending on local precipitation particularity), makes it possible to quantitatively analyze wide-variety of snowfall in places with weather conditions not necessarily similar to those in Kanazawa. This may undoubtedly boost the practical applicability of the method yet lies beyond the scope of this study.

We hope that these two future work vectors will result in an even better method useful in a range of meteorological purposes.

References

[1] Ohigashi, T. and Tsuboki, K. (2005) Structure and Maintenance Process of Stationary Double Snowbands along the Coastal Region. *Journal of the Meteorological Society of Japan*, **83**, 3, 331-349. http://dx.doi.org/10.2151/jmsj.83.331

[2] Harimaya, T., Kodama, H. and Muramoto, K. (2004) Regional Differences in Snowflake Size Distributions. *Journal of the Meteorological Society of Japan*, **82**, 3, 895-903. http://dx.doi.org/10.2151/jmsj.2004.895

[3] Brandes, E.A., Ikeda, K., Zhang, G., Schonhuber, M. and Rasmussen, R.M. (2007) A Statistical and Physical Description of Hydrometeor Distributions in Colorado Snowstorms Using a Video Disdrometer. *Journal of Applied Meteorology and Climatology*, **46**, 634-650. http://dx.doi.org/10.1175/JAM2489.1

[4] Hung, G., Bringi, V.N., Cifelli, R., Hudak, R. and Petersen, W.A. (2010) A Methodology to Derive Radar Reflectivity–Liquid Equivalent Snow Rate Relations Using C-Band Radar and a 2D Video Disdrometer. *Journal of Atomospheric and Oceanic Technology*, **27**, 637–651. http://dx.doi.org/10.1175/2009JTECHA1284.1

[5] Hung, G., Bringi, V.N., Moisseev, D., Petersen, W.A., Blivend, L., Hudake, D. (2014) Use of 2D-video disdrometer to derive mean density–size and Ze–SR relations: Four snow cases from the light precipitation validation experiment, *Atmospheric Research*, **153**, 34-48. http://dx.doi.org/10.1016/j.atmosres.2014.07.013

[6] Zhang, G., Luchs, S., Ryzhkov, A., Xue, M., Ryzhkova, L. and Cao, Q. (2011) Winter Precipitation Microphysics Characterized by Polarimetric Radar and Video Disdrometer Observations in Central Oklahoma. *Journal of Applied Meteorology and Climatology*, **50**, 1558–1570. http://dx.doi.org/10.1175/2011JAMC2343.1

[7] Nurzynska, K., Kubo, M. and Muramoto, K. (2010) 2D Feature Space for Snow Particle Classification into Snowflake and Graupel. *IEICE Transactions on Information and Systems*, E93-D, **12**, 3344-3351. http://dx.doi.org/10.1587/transinf.E93.D.3344

[8] Kruger, A. and Krajewski, W.F. (2002) Two-dimensional video disdrometer: a description. *Journal of Atomospheric and Oceanic Technology*, **19**, 602–617. http://dx.doi.org/10.1175/1520-0426(2002)019<0602:TDVDAD>2.0.CO;2

[9] Grazioli, J., Tuia, D., Monhart, S., Schneebeli, M., Raupach, T. and Berne, A. (2014) Hydrometeor classification from two-dimensional video disdrometer data. *Atmospheric Measurement Techniques*, **7**, 2869-2882. http://dx.doi.org/10.5194/amt-7-2869-2014

[10] Ishimoto, M. (2008) Radar Backscattering Computations for fractal-Shaped Snowflakes. *Journal of the Meteorological Society of Japan*, **86**, 3, 459-469. http://dx.doi.org/10.2151/jmsj.86.459

[11] Maruyama, K. and Fujiyoshi, Y. (2005) Monte Carlo Simulation of the Formation of Snowflakes. *Journal of the Atmospheric Sciences*, **62**, 1529–1544. http://dx.doi.org/10.1175/JAS3416.1

[12] Tolle, C.R., McJunkin, T.R., Gorsich, D.J. (2003) Suboptimal Minimum Cluster Volume Cover-Based Method for Measuring Fractal Dimension, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **25**, 1, 32-41. http://dx.doi.org/10.1109/TPAMI.2003.1159944

[13] Russ, J.C. (2011) The Image Processing Handbook. Sixth Edition, CRC Press, 604-610. http://www.crcpress.com/product/isbn/9781439840450

[14] Vapnik, V. (1998) Statistical Learning Theory, Wiley, New York, NY.

平成２７年　２月　３日

学位論文審査報告書（甲）

1．学位論文題目（外国語の場合は和訳を付けること。）

Statistical and Fractal Analysis of Particle Data from Two-Dimensional Video Disdrometer（２次元ビデオディスドロメータから得られる粒子データの統計解析およびフラクタル解析）

2．論文提出者　(1) 所　　属　電子情報科学　専攻

(2) 氏　　名（ふりがな：がぶりろふ　せるげい）　Gavrilov Sergey

3．審査結果の要旨（600～650 字）

平成２７年１月２７日に第１回学位論文審査委員会を開催、２月３日に口頭発表、その後に第２回審査委員会を開催し、慎重審議の結果、以下の通り判定した。なお、口頭発表における質疑を最終試験に代えるものとした。

降雨や降雪の継続的観測と予測は、動的に変化する気象現象の理論的理解および災害の低減において重要である。本研究では、雪やあられのように異なる形状的特徴を持つ固体粒子を解析し、高精度に自動識別する手法を提案した。２次元ビデオディスドロメータから得られる低解像度の画像ペアを元に、フラクタル理論に基づく特徴を導入し、カメラ固有の特徴をカメラ非依存の特徴に変換した上で、相関係数および主成分分析に基づく特徴解析を行うことにより、フラクタル次元に関係する特徴が重要であることを明らかにした。また、独自の特徴選択を行うことにより、粒子単位の２クラス分類で従来法を超える精度を達成した。最後に、構築したモデルを用いて粒子単位の分類予測を行うことにより、複数種類の降雪粒子量の動的な変化を把握できることを示した。

以上の研究成果は、北陸地方において特に重要な降雪粒子の高精度な分類と動態解析に大きく貢献するものであり、本論文は博士（工学）に値するものと判定した。

4．審査結果　(1) 判　　定（いずれかに○印）　合　格　・　不合格

(2) 授与学位　博　士（工学）