Frank S. Marzano

Remote Sensing of Volcanic Ash Cloud During Explosive Eruptions Using Ground-Based Weather Radar Data Processing

The ash ejected into the atmosphere by the Eyjafjalla Icelandic volcano during its recent eruption posed such a threat to flights over much of Europe that the ensuing cancellations resulted in an unprecedented disruption of the European commercial air transportation system [1]. Volcanic ash is not only a significant hazard to aircraft operations but also to public safety from volcanic ash fall at the surface (e.g., [2] and [3]). Given the significance of the hazards posed by volcanic ash, timely detection and tracking of the erupted ash cloud is essential to a successful warning process, particularly during and immediately following an eruptive event. In this article, we will discuss ground-based radar (radio detection and ranging) data processing for ash cloud remote sensing pointing to the physical basis of retrieval algorithms and an example of their application.

MONITORING VOLCANIC ASH CLOUDS

As pointed out by the Volcanic Ash Advisory Centers (VAACs), the largest uncertainty in the ability of numerical models to predict the spread of volcanic ash, and hence to advise aviation regulators, is in observations of the eruption itself: i) knowing how high the ash is being expelled and ii) what concentration of ash is being expelled. Current observations come from a range of sources: satellite (height and spatial distribution of the dispersed ash plume), cloud ceilometers and light detection and ranging (LIDAR) systems (ash cloud height and depth), seismic (volcano activity), and human (ash plume height and shape). Within this list, it should be added the use of ground-based meteorological microwave radars whose new role, within the volcanic ash monitoring network, is the goal of this short contribution.

Real-time and aerial monitoring of a volcano eruption, in terms of its intensity and dynamics, is not always possible by conventional visual inspections. A variety of satellite techniques have been successfully used to track volcanic ash clouds; however, these techniques have certain limitations [2]. As known, these data are subject to limitations in both spatial and temporal resolution. Issues involving the detection of ash clouds using infrared brightness temperature differencing, a commonly used method, have been addressed suggesting several scenarios where effective infrared satellite detection of volcanic ash clouds may be compromised. Ground microwave instrumentation, such as global positioning system (GPS) receivers and wind profiler radars, may play a complementary role, even though their operational utility is limited by the relatively small spatial coverage. On the other hand, ground-based LIDAR optical systems may show a higher sensitivity to ash contents with respect to microwave instruments but counterbalanced by stronger path attenuation effects.

Ground-based microwave radar systems can have a valuable role in volcanic ash cloud monitoring as evidenced by available radar imagery [3], [4]. These systems represent one of the best methods for real-time and areal monitoring of a volcano eruption, in terms of its intensity and dynamics. The possibility of monitoring 24 hours a day, in all weather conditions, at a fairly high spatial resolution (less than few hundreds of meters), and every few minutes after and during the eruption is the major advantage of using ground-based microwave radar systems. They can provide data for determining the ash volume, total mass, and height of eruption clouds.

There are still several open issues about microwave weather radar capabilities to detect and quantitatively retrieve ash cloud parameters [4], [5]. Exploitation of microwave weather radars for volcanic eruption monitoring is fairly limited due to their exclusive use for water clouds and precipitation observations. Several unknowns may also condition the accuracy of radar-derived geophysical products, most of them related to microphysical variability of ash clouds due to particle size distribution, shape, and dielectric composition. Moreover, the aggregation of volcanic ash particles within the eruption column of explosive eruptions may influence the residence time of ash in the atmosphere and the radiative properties of the ash cloud. Numerical experiments are helpful to explore processes occurring in the eruption column. Some advanced ash plume models can simulate the interactions of hydrometeors and volcanic ash and the radar response, including particle formation within a rising eruption column [6].

RADAR DATA PROCESSING

Weather radar systems, typically operated at S and C bands, can be used to monitor and measure volcanic eruption parameters, although they were designed to study hydrometeors and rain clouds. Both targets have the same measure principle: both rain clouds and

(continued on page 124)

Digital Object Identifier 10.1109/MSP.2010.939846
Date of publication: 17 February 2011

1053-5888/11/$26.00©2011IEEE

 continued from 128

ash clouds feature fragmentation and aggregation processes and cause backscattering and absorption of incident radiation, transmitted by the radar.

The measured weather radar backscattered power is proportional to the copolar horizontally polarized reflectivity factor Z_H. Microwave scattering from ash particles and from cloud water and ice droplets satisfies the Rayleigh approximation for frequencies up to X band. Under this condition, the simulated radar reflectivity factor Z_H, expressed in $\mathrm{mm}^6 \cdot \mathrm{m}^{-3}$, due to an ensemble of particles p is expressed as the sixth moment of particle size distribution (PSD) N_p as follows [5]:

$$Z_H = \eta_H \frac{\lambda^4}{\pi^5 |K_p|^2} = \int_0^\infty D^6 N_p(D)\, dD = m_6, \tag{1}$$

where η_H is the radar volumetric reflectivity, λ the wavelength, and K_p the dielectric factor of the particle ensemble of category p. It is noted that, keeping constant the ash particle amount, the reflectivity factor is higher for bigger particles. From (1), the variability of ash PSD modulates the radar reflectivity response.

The volcanic ash radar retrieval (VARR) methodology, devoted to quantitative remote sensing of ash cloud properties [4]–[6], includes two steps: i) ash classification and ii) ash estimation. Both steps, applied after an ash cloud detection procedure, are numerical algorithms trained by a physical-electromagnetic forward model, where the main PSD parameters are supposed to be constrained random variables. This is the reason why VARR is sometimes called a model-based supervised technique, whereas the generation of a simulated ash-reflectivity data set by letting PSD parameters vary in a random way can be framed within the so-called Monte Carlo techniques. The input information to current VARR algorithm is the measured reflectivity factor Z_{Hm} available at each radar range bin for a given elevation and azimuth angle. It is worth noting that the measured reflectivity factor Z_{Hm} differs from the simulated (intrinsic) reflectivity factor Z_H due to instrumental noise and calibration, propagation effects, and backscattering modeling errors.

For what concerns the classification step, its aim is related to the possibility to automatically discriminate between ash categories that were defined as fine, coarse, and large sizes. In the overall retrieval scheme, classification may represent a first qualitative output before performing parameter estimation. Maximum a posteriori probability (MAP) criterion can be used to carry out cloud classification in a model-based supervised context. If c is the ash class, then, by using the conditional probability density function (PDF) of a class c and given a measurement of the reflectivity factor Z_{Hm}, the MAP rule is expressed by [4]

$$\hat{c} = \mathrm{Mode}[p(c|Z_{Hm})], \tag{2}$$

where Mode is the modal value of the posterior PDF $p(c|Z_{Hm})$. Assuming a Gaussian probability framework to describe $p(c|Z_{Hm})$ and exploiting the Bayes theorem, then (2) can be transformed into the following expression [4]:

$$\hat{c} = \mathrm{Max}_c\left[-\frac{(Z_{Hm} - m_Z^{(c)})^2}{(\sigma_Z^{(c)})^2} - \ln(\sigma^{(c)}{}_Z)^2 + 2\ln p(c)\right], \tag{3}$$

where Max_c is the maximum value with respect to c. Computing (3) means to know the reflectivity factor mean $m_Z^{(c)}$ (also called class centroid) and standard deviation $\sigma_Z^{(c)}$ [dBZ] of Z_{Hm} for each ash class c. The prior PDF $p(c)$ can be used to subjectively weight each class as a function of other available information. Ash class perturbations are usually assumed uncorrelated. The statistical characterization of each cloud class can be derived from a simulated synthetic data set where PSD may be either arbitrarily defined or experimentally measured [5], [6].

Within the VARR technique, ash estimation is carried out by means of a regressive approximation of the training data set, as a function of the ash size and concentration class. A way to approach the quantitative retrieval problem is to adopt a statistical parametric model to describe the relation X-Z_{Hm} where X stands for either ash concentration C_a or ash fall-rate R_a [4]–[6]. Assuming a power-law model, we can write the estimated quantity for each class c as

$$\begin{cases} \hat{C}_a^{(c)} = \alpha[Z_{Hm}]^{\beta} \\ \hat{R}_a^{(c)} = \gamma[Z_{Hm}]^{\delta} \end{cases}, \tag{4}$$

where "^" indicates estimated quantity, whereas α, β, γ, and δ are the class-dependent regression coefficients. The latter are space-time variant (because they are related to ash cloud microstructure), whereas the synthetic measured reflectivity is simulated by assuming a zero-mean random noise due to instrumental and forward modeling uncertainties. Besides ash concentration, VARR can also provide for each range bin the ash fallout rate (where the terminal ash fall velocity and air updraft are needed).

APPLICATIONS TO VOLCANIC ASH MONITORING

The potential of VARR data processing in observing volcanic ash clouds has been analyzed using some case studies where volcano eruptions happened near an available weather radar:

- the Grímsvötn volcano eruption in 2004, analyzed together with the Icelandic Met Office (IMO), using a C-band weather radar (for details, see [3] and [4])
- the Augustine volcano eruption in 2006, analyzed together with the U.S. Geological Survey Alaska Volcano Observatory, using an S-band weather radar (for details, see [6]).

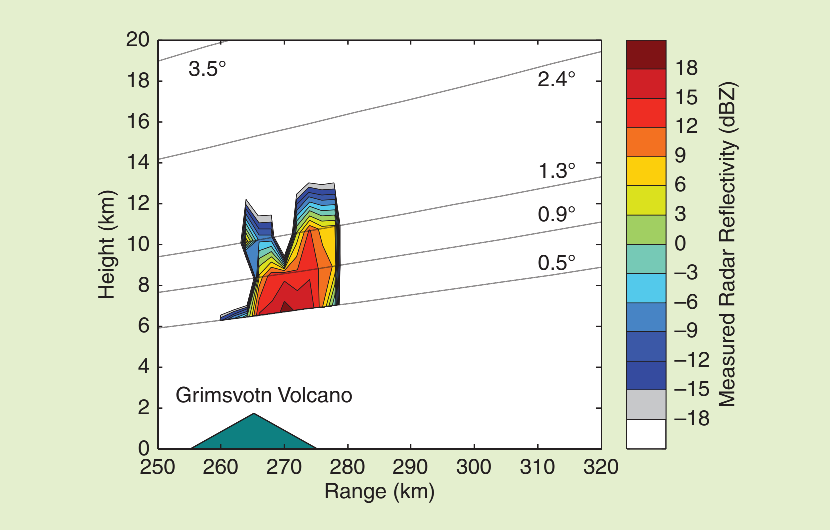
The recent explosive eruption of the Eyjafjalla Icelandic volcano started on 14 April 2010 and ended on 23 May 2010 is under evaluation, together with IMO, using an improved VARR technique.

The Icelandic case study in 2004 may be of particular interest. Grímsvötn is one of the most active volcanoes in Iceland, with a ~62 km^2 caldera covered by 150–250-m-thick ice. Its highest peak, Grímsfjall, on the southern caldera rim, reaches an elevation of

1722 m. Volcanic eruptions, numbering several per century, are water rich because of the ice cover, and they usually persist for days to weeks. The Grímsvötn eruption started in the evening of 1 November 2004 and was observed by a C-band weather radar located in Keflavik, Iceland [3], [4]. The first ash plume detected by the Keflavik radar was at 23:05 UTC (universal time coordinate) on 1 November 2004.

The eruption on the night of 2 November was followed by frequent ash plumes and the last one, detected by the weather radar, was at 08:30 UTC on 3 November. After this time, the ash plume was too low to be detected by the radar (reaching 6 km height or less). Radar volume scans were continuously acquired and data have been made available from 23:00 on 1 November 2004 till 06:00 UTC on 2 November 2004 every half an hour. Reflectivity data were radially averaged to 2 km to increase the measurement sensitivity (equal to about –5 dBZ around 260-km range). Considering the distance of about 260 km between the Keflavik radar and the Grímsvötn volcano, volcanic ash clouds can be detected at heights higher than 6 km using the minimum elevation of 0.5°. This means that the volcanic eruption cloud cannot be detected between the Grímsvötn summit at 1,725 m and 6,000 m altitude.

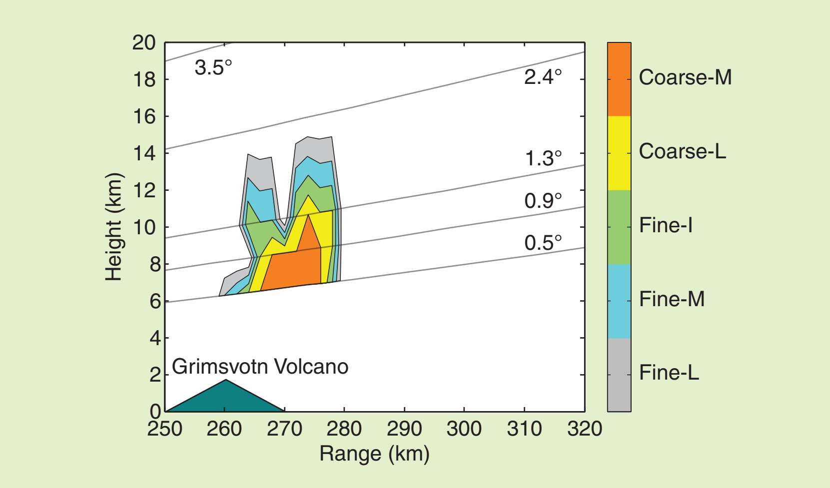
An example of C-band radar imagery can be easily pictured by plotting the so-called range-height indicator (RHI) diagram, illustrated in Figure 1. This figure stresses the fact that volcanic ash clouds can be detected from Keflavik only at heights higher than about 6 km using the minimum elevation of 0.5°. The signal of volcanic cloud is quite evident from the RHI signature with values up to 20 dBZ. If the classification algorithm is applied to radar RHI data, we can detect the ash class distribution displayed in Figure 2. The RHI maps strictly reflect the bimodal spatial structure of reflectivity measurements in Figure 1. Coarse ash particles are dominant in the lower part of volcanic plume, already moved toward northwest.



[FIG1] **RHI of the measured horizontally polarized reflectivity (in dBZ) along the Radar-vent cross section during the Grímsvötn volcano eruption on 2 November 2004 at 0300 UTC. The measured sector is visualized as a function of distance between the Keflavik Radar (64°01′ N, 22°38′ W) and Grímsvötn volcano (64°42′ N, 17°33′ W, schematically indicated by a filled triangle) with elevation angles between 0.5° and 3.5°.**

CONCLUSIONS

The possibility of monitoring 24 hours a day, in all weather conditions, at a fairly high spatial resolution and every few minutes after the eruption is the major advantage to using ground-based microwave radar systems. The latter can be crucial systems to monitor the volcanic eruption from its eruption early-stage near the volcano vent, dominated by coarse ash and blocks, to ash-dispersion stage up to few hundreds of kilometers, dominated by transport and evolution of coarse and fine ash particles. Of course, the sensitivity of the ground-based radar measurements will decrease as the ash cloud will be farther so that for distances greater than about 50 km fine ash might become “invisible” to the radar; but, in this respect, radar observations can be complementary to satellite, LIDAR, and aircraft observations. Moreover,



[FIG2] **The same as in Figure 1, but for estimated ash class, named as fine-L (fine ash with light concentration), fine-M (fine ash with moderate concentration), fine-I (fine ash with intense concentration), coarse-L (coarse ash with light concentration), and coarse-M (fine ash with moderate concentration). The triangle schematically indicates the volcano vent.**

radar-based products such as real-time erupted volcanic ash concentration, height, mass, and volume can be used to initialize dispersion model inputs.

Due to logistics and space-time variability of the volcanic eruptions, a suggested optimal radar system to detect ash cloud could be a portable X-band weather Doppler polarimetric radar. This radar system may satisfy technological, economical, and new scientific requirements to detect ash cloud. The sitting of the observation system, is a problematic tradeoff for a fixed radar system (as the volcano itself may cause a beam obstruction and the ash plume may move in unknown directions), can be easily solved by resorting to portable systems.

Further work is needed to assess the VARR potential using experimental campaign data. Future investigations should be devoted to the analysis of the impact of ash aggregates on microwave radar reflectivity and on the validation of radar estimates of ash amount with ground measurements where available. The last task is not an easy one as the ash fall is dominated by wind advection and by several complicate microphysical processes. This means that what is retrieved within an ash cloud may be not representative of what was collected at ground level in a given area. Spatial integration of ground-collected and radar-retrieved ash amounts may be considered to carry out a meaningful comparison. Preliminary results for the Grímsvötn case study show that the radar-based ash mass retrievals compare well with the deposited ash estimated from in situ ground sampling within the volcanic surrounding area.

AUTHOR

Frank S. Marzano (marzano@die.uniroma1.it) is an associate professor in the Department of Information Engineering, Electronics and Telecommunications (DIET), Sapienza University of Rome, Italy, and vice-director of the Center of Excellence on Remote Sensing and Severe Weather Forecast (CETEMPS), University of L'Aquila, Italy.

REFERENCES

[1] M. Trevelyan. (2010, Apr. 17). Ash cloud over Europe deepens travel chaos. *Reuters* [Online]. Available: http://www.reuters.com/article/idUSTRE63E1TM20100417

[2] A. Tupper, I. Itikarai, M. S. Richards, F. Prata, S. Carn, and D. Rosenfeld, "Facing the challenges of the international airways volcano watch: The 2004/05 eruptions of Manam, Papua New Guinea," *Weather Forecast.*, vol. 22, pp. 175–191, 2007.

[3] F. S. Marzano, S. Barbieri, E. Picciotti, and S. Karlsdóttir, "Monitoring sub-glacial volcanic eruption using C-band radar imagery," *IEEE Trans. Geosci. Remote Sensing*, vol. 58, no. 1, pp. 403–414, 2010.

[4] F. S. Marzano, S. Barbieri, G. Vulpiani, and W. I. Rose, "Volcanic cloud retrieval by ground-based microwave weather radar," *IEEE Trans. Geosci. Remote Sensing*, vol. 44, no. 11, pp. 3235–3246, 2006.

[5] F. S. Marzano, G. Vulpiani, and W. I. Rose, "Microphysical characterization of microwave radar reflectivity due to volcanic ash clouds," *IEEE Trans. Geosci. Remote Sensing*, vol. 44, pp. 313–327, 2006.

[6] F. S. Marzano, S. Marchiotto, S. Barbieri, C. Textor, and D. Schneider, "Model-based weather radar remote sensing of explosive volcanic ash eruption," *IEEE Trans. Geosci. Remote Sensing*, vol. 48, pp. 3591–3607, 2010.

[SP]

from the **GUEST EDITORS** continued from page 15

various machine learning and signal processing problems involving NMF, sparse PCA, LARS, OMP, and SOMP: http://www.di.ens.fr/willow/SPAMS/

- Bayesian compressive sensing: http://people.ee.duke.edu/~lcarin/BCS.html
- Orthogonal matching pursuit and KSVD: http://www.cs.technion.ac.il/~ronrubin/software.html
- Low-rank matrix recovery and completion (RPCA): http://perception.csl.uiuc.edu/matrix-rank/home.html

OTHER REFERENCES AND APPLICATIONS

- Compressive Sensing Repository: http://dsp.rice.edu/cs
- Robust Face recognition and others: http://perception.csl.uiuc.edu/recognition/Home.html

ACKNOWLEDGMENTS

We would like to thank all the authors who have contributed to this special issue and all the reviewers who have provided valuable comments. We thank *IEEE Signal Processing Magazine* for supporting this special section, with special thanks to Prof. Dan Schonfeld of UIC for recommending this idea to the editors and the board. We thank IEEE staff, especially Sonal Parikh and Rebecca Wollman, for their professional support with the editorial matters during the preparation of this special issue.

SPECIAL TRIBUTE TO PROF. PARTHA NIYOGI

During the preparation of this special issue, one of the guest editors, Prof. Partha Niyogi of the University of Chicago, passed away. We all have been deeply saddened by the sudden loss of a great scholar, a colleague, and a friend. Prof. Niyogi has made some of the most fundamental contributions to the theory of manifold learning and has been well known as a world leading scientist in this new area. Prof. Niyogi agreed to serve as a guest editor of this special issue despite his medical condition at the time, which had shown his great passion and dedication to this research topic. All the editors are very much honored to have served with him as guest editors on this important special issue during his last days.

REFERENCES

[1] M. Belkin and P. Niyogi, "Laplacian eigenmaps for dimensionality reduction and data representation," *Neural Comput.*, vol. 15, no. 6, pp. 1373–1396, 2003.

[2] E. Candèes and T. Tao, "Decoding by linear programming," *IEEE Trans. Inform. Theory*, vol. 51, no. 12, 2005.

[3] S. Chen, D. Donoho, and M. Saunders, "Atomic decomposition by basis pursuit," *SIAM Rev.*, vol. 43, no. 1, pp. 129–159, 2001.

[4] C. Eckart and G. Young, "The approximation of one matrix by another of lower rank," *Psychometrika*, vol. 1, pp. 211–218, 1936.

[5] G. Haro, G. Randall, and G. Sapiro, "Stratication learning: Detecting mixed density and dimensionality in high-dimensional point clouds," in *Proc. NIPS*, 2008.

[6] Y. Ma, H. Derksen, W. Hong, and J. Wright, "Segmentation of multivariate mixed data via lossy data coding and compression," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 29, no. 9, pp. 1546–1562, 2008.

[7] Y. Ma, A. Yang, H. Derksen, and R. Fossum, "Estimation of subspace arrangements with applications to modeling and segmenting mixed data," *SIAM Rev.*, vol. 50, no. 3, 2008.

[8] J. Tenenbaum, V. de Silva, and J. Langford, "A global geometric framework for nonlinear dimensionality reduction," *Science*, vol. 290, no. 5500, pp. 2319–2323, 2000.

[9] R. Vidal, Y. Ma, and S. Sastry, "Generalized principal component analysis (GPCA)," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 27, no. 12, pp. 1–15, 2005.

[SP]