Support Vector Machine Hydrometeor Classification for dual-polarization radar: application to avionic systems and meteorology
Support Vector Machine Hydrometeor Classification pour radar à double polarisation : application aux systèmes avioniques et à la météorologie

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Abstract

During the last few decades, most of the worldwide weather radar infrastructure has been upgraded to dual-polarization. Plans to demonstrate the utility of such technology for civil aircraft radars were undertaken by the EU Clean Sky Joint Technology Initiative (www.cleansky.eu). Dual polarization offers appealing advantages for avionic applications, such as the ability to correct X-band attenuation due precipitation and the possibility of implementing automated Hydrometeor Classification Algorithms (HCA). HCA can be useful to detect the presence of dangerous weather conditions related to the presence of hydrometeors like hail or graupel, typically associated with convection. Most of implemented HCAs rely on Fuzzy Logic (FL) methods. Supervised learning models based on a Support Vector Machine (SVM) are widely used for classifying remote sensing imageries and offer advantages in terms of computing time. The major problem of the SVM HCA is preforming the learning phase. This process has been implemented off-line using results obtained by a FL classifier. Effectiveness of the SVM HCA has been tested by using simulated scenarios relative to an intense convective event that occurred on 15 October 2012 in the Southern Mediterranean and with real data collected by C-band dual-polarization ground-based radars.

Résumé

Ces dernières décennies, à l'échelle mondiale, la plupart des radars météorologiques ont été équipés de double polarisation. Plusieurs études ont été entreprises dans le cadre de l'initiative EU clean Sky Joint Technology (www.cleansky.eu) afin d'illustrer l'utilité de cette technologie pour les radars des avions de ligne. La double polarisation apporte des avantages intéressants pour les applications avioniques, tels que la capacité de corriger de l'atténuation liée aux précipitations pour la bande X ainsi que la possibilité d'implémenter des algorithmes automatisés de classification des hydrométéores (HCA). Les HCAs peuvent être utiles pour détecter la présence de conditions météorologiques dangereuses liées à la présence d'hydrométéores tels que la grêle ou les graupels, ceux-ci étant habituellement associés à la convection. La plupart des HCAs utilisent des méthodes de logique floue (FL). Les techniques d'apprentissages supervisées basées sur l'utilisation d'un Support Vector Machine (SVM) sont largement utilisées pour la classification des images de télédétection et sont très performantes en terme de temps de calcul. Le principal problème des HCA utilisant un SVM est la mise en forme de la base de données d'apprentissage . Cette étape a été implémentée à part en utilisant la classification issue d'un algorithme de FL. Les performances du SVM-HCA ont été évaluées au moyen de simulations d'un événement de convection intense qui s'est déroulé le 15 octobre 2012 dans le sud de la Méditerranée et avec des observations issues de radars sols en bande C équipés de double polarisation.

1 Introduction

Within the 7th framework programme of the European Commission, several projects of the Clean Sky Joint Technology Initiative (JTI) aimed at improving the weather radars that are used on board the civil aircrafts to detect (and avoid) adverse weather along the flight. State-of-the-art systems commercially available are pulsed single polarization X-bands radars that estimate the effective radar reflectivity factor, which is displayed in a few colours coded according to specific standards and suggest proper actions: areas in red must be avoided. In addition, some radars have Doppler capabilities and detect the turbulence associated to the motion of cloud particles within a certain distance. Dual polarization that nowadays can be considered as the technology standard for ground-based operational and research weather radars (during the last few decades, most of worldwide weather radar infrastructure has been upgraded to dual-polarization.), has not used yet for aircraft systems. However, dual-polarization has interesting characteristics that can make it appealing for civil aircraft applications ([1][2]). First, dual-polarization can enable quite robust methods for compensating the X-band attenuation caused by propagation through precipitation. Attenuation can lead to underestimate the severity of some convective cell and the associated risk when the measured reflectivity is lowered by attenuation. Second, the possibility of implementing automated hydrometeor classification procedures to detect the presence of dangerous weather conditions such as those characterized by specific hydrometeors associated to the insurgence or to the presence of convection.

This paper focuses on this second aspect. Among the meteorological products and applications based on dual-polarization radar measurements, the identification of hydrometeor type has become one of the most successful. Different Hydrometeor Classification Algorithms (HCA) have been proposed along the years, but almost all of them are based on empirical approaches allowing to deal with approximate knowledge of the actual relationships between radar measurements and microphysics of precipitation within a resolution volume, such as the fuzzy logic (FL) methods. References [3] and [4] are early papers on HCA, while [5]-[7] are more recent studies aiming at operational implementations in operational radars at different bands. Such classifiers achieve hydrometeor classification by analyzing the set of dual-polarization measurements pertinent to a single radar measurement sampling. Attempts to improve the robustness of the fuzzy logic approach exploit measurements in the neighbouring bins to enhance the spatial coherency of classification maps [8]. A similar approach, but based on convolutional neural network deep learning approach is explained in [9]. Unsupervised clustering to define the number of classes and the membership functions has been explored [10], while a semi-supervised approach, exploiting fuzzy logic for defining the constraints of an unsupervised approach has been proposed [11]. Actually, a few HCA implementations based on supervised learning methods can be found in the literature. Neural networks have been used in [3] and [9] to adjust membership functions based on observed data. Supervised learning models based on a Support Vector Machine (SVM) [12] are widely used for classifying different remote sensing imageries (see [13] for a review), including meteorological satellite observations ([14][15]). Therefore, the SVM approach is worth to be investigated for hydrometeor classification using dual-polarization radar measurements, also for avionic applications.

An SVM classification algorithm consists of two phases: the training phase, in which the relation between input variables (i.e. radar measurements) and class labels output (i.e. hydrometeor classes) is established, and the predict phase, in which the most likely class is assigned to an input sample measurements (Fig. 1). The supervised algorithm is typically trained once and out of the classification prediction scheme. The SVM classifier usually proceeds for the two-classes problem in three stages. The first one is the basic margin classifier where separation between two classes is tried with a linear decision boundary (a hyperplane). For problems that are not separable by a linear decision, in a second step the classifier is modified to tolerate misclassification (soft margin) by introducing a penalty. At the last stage, the classifier can be nonlinearly generalized by using a kernel method. The support vector machine can be regarded as a linear classifier that finds the best linear separation between samples belonging to two classes. This binary scheme can be extended for multiclass classification by combining several binary classifiers, whereas one-step multiclass solutions are generally more expensive fom a computational view. An accurate strategy used for this purpose is the one-against-all (OAA) that is used in this work. It consists in applying binary SVM to separate members of one class to members of other classes. The algorithm is based on a parallel architecture composed by N SVMs, one for each class.

In the framework of research activities developed in Clean Sky, a reference architecture has been defined that designates a decision support system (DSS) to host end-user applications using dual polarization measurements as input . Avionic devices acting as DSS on board of civil aircrafts must be certificated and must respect strict specifications (e.g., [16]) and have relatively poor performances in terms of both computational and storage capabilities. The EFB by Astronautics NEXIS Flight-Intelligence System co., has been adopted for development. Classification output can be both displayed to the pilot (se Fig. 1, right), associated to the label of hydrometeors (or to a set of new labels) or associated to a level of risk related to the presence of a given type of hydrometeor. Ultimately, the level of risk can be handle by a process that helps a pilot to choose an optimal route (Fig. 1, center and right where different display mode available to the pilot are shown) [17]. However, the HCS should be also accurate, at least not less than a standard fuzzy logic HCA.

This paper summarizes some basic concepts of SVM and the solution that has been adopted apply this approach to dual-polarization weather radars [23]. Testing with a simulated scenario allows to reveal important properties of SVM that must be taken into account in implementations.

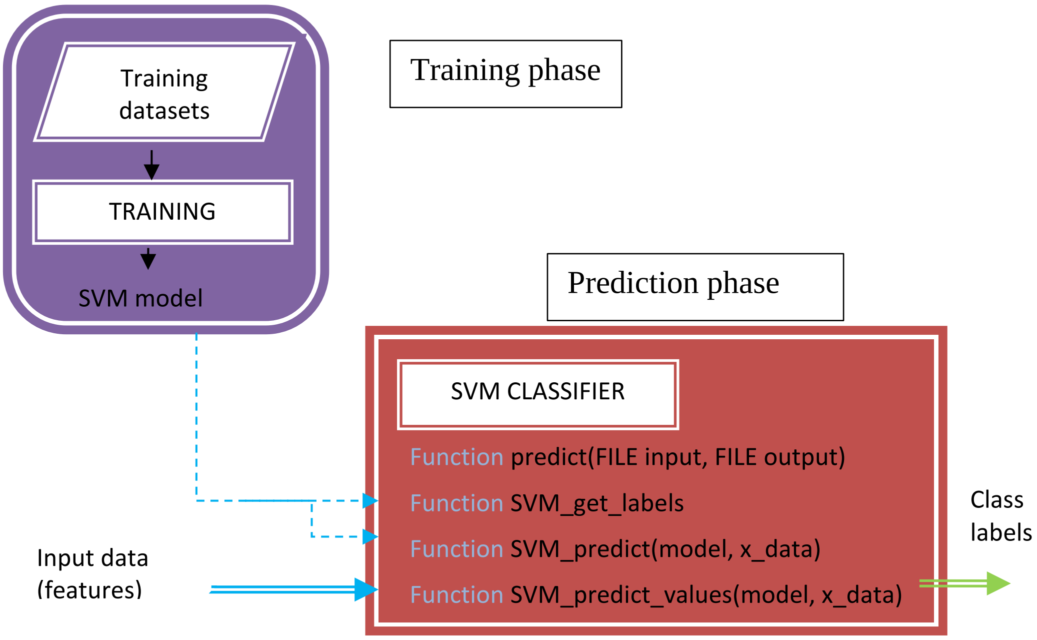

Figure 1: Scheme of implementing Support Vector Machine

Finally, testing with actual dual polarization data indicates that the SVM HCA developed and shown in this paper is generic and can be effectively used for ground-based weather radars.The useful approach used for hydrometeor classification for gound-based radar can be time consuming and could not be enough efficient for avionic weather radar. If the aircraft speed is approximately 800 km h^{-1} and that the radar antenna sweeps 120° in azimuth with 3° angular resolution in 10 s, with 150 km of maximum range and 150 m range resolution, each sweep implies 1000 range bins for about 40 azimuth lines implying labeling 1000 samples at least every 250 ms, or equivalently, at least 4000 labels s^{-1}. The SVM HCA proposed in [1] was found to be able to generate 7000 labels/s (running on an x86_64 Linux machine Eight core, Intel-i7@2,80GHz processor). These results highlight the SVM algorithm capability in terms of computational time and indicate it as a candidate for hydrometeors classification on an EFB machine.

2 Support Vector Machine Implementation of HCA

The SVM training phase provides the grounds of the HCA by defining the support vectors, defined through unknown linear relations between observations for which labels are known. This phase, in the case of hydrometeor classification, could involve processing of large sets of data. Since fuzzy logic is a well established method for HCA, the training phase is conducted using an FL-HCA. Fuzzy logic HCAs have as input the radar measurements, as output the hydrometeor classesand membership functions that define the degree of truth of the class of hydrometeor given some inputs. Membership functions are determined both by investigating physical scattering and propagation behavior of the different hydrometeors, by analyzing empirical measurements, or by synthesizing the knowledge available from existing studies. The FL-HCA used in this paper is in use at Institute of Atmospheric Sciences and Climate of the Italian National Research Council (ISAC–CNR) and is tailored to identify meteorological targets, with a particular emphasis on the hydrometeors involved in convective events [19]. It is not far from different schemes described in the literature and therefore it is reasonable to consider SVM results as not significantly influenced by the choice of FL classifier. Input measurements are the radar reflectivity factor (Z_h in dBz), differential reflectivity (Z_{dr}, in dB), specific differential phase shift (K_{dp} in deg/km), copolar correlation coefficient (ρ_{hv}), and the height of the 0° isothermal. The output class set is the following: *i) Rain:* includes light, moderate, and heavy rain; in rain, Z_h varies from 10 to 60 dBZ and Z_{dr} is positive, due to the oblateness of rain drops; *ii) Dry Snow*: includes all the non-wet ice particles detectable above the 0°C isothermal, such as aggregates, plates, and columns, associated to low values of Z_h; *iii) Wet Snow:* this class typically refers to melting ice particles that form the "melting layer" where ice particles melts below the 0°isothermal to form raindrops; *iv) Graupel:* they are iced particles detectable both above (in convection) and within the melting layer, but can reach the reach ground for downdaft; they produce Z_{dr}~0, or even negative values for conical graupel; *v) Hail:* the presence of hailstones characterizes deep convective events and can be found from the ground up to heights well above the melting layer; hailstones have high variability in size and shape, but typically determines high Z_h, but Z_{dr} and K_{dp} values close to 0; *vi) Hail Mix* is a class that accounts for mixture of raindrops lifted by updraft, supercooled raindrops, hail, small hail, and graupel. The typical radar signature of this class is high values of Z_h and low values of ρ_{hv}, a measurement that is sensitive to heterogeneity of scatterers within the radar sample volumes.

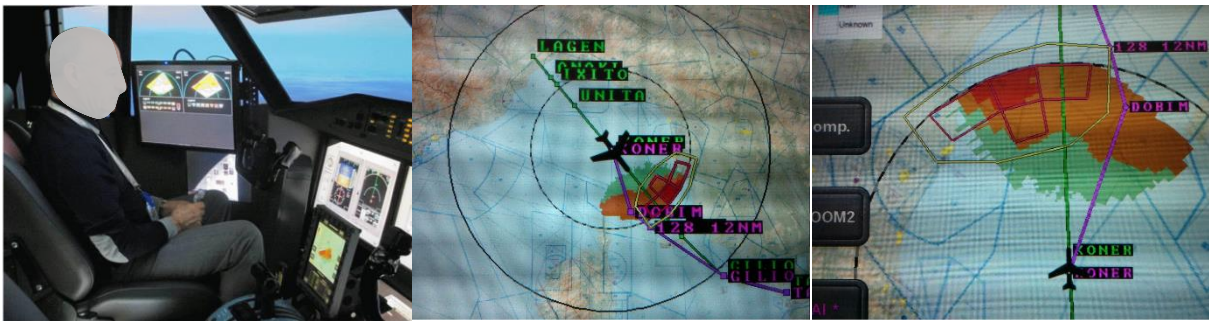

Figure 1: Position of EFB on the cockpit (right) (from [2]*) and display of the classification results with identification of risk zones and route suggested to pilot. Two different display and zoom options can be used (center and right panels)*

To perform a meaningful training phase, the training set should be representative of the physical phenomena to be classified. A large variety of cases should form the training set. Some processing steps are required to select a training set of radar measurements that are not contaminated by clutter and are compensated for biases due to attenuation or partial beam blocking. For measurements collected at high elevation angle, a compensation for polarimetric measurements is also necessary [20]. One of the input of the HCA is the level of 0° isothermal. It can be estimated also using radar, but in this study is considered as estimated by radio soundings for gound-based systems or (using some assumptions) from measurements collected by devices on-board an airplane, or from weather model. The SVM algorithm is trained on classification maps generated by a FL classification approach. For each class the SVM descriptors are extracted. Radar data are scaled into a specific range because, in general, they (and in general, input features) have values that ranges in different scales and therefore are not commensurable. For nonlinear SVM using radial basis function (RBF) kernel, the penalty and the kernel parameters, usually denoted with symbols C and γ, determining the capability of the algorithm to separate the hyperplanes, need to be estimated. The better these parameters are identified, the more accurate is the prediction of the classifier. Their identification is performed during the training phase using a cross-validation (CV) procedure.

3 Validation with a simulated datasets

The Weather Research and Forecasting model (WRF) numerical weather prediction code outputs the atmospheric quantities from which the radar measurements are simulated. The Milbrandt-Yau 2-moment microphysics option of WRF [21] is used to obtain microphysical parameters such as mixing ratio (q in Kg/Kg) and concentration of particle (N in m^{-3}) for 4 different classes (rain, snow, graupel and hail). A corresponding scenario of radar measurements is obtained following the procedure described in [22][23]. Since the hydrometeor classes provided by the weather model used are four, and the classes of the SVM HCA are six, some HCA classes are obtained mixing two WRF classes. Difference are in snow class (HCA split snow in two classes: wet snow and dry snow), and in Mix Hail class (this class is present only in HCA and it is a mixed of rain and hail).

The WRF model is run for an intense precipitation events occurred in the afternoon 15 October 2012 in South Mediterranean and off the coasts of Tunisia. The obtained scenario is composed of a cube of 800 × 682 × 52 elements of 0.300 km × 0.300 km × 0.150 km for which the microphysical characteristics, i.e. q and N, and meteorological parameters (pressure, temperature, wind speed and direction) are provided by WRF and by the simulator in [22], radar measurements are calculated at frequency of 9.353 GHz. An SVM algorithm has been implemented for the WRF scenario using the radar measurements and the height of 0° level given by the WRF model. The training set is obtained random sampling the elements of the WRF cube. A training set composed by 104 samples (l) was randomly sampled, while a test set of 3×106 samples (m, randomly sampled excluding the samples belong to the training set) were used to test the SVM-HCA. In order to get an estimate of the generalization performance of a model typical steps are (i) find optimal tuning parameters using cross-validation

(CV), (ii) train a model using these optimal parameters on the full training set and (iii) test this model on the test set. For the model used in this work, the RBF kernel is identified by the parameters C and γ. The better these parameters are identified, the more accurate is the classifier prediction. A CV is therefore used also to get an estimation of the generalization error when certain tuning parameters are used. A "grid-search "on C and γ using CV is computed. Various pairs of (C,γ) values are tried and the one with the best CV accuracy is picked.

It important to estimate how large a training set should be to have an accurate model. To this purpose, a large subset of training set is obtained. It is expected that larger training subsets increase the CV accuracy. It was found that over a certain size (it is 10^4 in this case as reported in [16], the CV accuracy is stabilized. This number is considered to be the number of observations necessary to train the SVM model with an high accuracy (94.8%) and in a reasonable time processing (less than 1 minute). It is important to assure that all the classes in the training are well represented by the SV. In fact, when the training is made using random sampling the classes that have low occurrences should not be sampled enough to establish a robust relation. In order to allow a good representation of all the classes in the model the training set should be quasi-equally divided among the classes.

The validation of the classes predicted by the SVM with respect to the WRF microphysical expresses in terms of the *q* parameter is assessed. Several metrics can be used, namely the confusion matrix (CM) calculated between the truth and the predicted hydrometeor classes applied at the same test set. The elements CM(i,j) contain the number of observations classified in i_{th} class, which in reality belong to the j_{th} class. The diagonal contains the same classification for both algorithms (correct classification). Given CM, the global performance of SVM is quantified by the overall accuracy (*OA*) and Cohen's Kappa (*K*). In spite of the differences between the WRF and SVM classes definition, good performance are obtained for SVM classifications using the metric above. The two classificators are in good agreements with an *OA*= 74% and *K*= 0.62. This result indicates that the SVM well predict the WRF classes via the FL reference.

4 Examples of application of SVM HCS to ground-based weather radar

The SVM model trained by FL classification presented in previous sections has been applied to real polarimetric ground based measurements collected at C-band by the Polar 55C dual-polarization radar of CNR-ISAC installed at the Rome branch of ISAC. Considered are convective events occurred in October 2012 [24] and October 2015 [25]. The training phase was implemented using the Fuzzy Logic classification scheme [19]. Fig. 3 compares hydrometeor classification results obtained with SVM (left) and FL (right) classifier for a sweep collected on 14 October 2015 at 01:05 UTC (top) and a vertical cut at 45° of the radar volume (bottom) composed by a sequence of sweeps containing that sweep. Output of the classifier are quite similar as expected, since the SVM classifies was trained with the FL. In the plot showing the vertical section, the figure obtained with SVM presents a lower number of "nodata" and more a spatially homogeneous graupel region is found in a precise region above the melting layer.

5 Conclusions

This work has presented a supervised hydrometeor classification approach based on a learning machine method, namely, the Support Vector Machine. The development of this SVM HCA was stimulated by the perspective application for a dual-polarization weather radar for civil aircrafts. However, the architecture is a generic one and the resulting classificator can be applied to the dual-polarization weather radars widely adopted by weather services. The implementation presented requires 4 dual-polarization radar measurements and the height of the 0 °C level. Having established robust relations between input variables and known samples during the training phase by means of a well consolidated fuzzy logic HCA, in the prediction phase, the SVM HCA predicts output classes for a given sample. Validation has been conducted both with realistic scenarios generated by the numerical weather prediction model WRF (in this case a "truth" reference is available) and with real radar measurements through comparison with an FL output. Besides the good performance of SVM in terms of hydrometeor identification, the SVM approach has also exhibited a superior computational efficiency with respect to the FL approach. These aspects recommend to use the SVM HCA in quasi-real-time tasks. The approach used to develop the HCA can be easily extended to include more input variables and an extended set of output variables.

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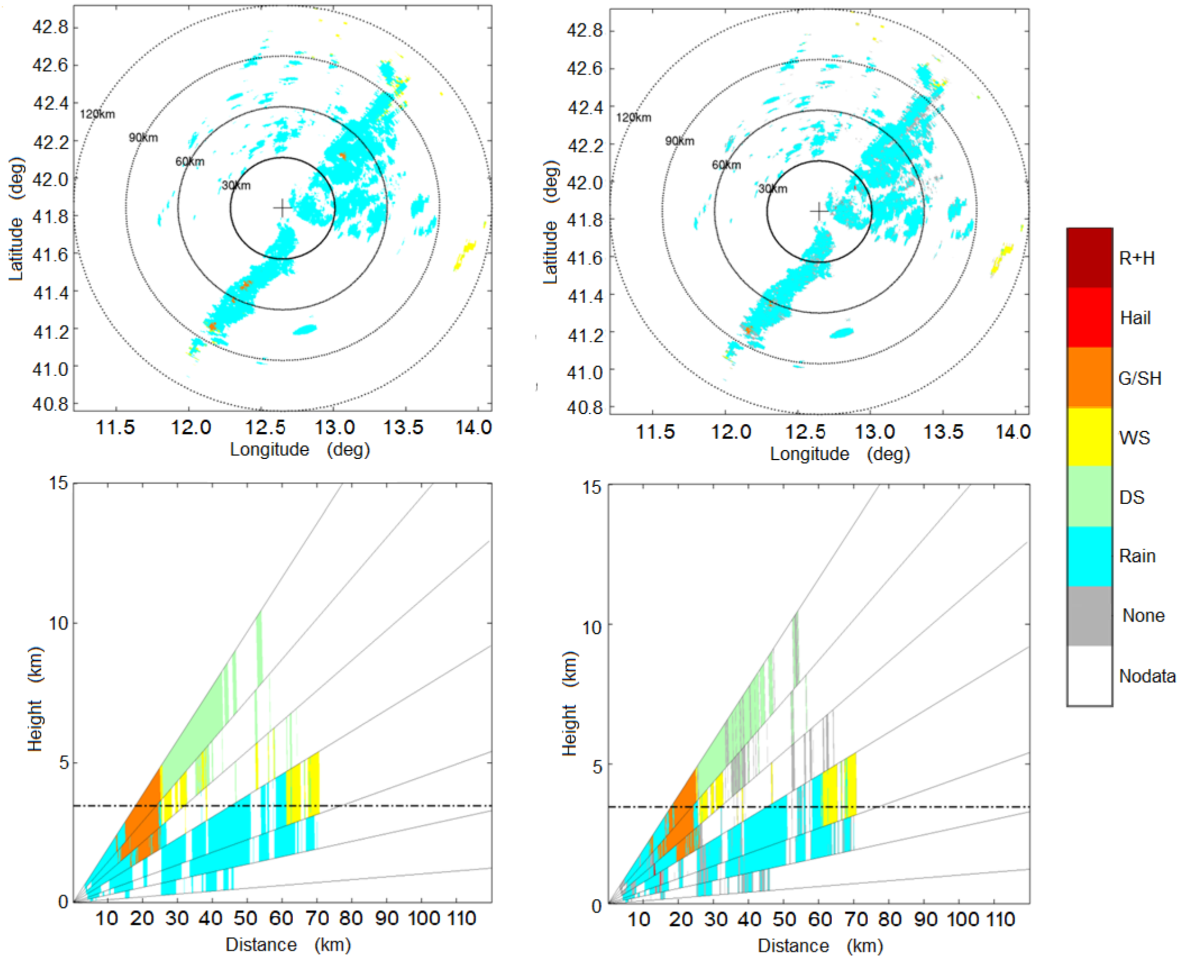

Figure 3: Example of SVM (left) and FL (right) classification for a radar volume collected by the Polar 55C radar on 14 October 2015 at 13:05 UTC. On top a sweep collected at 1.6° elevation angle is shown. On bottom, a vertical cut at 45° azimuth is reconstructed using six sweeps at different elevations is shown. “R+H” stands for hail mix; “G/SH” stands stands for wet snow. “DS” stands stands for wet snow; “DS” stands for dry snow; “none” stands for not classified; and “nodat” stands for no data.

References

[1] Cuccoli A. Lupidi L. Facheris L. Baldini "Polarimetric radar for civil aircrafts to support pilots' decision in bad weather conditions, 2015 IEEE Int. Geosci. Remote Sens. Symp pp. 2327-2330, 2015.

[2] Lupidi A., F. Cuccoli and S. Lischi, Polarimetric radar for flight support system with a reconfigurable electronic flight bag, 2016 IEEE Metrology for Aerospace (MetroAeroSpace), Florence, pp. 108-112 2016.

[3] Liu, H., Chandrasekar, V, Classification of hydrometeor type based on multiparameter radar measurements: development of a fuzzy logic and neuro fuzzy systems and in-situ verification. J. Atmos. Ocean. Technol. 17, pp. 140–164, 2000.

[4] Zrnić, D.S., Ryzhkov, A., Straka, J., Liu, Y., Vivekanandan, J. Testing a procedure for automatic classification of hydrometeor types. J. Atmos. Ocean. Technol. 18, pp. 892–913, 2001.

[5] Dolan, B., Rutledge, S.A. A theory-based hydrometeor identification algorithm for X-band polarimetric radars. J. Atmos. Ocean. Technol. 26, pp. 2071–2088, 2009.

[6] Dolan, B., Rutledge, S.A., Lim, S., Chandrasekar, V., Thurai, M. A robust C-band hydrometeor identification algorithm and application to a long-term polarimetric radar dataset. J. Appl. Meteorol. Climatol. 52, pp. 2162–2186, 2013.

[7] Al-Sakka, H., Boumahmoud, A.A., Fradon, B., Frasier, S.J., Tabary, P., A new fuzzy logic Hydrometeor Classification Scheme applied to the French X-, C-, and S-band polarimetric radars. J. Appl. Meteorol. Climatol. 52, pp. 2328–2344, 2013

[8] Bechini, R., Chandrasekar, V., A semisupervised robust hydrometeor classification method for dual-polarization radar applications. J. Atmos. Ocean. Technol. 32, pp. 22–47, 2015.

[9] Wang, H., Ran, Y., Deng, Y. et al. J Wireless Com Network. 2017: 173. https://doi.org/10.1186/s13638-017-0965-5

[10] Grazioli, J., Tuia, D., Berne, A., Hydrometeor classification from polarimetric radar measurements: A clustering approach. Atmos. Meas. Tech., 8, pp. 149–170, 2015.

[11] Besic, N., Figueras i Ventura, J., Grazioli, J., Gabella, M., Germann, U., Berne, A., Hydrometeor classification through statistical clustering of polarimetric radar measurements: A semi-supervised approach. Atmos. Meas. Tech. 9, pp. 4425–4445, 2016.

[12] Scholkopf, B., Smola, A.J., Learning with Kernels: Support Vector Machines, Regularization, Optimization, and Beyond. MIT Press: Cambridge, MA, USA, 2001.

[13] Mountrakis, G., Im, J., Ogole, C., Support Vector Machines in remote sensing: A review. ISPRS J. Photogramm. Remote Sens. 66, pp. 247–259, 2011.

[14] Lee, Y., Wahba, G., Ackerman, S.A., Cloud classification of satellite radiance data by multicategory Support Vector Machines. J. Atmos. Ocean. Technol. 21, pp. 159–169, 2004.

[15] Rossi R., Basili F., Del Frate F., Luciani M., Mesiano F., Techniques based on Support Vector Machines for cloud detection on quickbird satellite imagery, Proc. IEEE Int. Geosci. Remote Sens. Symp., pp. 515-518, 2011.

[16] Federal Aviation Administration: Guidelines for the Certification, Airworthiness, and Operational Use of Electronic Flight Bags. https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_120-76C.pdf.

[17] Serafino, G., Multi-objective aircraft trajectory optimization for weather avoidance and emissions reduction. In Int. Workshop on modelling and simulation for autonomous systems; Cham, Switzerland,, pp. 226–239, 2015.

[18] Roberto N., Baldini L., Adirosi, E., Facheris L., Cuccoli F., Lupidi, A., Garzelli, A., A Support Vector Machine hydrometeor classification algorithm for dual-polarization Radar,"Atmosphere, 8, pp. 134, 2017.

[19] Baldini, L.; Gorgucci E., Chandrasekar V., Petersen, W., Implementations of CSU hydrometeor classification scheme for C-band polarimetric radars. 32nd Conf. on Radar Meteorology, Albuquerque, N. M., Amer. Meteor. Soc., 2005.

[20] Baldini, L., Roberto, N., Gorgucci, E., Fritz, J., Chandrasekar, V., Analysis of dual polarization images of precipitating clouds collected by the COSMO SkyMed constellation. Atmos. Res. 144, pp. 21–37, 2013.

[21] Milbrandt, J.A., Yau, M.K., A multimoment bulk microphysics parameterization. Part II: A proposed three-moment closure and scheme description. J. Atmos. Sci., 62, pp. 3065–3081, 2005.

[22] Lupidi, A., Lischi, S., Berizzi, F., Cuccoli, F., Roberto, N., Baldini, L., Validation of the advanced polarimetric Doppler weather radar simulator with Polar55C Real Observations. In Proc. of the 15th International Radar Symposium (IRS), Gdansk, Poland, 16–18 June 2014.

[23] Roberto, N., Baldini, L., Adirosi, E., Lischi, S., Lupidi, A., Cuccoli, F., Barcaroli, E., Facheris, L. Test and validation of particle classification based on meteorological model and weather simulator. In Proc. of the 13th European Radar Conference (EuRAD), London, UK, 11–13 October 2016.

[24] Roberto, N., Adirosi, E., Baldini, L., Casella, D., Dietrich, S., Gatlin, P., Panegrossi, G., Petracca, M., Sanò, P., Tokay, A., Multi-sensor analysis of convective activity in central Italy during the HyMeX SOP 1.1. Atmos. Meas. Tech., 9, pp. 535-552, 2016.

[25] Montopoli, M., Roberto, N., Adirosi, E., Gorgucci, E., Baldini, L., Investigation of weather radar quantitative precipitation estimation methodologies in complex orography. Atmosphere, 8, pp. 34, 2017.