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Atmospheric Measurement Techniques
Discussions

Interactive comment on "The Passive microwave Neural network Precipitation Retrieval (PNPR) algorithm for AMSU/MHS observations: description and application to European case studies" *by* P. Sanò et al.

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We would like to thank Referee#1 for his/her review of our paper and the important comments and suggestions provided. Please, find below our responses to the Referee's comments and the details on how we will address them in the new version of the manuscript.

Major: More conservative words should be used in the conclusion part. I have not doubt that this NN algorithm works well for all four cases shown in this paper. But

I don't think you can generalize to say that in the conclusion part "The comparison with the HSAF H02 v2.3 algorithm (operational until June 2013) confirmed the good performance of PNPR and better agreement with the ground-based precipitation data." All the statistics (Fig. 16 and Table 3) are solely based on the four cases. Therefore, before more comprehensive comparisons have been done, this conclusion can only be applied to these four cases. Maybe, the over-all performance of the H02 and NN are similar.

Authors' Reply: The suggestion is accepted. This paper is focused on the description of the algorithm design and we have shown only four case studies to provide examples of how the algorithm works. These four case studies are part of a larger set of cases presented in Panegrossi et al. (2013) where the validation results of PNPR for 19 different meteorological events over the European area are presented. Also in this study, the comparison with the HSAF H02 v2.3 algorithm showed a good performance of PNPR and better agreement with the ground-based precipitation data. Moreover, we are currently working on a second paper describing the results of the validation of PNPR over the African area and over a two year period (2011-2012) where we use the TRMM-Precipitation Radar precipitation products as "truth" (presented in Panegrossi et al., 2014). (See also Answer (11) to Referee 2)

According to the Referee's suggestion, the sentence will be changed to clarify this point in the Conclusion section of the revised version of the manuscript, and more conservative words will be used.

Revised version (Section 4 "Summary and conclusions", lines 22-25, pag. 9380): The comparison with the HSAF H02 v2.3 algorithm (operational until June 2013), although limited to four cases, showed a good performance of PNPR and better agreement with the ground-based precipitation data. It should be mentioned that a more extensive verification study (19 case studies selected from the H-SAF PPGV team reports for the period 2009-2011) has been carried out (Panegrossi et al. (2013)) and the results are in line with what shown here, and with what has been obtained in the comparison with the HSAF H02 v2.3. PNPR shows improved ability in the screening and retrieval of precipitation over different background surfaces, in the identification and retrieval of heavy rain for convective events, and, in some cases, in the identification of precipitation over cold/iced background. Moreover, these results are also confirmed by the validation of PNPR over the African area over a two year period (2011-2012) where we use the TRMM-Precipitation Radar precipitation products as "truth" (presented in Panegrossi et al., 2014).

Panegrossi, G., Casella, D., Dietrich, S., Sanò, P., Petracca, M., and Mugnai, A.: A Verification study over Europe of AMSU/MHS and SSMIS passive microwave precipitation retrieval, Proc. 2013 Joint EUMETSAT/AMS Meteorological Satellite Conference, Vienna Sept., 2013, 2013. https://www.eumetsat.int/website/home/News/ConferencesandEvents/PreviousEvents/DAT_

Panegrossi G., D. Casella, S. Dietrich, A. C. Marra, L. Milani, M. Petracca, P. Sanò, and A. Mugnai, CDRD and PNPR passive microwave precipitation retrieval algorithms: extension to the MSG full disk area, Proc. 2014 EUMETSAT Meteorological Satellite Conference, Geneva, Sept. 2014, https://www.eumetsat.int/website/home/News/ConferencesandEvents/DAT_2076129.html

Minor: 1. It seems that the authors imply that the NN method is more computationally efficient than Bayesian framework. (It is worth noting that NNs are able to handle such large databases being at the same time computationally very efficient, as opposed to a Bayesian approach (i.e., Kummerow et al., 2001; Marzano et al., 1999; Sanò et al., 2013) which is usually employed for conically scanning radiometers characterized by one constant viewing angle.). Bayesian algorithm should be as efficient as any other algorithms. It really depends on how to set the search radius and how to construct the databases.. Some previous work showed that the Bayesian framework could be very efficient (e.g., Petty, Grant W., and Ke Li. "Improved passive microwave retrievals of rain rate over land and ocean. Part I: Algorithm description." Journal of Atmospheric and Oceanic Technology 30.11 (2013): 2493-2508. and You, Yalei. "A new over-land

rainfall retrieval algorithm using satellite microwave observations." (2013)). Even in the framework used by Kummerow (2001), by adjusting the search radius, the speed will not be a big issue.

Authors' Reply: Our observation concerning the efficiency of the Bayesian algorithm is in fact inaccurate and can lead to confusion. In the Bayesian approach, the use of TBs derived variables (such as those obtained by Principal Component Analysis or the "pseudochannels"(Petty and Li, 2013)), that tend to reduce the database size, improves the efficiency of the Bayesian approach. In any case the Bayesian approach requires processing all the database elements for each pixel and a compromise between the processing time and the search radius is necessary to optimize the efficiency of the retrieval, especially for near real time applications. Moreover the search radius in the Bayesian algorithms depends strictly on the error covariance matrix that defines the multidimensional space in which the search radius is defined and not only on the "optimization" of the algorithm. Alternatively the NN approach, using the database only in the training phase, provides an immediate response without requiring compromises between processing time and quality of the retrieval. We also would like to point out (as done in the response to Reviewer 2) that the use of a Bayesian approach for cross-track scanning radiometer measurements is problematic because of the changing viewing angle and footprint size across the scan, and the concomitantly changing atmospheric path, introducing viewing angle-dependent errors in the Radiative Transfer Equation Modeling System (RMS) calculations. This is unlikely the case for conical scanners where RMS-generated errors are consistent across the scan passage and thus easily detected as systematic errors when conducting validation checks. When view-angle dependent errors enter retrievals, they complicate how systematic error should be expressed and impose a reduced confidence in formulating Bayesian probabilities. It is this confidence issue that motivates a turn to a neural network approach when using cross-track scanner data (at the expense of moving away from a pure physics-based solution). Therefore, keeping in mind the possible confusion generated by a so synthetic comparison on the efficiency of the two approaches, in the revised version of the manuscript the phrase will be simplified, avoiding the comparison. Revised version (Section 2.2 "The neural network", lines 6-10, pag. 9361): It is worth noting that NNs are able to handle such large databases being at the same time computationally very efficient. A sentence will be also added to section 1 (Introduction) of the revised manuscript to be submitted, also to answer to Reviewer 2 comment (see (6) in Answer to Referee 2). Revised version (line 29, pag. 9357) The motivation for using a neural network algorithm for AMSU/MHS cross-track scanning radiometers stems from the geometry of radiometers measurements. These are less manageable for a Bayesian solver because the changing viewing angle across a scan passage, and the concomitantly changing atmospheric path, introduce viewing angle-dependent errors in the Radiative Transfer Equation Modeling System (RMS) calculations (see Mugnai et al. (2013b)).

2. I am not sure I understand how the CCA has been done. ("A linear combination of TBs (LCT) at 50.3, 89, 150 GHz whose coefficients are obtained from the CCA with respect to the surface rain rate. These channels showed the highest correlation coefficients in the CCA analysis in the database for all types of background surfaces"). Generally, the CCA is applied to two multiple variables fields. Here the Tbs are multiple variables (50.3, 89 and 150), but the rain rate is single variable. So I am a little bit confused about this. Do you mean, you do PCA to the Tbs and find the best PC with rainrate based on correlation? please explain.

Authors' Reply: The description in the paper of the CCA methodology used is too concise, and not sufficiently clear. We have chosen the CCA methodology (we preferred the CCA approach instead of the one based on PCA) for measuring (canonical) correlations existing in the database between different linear combinations of the TBs in the various channels and the surface rain rate. The result is the linear combination of the TBs (canonical variable) for the channels best correlated, in terms of CCA, with the rain rate. In other words, we could evaluate the effect of the different channel combinations on the correlation and, by eliminating the channel combinations with a relatively

low correlation, build the most effective input canonical variable to the NN. To clarify this point the sentence on page 9364, lines 16-18 (Section 2.2 "The neural network"), "Canonical correlation analysis (CCA) (Hair et al., 1998) was also carried out to find the linear function of the input channels with maximum correlation with the surface precipitation" will be rephrased in the revised version of the manuscript. Revised version (Section 2.2 "The neural network", lines 16-18, pag. 9364): Canonical correlation analysis (CCA) (Hair et al.,1998; Wilks,1995) was also carried out to find the linear combination of the TBs (canonical variable) of the various channels with maximum correlation with the surface precipitation. Particularly, we chose to use the CCA methodology for measuring canonical correlations existing, in the database, between different linear combinations of the TBs in the various channels (canonical variable) and the surface rain rate. Through this procedure we could evaluate the effect of the different channel combinations on the correlation and, by eliminating the channel combinations with a relatively low correlation, build the most effective input canonical variable to the NN.

3. It is mentioned that "The algorithm provides also the phase of the precipitation ... ". Is it possible that a snow-fall case is provided? Or the Hungary (1 Dec, 2009) is the snow case?

Authors' Reply: We have not shown images of the precipitation phase as for the case studies examined the phase was always liquid (also for the Hungary case on 1 Dec, 2009). Figures related to case studies with snow are reported in Panegrossi et al. (2013) (in particular for a winter case occurred in Germany on December 6th, 2010, see Figure A below). In our manuscript we excluded snowfall cases because of the difficulty to compute statistical scores due to the poor reliability of the quantitative estimate of snowfall also from ground-based data. On page 9369, on lines 5-6 (Section 2.3 "PNPR flow diagram description"), for no-rain pixels we have stated that "The presence of snow/ice on the background surface lowers the value of the PCI which is limited to 10", and similarly on lines 11-13 for rainy pixels we have stated that "the presence of snowy/iced background on areas with precipitation lowers the value of the PCI (the

PCI value is limited to 10)". This low value of PCI reflects the low reliability expected for snowfall cases.

Figure A. PNPR precipitation rate (with phase and quality flag index) (top row) and comparison with radar (middle row) and gauge data (bottom row) for winter storm on December 6th, 2010 at 0947 UTC

Revised version (Section 4 "Summary and conclusions", line 21, pag. 9380): The phase flag is evaluated only for pixels flagged as precipitating after the screening procedure and it is not available over coastal background surfaces (examples of phase determination results, for liquid, snow and iced precipitation, are shown in Panegrossi et. al. (2013)).

4. It may be better to put all the figures for one case all together (e.g., Figs. 10, 11, 12). 6 panels in one figure is much easier to compare the different features.

The suggestion is accepted. The figures will be rearranged in the revised version of the manuscript.

5. Do you see any beam-filling effect for the different viewing angle? What I mean is: the rainrate over the edge will be always smaller since the larger pixel size. Does this contribute to the underestimation of the rainfall in Fig. 16?

Authors' Reply: Yes, a contribute to the underestimation of the precipitation is also very likely linked to the non uniform beam filling effect, mainly in the larger pixels at the edges of the scan. As a matter of fact, the quality flag is lowered for these pixels (scan geometry coefficient in determining the PCI index) as described in the text (Section 2.3 "PNPR flow diagram description", lines 19-20, pag. 9369). A more detailed analysis of the effect of the beam filling will be done in the mentioned validation study of PNPR over the African area.

Please also note the supplement to this comment:

http://www.atmos-meas-tech-discuss.net/7/C4392/2015/amtd-7-C4392-2015-supplement.zip

Interactive comment on Atmos. Meas. Tech. Discuss., 7, 9351, 2014.