Atmos. Meas. Tech. Discuss.,
doi:10.5194/amt-2020-297-AC1, 2021

Atmospheric Measurement Techniques
Open Access
Discussions

Interactive comment on "PHIPS-HALO: the airborne particle habit imaging and polar scattering probe – Part 3: Single Particle Phase Discrimination and Particle Size Distribution based on Angular Scattering Function" *by* Fritz Waitz et al.

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Received and published: 18 January 2021

We thank the anonymous reviewer for his/her helpful comments. These comments helped to substantially improve the manuscript. Below we give detailed answers to the reviewer's comments that are highlighted in *cursive*.

Classification and phase discrimination of cloud particles, especially of mixed phase clouds, are of importance in a number of applications: modelling of the earth radia-

tive balance and the clouds life cycle, interpretation of remote sensing data and so on. Phase discrimination and classification along with size estimation are usually performed using particles images. Several approaches and algorithms were reported in the literature and showed a good performance when applied to particles images. At the same time, based-on-images discrimination between droplets and quasi-spherical particles is an extremely challenging task. It is well known that there exist significant differences between phase functions of water droplets and atmospheric ice particles. That fact was proved in a large number of modeling works. It was confirmed in experimental works where angular scattering intensities were measured in situ. The advantage of the PHIPS-HALO probe consist in the fact that a particle stereo-image and the corresponding angular distribution of the scattered light are recorded simultaneously. The synergy of those data provides significant improvement of the discrimination quality. The work under reviewing addresses relevant scientific questions it is within the scope of AMT. I recommend that the paper be published in AMT after minor revisions.

We thank the reviewer for this encouraging general comment. Below we have addressed the proposed minor revisions.

Specific comments: Figs. 1, 2 and 5; page 4 line 15; page 5 lines 11 – 14. Single spherical particles, the authors are dealing with, have the size parameter of 590 or higher. Phase functions of large spheres can be found in numerous textbooks and they differ much from "theoretical scattering functions" shown in Figs. 1-2. Mie calculations are mentioned several times in the text of the preprint before it is underscored (line 16 of the page 6) that "the calculated theoretical Mie scattering is integrated over the field of view of the polar nephelometer channels". Such important point should be underscored at the first mention of Mie calculations. And, I believe that the data from the light scattering databases by Baum et al. (2011) and Yang et al. (2013) were integrated over the field of view as well.

An explanation that the theoretical scattering data is integrated over the field of view of each nephelometer channel was added in Fig. 1 when Mie calcula-

tions are first mentioned. Also, it is now noted again in 3.2, that the scattering data from Baum et al. (2011) and Yang et al. (2013) is also integrated over the nephelometer channel field of view. A subsection explaining the integration of the ASF over the field of view of the nephelometer channels was added in the supplementary information (S6).

Fig. 1. It is written: “SOCRATES, RF02, #613, Spherical Ice”. The particle shown in in Fig. 1b is not spherical; I would say it is quasi-spherical. Moreover, to my knowledge, there are no spherically symmetric particles that are able to provide such kind of the angular scattering function (ASF) as the red curve in Fig. 1c. The surface roughness and/or small internal inclusions cannot lead to an ASF that is increasing within the range [42 – 74] degrees. In my opinion, that ASF is the outcome of the deviation from the spherical symmetry. If the authors can provide another explication, it would be useful to see it in the paper text.

The reviewer is correct that a spherical ice would not result into the measured ASF, and thus, the caption was corrected to “quasi-spherical ice”.

page 5 lines 11 – 23. That part of the text should be revised. It is very difficult to understand how “the first discrimination feature f_1” is computed even for an experienced reader. If I have understood correctly, the first step is the normalization of EVERY measured ASF by the ASF that corresponds to the spherical particle with the diameter of 100 µm.

We agree, this part of the text was difficult to understand. Hence, we have added a step-by-step explanation of the determination of the f_1 parameter based on two exemplary droplets including graphical explanation (Figure 4) of the in-between-products q, $\bar{q}$ and q’. This should make it easier to understand.

Next. What does it mean “the median over all channels”? How it is computed?

The “median over all channels”, $\bar{q}$, is calculated as the median of all values

$q(\theta)$ of each channel θ. $q(\theta)$ is the ratio of the measured scattering intensity $I_{exp}(\theta)$ to the theoretical Mie calculation $I_{Mie}(\theta)$ for every channel θ.

Next. If the meaning of the “feature f1” is “the deviation of the observed ASF from the calculated Mie scattering”, why it has such high values for spheres as in Figs. 4a and 5a?

The "Mie-comparison-feature" f_1 is based on the relative difference between the measured and calculated ASF of a reference Mie-sphere with diameter D=100 µm. By definition, the f_1 value for a simulated droplet with D=100 μm, of course, is zero since basically the input equals the reference, i.e. I_{Exp} = I_{Mie}. However, this method is sensitive to small deviations from the theoretical curve (i.e. the Mie calculation for D=100 µm). For example, if you take the calculated I_{Mie}(D=100 μm) and alter the intensity of every other channel by +/- 2%, the resulting f_1 value = 1.1. Further, the difference between the shape of Mie calculations for different diameters is very small, but non-vanishing. For example, for a Mie-sphere with D=200 μm has f_1= 2.2. For actual, in-situ measured droplets, this deviation can be even larger due to deformation and impurities. E.g., the exemplary measured droplet shown in Fig. 2 has f_1=3.7. This example is now also discussed in section 3.1.1.

Figs. 4a and 5a Why the Gaussian fit of the feature f1 for droplets in Fig. 4a has the mean value (about 3.8) that differs much from the value (about 2.5) in Fig. 5a?

The f_1 parameter value, i.e. the difference between Mie calculation and measured ASF, is supposed to be quite small for simulated particles (as the reviewer rightfully pointed out in her/his previous comment). For measured droplets, the difference can be slightly higher due to fluctuations or slight deformation, as already mentioned in the previous comment. Hence this relatively large discrepancy and shift towards higher values is to be expected, compared to the good agreement of the other features. However, we agree *with the reviewer, that a detailed comparison and discussion of the feature-parameter-distribution-plots is missing. This was added in section 3.3: "The plots show that the distribution of the four aforementioned feature parameters are clearly distinct for droplets and ice and thus represent features that can be used to discriminate droplets from ice. Further, it can be seen that these normalized occurrences (f_i) are normally distributed. The distributions of the four feature parameters based on the measurements (Fig. 6) show a similar trend to the simulations (Fig. 5). The width of the distributions of feature parameters for measurements is much broader compared to the simulations. This can be explained by the single-orientation of the measured crystals compared to the orientation-averaging that was used in the simulations. Orientation-averaging tends to smooth out features in the ASFs and thus cause more narrow feature parameters. It should be also noted that the theoretical computations are for idealised crystals. Nevertheless, the mean values of the distributions agree very well. The only exception to this is the mean value of the distribution of droplets for f1, which is shifted slightly to larger values compared to the simulations. This is to be expected because the "Mie-comparison-feature" f_1 is based on the relative difference between the measured and calculated ASF. This difference is much smaller for simulated particles as discussed in 3.1.1."*

Section 3.2 The PHIPS-HALO provides ASFs for a particle that has random but fixed orientation in the space. To my knowledge, the databases from Baum et al. (2011) and Yang et al. (2013) provide scattering properties averaged over random orientations of particles. If so, Fig. 5 only shows that the proposed method is not in contradiction with properties of ensembles of ice particles.

This is true. This is noted in the added discussion comparing the simulated and measured feature-parameter-distribution-plots mentioned in the answer to the previous comment.

Section 3.3 I would say that the calibration-and-verification approach, the authors used,

is somewhat similar to methods of the neural networks. Of course, the choice of parameters in the work under reviewing is well grounded and corresponds to general features of scattering by spherical and non-spherical particles. At the same time, it would be interesting to see in future works comparison with performance of neural networks algorithms.

Yes, the calibration-and-verification approach is quite similar to the approach of neural networks or machine learning algorithms. Classification using machine learning, both based on either the raw ASF data as well as the derived features [f1,f2,f3,f4], was tried. The classification accuracy was almost as good (96.4-98.4%, depending on the used algorithm) as the "analytical approach" presented in this work. However, machine learning also has one main disadvantage: it is hard to understand what the algorithm is doing in detail. Basically, what you end up with, is a "black-box" that classifies input data with a given confidence, but you cannot tell why. Hence, it is very hard to analyse which features are relevant for the classification. Further, since the machine learning knows only statistics, not physics, it is possible that the machine learning algorithm links the classification to "un-physical parameters" that can introduce systematical biases. For example, it could be possible that the machine learning algorithm learns, that large particles (with a corresponding high total scattering intensity) are typically ice, whereas droplets are typically smaller and hence scatter less light. Thus, it would look at the "amplitude", rather than the "shape" of the ASF and classify all "large particles" as ice. Since the number of large droplets in the used data-set is rather small, the overall discrimination accuracy would be quite high, however there would be the systematical bias that the few large droplets would tend to be misclassified. Hence, and because it yields better discrimination accuracy, for this work, it was chosen to go with the "analytical approach" instead of machine learning. The results of the machine learning as well as a detailed discussion are now included in section 3.5.

page 18 line 11. The HIAPER cloud radar is capable of collecting observations in a staring mode between zenith and nadir or in a scanning mode. Thus, it is worth mentioning in the text that the HCR beam was in nadir pointing mode for all Case Studies of Section 5.

A note was added in section 5 that the HIAPER cloud radar was in nadir pointing mode for all case studies.

Supplement (Fig. 9) In my opinion, the measured ASF differs much from the Mie calculation, especially in the range of [18 – 50] degrees. Nevertheless, the algorithm misclassified it. Thus, some improvements of the authors' approach can be done in the future.

The first channels are often times saturated and hence are not taken into account. The rest of the ASF for this particular particle looks quite similar to a droplet's. Approaches that only exclude the first channels if they are saturated and include them otherwise, were tried and could be able to correctly classify particles as this one, but resulted in an overall decrease of the discrimination accuracy (i.e. particles that are classified correctly now would then be misclassified). The algorithm was calibrated to optimize the overall discrimination accuracy, i.e. that the highest fraction of particles is classified correctly. Nevertheless, there might be quite possibly be more room to improve the presented algorithm in the future with more data from future campaigns. This discussion was also added in the SI.

Interactive comment on Atmos. Meas. Tech. Discuss., doi:10.5194/amt-2020-297, 2020.