An Algorithm for Reconstruction of Liquid Water Content Distribution in Convective Clouds Based on Passive Microwave Sounding

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Abstract — An algorithm for retrieving liquid water content (LWC) fields in convective clouds is considered. It is based on microwave radiometric sounding of clouds. Proposed sounding scheme can be realized in practice. Neural Networks (NNs) and Computerized Tomography (CT) approaches are used for sounding data analysis. Searching an optimal configuration of a neural network and the best CT-technique is carried out. Potentialities of the said algorithm are assessed using a closed scheme of numerical experiment.

Keywords: microwave remote sounding, convective clouds, liquid water content.

1. INTRODUCTION

Information on Liquid Water Content (LWC) fields in convective clouds is of great interest for atmospheric physics and different practical tasks. In principle, this information can be obtained by a microwave radiometric sounding of clouds using Neural Networks (NNs) and Computerized Tomography (CT).

An approach based on CT techniques has been suggested for LWC fields retrieval in convective clouds by microwave radiometric measurements (Warner et al., 1984; Altunina et al., 1988; Bobylev et al., 1998). However, only rather simplified sounding cases were considered in those works. Those works explored sounding of Cumulus clouds by ground-based and airborne radiometers located under the targeted cloud.

More complex sounding scheme was considered in the paper (Samsonov et al., 2001). According to this scheme, the sounding is conducted from an aircraft flying above a targeted cloud located above a water surface (Fig. 1). The scheme can be more realistically realized in practice.

Models of calm sea surface and atmosphere with constant Water Vapor Path (WVP) were used. For this scheme, the problem of LWC field reconstruction can be divided on two parts. The NNs approach is applied for retrieving Total Liquid Water Content (TLWC) values from sounding data for each sounding direction (1st part of the inverse problem). The task of reconstruction of LWC distribution from the set of TLWC values and data on cloud location is solved using three CT-techniques (2nd part of the inverse problem).

In the present study, the algorithm of reconstruction of LWC distribution is considered for a more complex case of rough sea surface and variable WVP of atmosphere. Parameters of sounding is more closed to real conditions. Spatial resolution of the algorithm is assessed.

2. SOUNDING SCHEME OF CLOUDS

The algorithm makes it possible to retrieve the LWC field in a certain vertical section of a cloud (10×10 cells) from the relevant microwave data of remote sounding. Let the sounding is conducted from an aircraft in according to the considered scheme (Fig. 1). Scanning is performed downwards in the vertical plane in various directions, with different positions of the aircraft above the cloud. Radiometric sounding gives data on the cloud microwave emission for several frequencies and two (vertical and horizontal) polarizations. Two frequencies (37 and 89 GHz) were chosen for algorithm development.

3. FORWARD PROBLEM

Numerical simulations of microwave radiation transfer in the atmosphere-sea system in the presence of a convective cloud and radiation measurements were carried out (forward problem). The simulations included development of numerical models of atmosphere, sea surface and convective cloud based on empirical data. It is possible to variate parameters of environment used standard deviation about mean values. Plain-parallel atmosphere with presence of a local spatial-nongomogeneous cloud located above a rough sea surface was considered in simulations. The used convective cloud model was developed as a simple 3D model of clouds like Cu med. and Cu cong. with vertical extension from 2 up to 4 km without complicated microphysics (cases of rain droplets and ice crystals).

Cloud scanning in numerical simulations was modeled as close as possible to real scanning from aircraft by the airborne radiometer PSR (Piepmeier at al., 1996). Modeled radiometer has two channels of emission receiving centered on 37 and 89 HGz frequencies. Divide of measured emission on vertical and horizontal polarizations is possible.

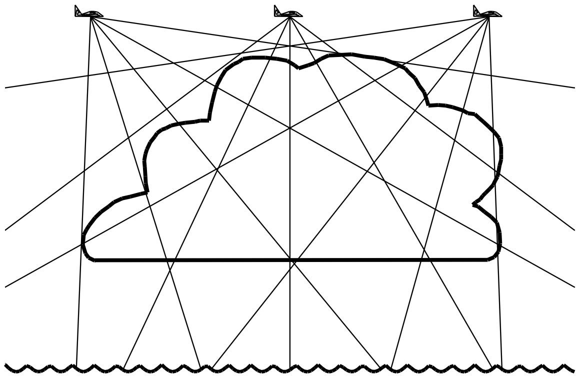

Figure 1. Sounding of a convective cloud by a microwave airborne radiometer

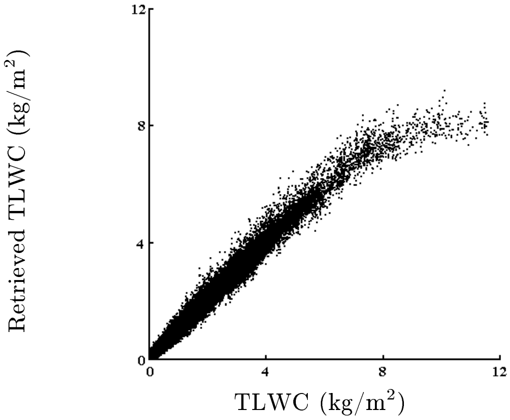

Figure 2. Validation of TLWC retrieval on test modeled data using the neural network

Table 1. Range of main parameters from data sets collected during forward problem solving

Parameters	Q	V_S	H	$w_{\max}$	K	θ_k	W_k	T_k^{37H}	T_k^{37V}	T_k^{89H}	T_k^{89V}
	(kg/m^2)	(m/s)	(km)	(g/m^3)		(grad)	(kg/m^2)	(K)	(K)	(K)	(K)
Minimum	10,4	0	2	0,7	419	110	0	126	153	185	200
Maximum	36,5	15	4	5,4	552	250	12,4	269	270	276	283

Numerical simulation of the forward problem allowed to creative three data sets that were used for inverse problem solution. There are training, validation and testing sets. Each set from its contains data about ~ 130 different cloud realizations. Data saved for each cloud realization included following parameters: 1) parameters characterized atmosphere and sea surface condition, such as, for example, WVP of cloudless atmosphere Q and wind speed near sea surface V_S; 2) parameters of studied vertical cloud section - its spatial position and extension, LWC distribution. Its are, for example, vertical cloud extension H, altitude of cloud top H_t and maximum value of LWC w_{max}; 3) parameters of cloud sounding, such as coordinates of positions and directions (θ_k, $k = 1 \dots K$) of sounding; 4) parameters for each k-th sounding direction: values of antenna temperatures for chosen frequency channels (37 and 89 GHz) and two polarizations (vertical — V, and horizontal — H) — defined as T_k^{37H}, T_k^{37V}, T_k^{89H}, T_k^{89V}, and TLWC value of the cloud in k-th direction W_k.

A brief characteristics of mentioned parameters for all three data sets showed in Table 1.

4. INVERSE PROBLEM (1st part)

The first part of the inverse problem is retrieving TLWC values W_k from sounding data for each k-th sounding direction. It is non-correct task because of lack of input data. Neural Networks (NNs) approach can be applied in order to the problem . NNs method is a mathematical approach. Essence of it is building a non-linear function associating input and output data by a known empirical data. A network used in the work produces approximation of a function $W_k = f(\vec{x}_k)$, where W_k is the target TLWC value and $\vec{x}_k$ is the vector of the sounding data. The feed-forward back-propagation multi-layer network (Atkinson et al., 1997) being most commonly employed in remote sensing is used in the present research. Input data of the Neural Network for each (k-th) sounding direction in the considered algorithm are presented by the vector

$$\vec{x}_k = [T_k^{37H},\, T_k^{37V},\, T_k^{89H},\, T_k^{89V},\, \theta_k,\, H,\, H_t,\, Q,\, V_S]\,.$$

The TLWC value (W_k) is the output data. It was obtained by analysis of neural network weights that all elements of the input vector are important to get the minimum of mean square error of TLWC retrieving.

A neural network according to the task was tuned by Stuttgart Neural Network Simulator (SNNS, 1995) used training and validation data sets. Application of algorithms for network optimization allowed to decrease number of neurons on hidden layer up to 8, number of net connections up to 51. Results of TLWC retrieving using the network are shown in Fig. 2. An error of retrieval was assessed for each modeled cloud as mean squared error of retrieval in relative to standard deviation of TLWC values in form $E_{11} = \sigma_{(\hat{\mathbf{W}}-\mathbf{W})}/\sigma_{\mathbf{W}}$, where $\sigma_{\mathbf{y}}$ is standard deviation for a vector $\mathbf{y}$. The value of E_{11}, averaged on cloud realizations of test modeled data, was obtained to equal 13 ± 4 %. Analysis of demonstrated on Fig. 2 results shown satisfactory TLWC retrieval up to 8 kg/m^2 TLWC value. Retrieval of bigger TLWC values provides regular mark down of retrieved values in comparison with "true" values. The fact can be explained by the following. Dependence of measured antenna temperatures on TLWC values bigger than 8 kg/m^2 is closed to saturation. TLWC values increasing provides an insignificant antenna temperatures increasing compared with own radiometer noise.

CT technique	E_{21} (%)	E_{23} (%)	E_{24} (%)
SRT	24 ± 8	100 ± 7	7 ± 3
RTLS	24 ± 8	100 ± 7	7 ± 3
SIRT	52 ± 8	64 ± 8	14 ± 9

Table 2. Result of LWC field reconstruction by three CT techniques

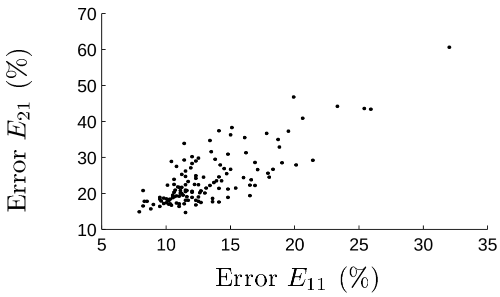

Figure 3. Dependence of LWC field reconstruction error (E_{21}) on TLWC retrieval error (E_{11})

Obtained neural network was tested on work stability to variations in cloud parameters and to errors of assessing input parameters of the net.

The error E_{11} is decreased from 20 up to 13 % when maximal LWC value is increased from 1 up to 2.2 g/m^3. After that the error E_{11} is increased up to 22 % (max(LWC)=5 g/m^3). It can be explained by the following fact. The neural network more exactly retrieves more statistically available TLWC values, that are in corresponding with the mentioned value of LWC. Error E_{11} very weekly depended on vertical extension of clouds. Actually, content of liquid water can be variable ($\pm$30 %) for identical vertical cloud extensions.

Increasing error of antenna temperatures in three ones (from 0.44 up to 1.33 K for 37 GHz, and from 0.67 up to 2.02 K for 89 GHz) leads to increasing error $\widetilde{E}_{11}$ (it is E_{11}, averaged on all cloud realizations in test data set) from 13.1 up to 16.5 %. Increasing error of WVP (Q) assessing from 2 up to 4 kg/m^2 leads to few increasing error $\widetilde{E}_{11}$ from 13.1 up to 13.4 %. Increasing error in retrieval wind speed above sea surface from 2 up to 4 m/s leads to small increasing error $\widetilde{E}_{11}$ from 13.1 up to 14.3 %.

5. INVERSE PROBLEM (2nd part)

The task of reconstruction of the LWC spatial distribution from set of TLWC values was solved using different three CT techniques. It is the second part of the inverse problem. Basis approach to the reconstruction was described in details in (Samsonov et al., 2001). Accordingly Equation 2 in the mentioned paper we can pass over to a large system of linear equations

$$\hat{\mathbf{W}} = \mathbf{S}\mathbf{w} + \mathbf{E}\,, \tag{1}$$

where $\hat{\mathbf{W}}$ is the vector of retrieved TLWC values; $\mathbf{S}$ is the array of values $S_{k,n}$ (length of k-th ray in the n-th cell of a cloud section); $\mathbf{w}$ is targeted LWC values in the cloud section; $\mathbf{E}$ is the vector of errors of TLWC retrieval.

To solve the system of equations (1), various tomographic techniques can be used. Three tomographic techniques were considered aiming to comparison of LWC field reconstruction result. These ones are following: 1) Statistical Regularization Technique (SRT); 2) Recursion Technique of Least Squares (RTLS); 3) Simultaneous Iterative Reconstruction Technique (SIRT). SRT and RTLS techniques are widely famous. SRT technique was used as the method of minimum of apriory information. Both of these techniques (SRT and RTLS) solve the equation (1) in matrix presentation and use an apriory information about standard deviation for vectors $\mathbf{w}$ and $\mathbf{E}$ in order to construction of covariance arrays. The RTLS technique use recurrent procedure and, respectively, more computer time on calculations. The SIRT-technique was used in (Altunina et al., 1988; Bobylev, 1997) for sounding from an aircraft flying under the targeted cloud. The technique solves the equation (1) processing only non-zero elements of array $\mathbf{S}$ and using principle "row by row". It was significant early in order to decrease of computer time and memory on calculations. Apriory information do not used in the technique. However an artificial regularization procedure (selective smoothing) is used to provide of convergence of iterative solution.

Comparison of chosen CT techniques was carried out on test data set (133 cloud realizations). The following parameters were used in order to assess of LWC field reconstruction quality for each cloud:

$$E_{21} = \frac{\sigma_{(\hat{\mathbf{w}}-\mathbf{w})}}{\sigma_{\mathbf{w}}}\,;\; E_{23} = \frac{\max(\hat{\mathbf{w}})}{\max(\mathbf{w})}\,;\; E_{24} = \frac{dR_{max}}{\bar{D}}\,.$$

There E_{21} is the analog of error E_{11}; E_{23} is the parameter for checking over quality of LWC maximum retrieval; E_{24} is the parameter for control of retrieval of LWC maximum spatial position calculated as ratio of a position error to the mean cloud section extension along horizontal and vertical directions.

Result of the comparison is presented in Table 2. Both techniques — SRT and RTLS — provided the same reconstruction quality. SIRT technique gave less quality results. The selective smoothing procedure used in the last technique for iterative convergence leads to make down of field maximum and to deform of field structure. Techniques SRT and RTLS gave better quality results since its used apriory information about LWC fields and about error of TLWC retrieval. First of these techniques (SRT) provides less calculation time and thereby is more preferential to using.

An analysis of chosen SRT algorithm was carried out. In frames of the report we consider only one from general dependencies. It is dependency of errors of LWC field reconstruction (E_{21}) on errors of TLWC retrieval (E_{11}) showed on Fig. 3. Algorithm of LWC field reconstruction based on data obtained by solving the first part of inverse problem. Increasing errors in the first part of inverse problem lead to natural increasing errors in the second part. It is caused by additional errors arisen during solving of second part of the inverse problem. Values of E_{21} exceed values of E_{11} not smaller then half again.

6. SPATIAL RESOLUTION OF THE ALGORITHM

Spatial resolution of developed algorithm of LWC field reconstruction was assessed by an analysis of smoothing array **A**. Definition and calculation algorithm of the array described in details (Rodgers, 2000). To simplify the necessary complicated calculations, only three numerical cloud realizations were considered. It is cloud models with minimal ($H = 2$ km), mean ($H = 3$ km) and maximal ($H = 4$ km) vertical extensions.

The spatial resolution of the algorithm was assessed to each element of cloud section. Obtained results shown satisfactory spatial resolution of the algorithm for reconstruction of LWC distribution in convective clouds. A parameter characterized the spatial resolution of the algorithm in convective clouds with vertical extension $H = 2$, 3 and 4 km do not exceed 219, 311 and 410 m correspondingly. Sizes of cloud cells for these clouds are approximately 200×200, 300×300 and 400×400 m correspondingly.

7. CONCLUSIONS

Described numerical investigation allowed to assess of developed algorithms in order to Total Liquid Water Content (TLWC) values and Liquid Water Content (LWC) fields in convective clouds, such as Cu med. and Cu cong. with vertical extension up to 4 km and without complicated microphysics positioned above rough sea surface. Obtained results confirmed possibility of consequent application of Neural Networks and Computerized Tomography (CT) techniques in order to treatment of sounding data.

Mean squared error of TLWC retrieval by the tuned neural network is equaled 13 % in relative to standard deviation of TLWC values. Optimal CT technique was chosen from three ones. It is Standard Regularization Technique (SRT as method of minimum of apriory information). Mean squared error of LWC field reconstruction for the technique is equaled 24 % in relative to standard deviation of LWC values. Averaged on cloud realizations value of LWC maximum is closed to its true value. Assessed spatial resolution of considered algorithm be in accord with size of cloud section cells.

There is needed to note that in order to correct work of the developed algorithm in more complicated environment conditions the algorithm should be modified used detailed apriory data about reconstructed LWC fields. These detailed data can be obtained used, as a variant, the practical realization of the described algorithm.

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