Neural Network Identification Algorithm for Weather Radar

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1. Introduction.
The advent of Doppler-polarimetric technique for observation of clouds and precipitation is accompanied by the sharp growth of measurable variables [1], or measurands. The potential of data interpretation becomes higher, but also processing is more complicated. Because of complexity, sometimes it becomes very difficult to implement signal processing in real time that results in restriction of practical applications of new promising scientific achievements. That is why operative radar data interpretation to derive necessary information arises as very important problem. A number of Doppler-polarimetric measurands that together with conventional parameters like reflectivity and Doppler spectrum width can be associated with desired parameters of weather objects. Recently spectral differential reflectivity $sZdr$ and spectral linear depolarization ratio $sLdr$ were introduced [2], [3] as well as differential Doppler velocity [4], [5] and other Doppler-polarimetric functions and parameters. Estimation of such parameters requires rather sophisticated signal and data processing algorithms. Direct implementation of similar procedures into surveillance weather radar systems is not expedient because of computational complexity and inconvenience. Fuzzy logic and neural network approaches give possibilities to avoid bulky computations and time losses during signal processing while they can take into account all significant measurands applying the last scientific achievements into the practice. Fuzzy logic approach was successfully applied to such kind of tasks in [1] for classification of hydrometeor type and in [6] for hydrometeor type and turbulence intensity determination. In this paper we research a neural network application to develop weather radar data algorithms for automatic classification of both hydrometeor type and turbulence intensity.

2. Radar variables and measurements.
We consider a number of measurands that are typical for polarimetric weather radar, such as differential reflectivity $ZDR$, linear depolarization ratio $LDR$, copolar correlation coefficient between orthogonally polarized signals $\rho$, specific differential phase $\Delta\phi$. But this work uses also some new measurable parameters, which are briefly explained below. Spectral differential reflectivity $sZdr$ [2], [3] is defined as $Zdr(v) = 10\log\left(\frac{S_{hh}(v)}{S_{vv}(v)}\right)$ with $S_{hh}(v)$ and $S_{vv}(v)$ as Doppler spectra estimations at $hh$ and $vv$ polarizations. Parameter $EPS$ can be called “equivalent eddy dissipation rate”. It is calculated by using the algorithm described in [2]. Model validation as well as neural network algorithm check was done by using data acquired with the Transportable Atmospheric Radar (TARA) of the Delft University of Technology (TU-Delft), The Netherlands. TARA is S-band CW FM radar with high resolution, particularly the mode of 15 m range resolution was used during the observations of widespread and continuous rain on September 19, 2001 in Cabauw Experimental Site for Atmospheric Research, located in the center of the Netherlands.

3. Neural network algorithm.
The central idea of neural networks is that neuron parameters can be adjusted so that the network exhibits some desired or interesting behavior. Thus, one can train the network to do a particular job by adjusting the weight or bias parameters, or perhaps the network itself will adjust these parameters to achieve some desired end. The neural network of hydrometeor classifier consists of three layers. Each output of each layer is connected with each input of next layer. Example of neural network classifier is shown in Fig. 1 (upper panel). First hidden layer consists of 5 neurons (in accordance with number of input). Second hidden layer consists of 10 neurons (in accordance with number of classes). Hidden layers use hyperbolic tangent transfer function. The output layer has only one neuron and uses linear transfer function. Turbulence intensity classifier is shown at lower panel. Four parameters are considered and used in turbulence estimation. They are $EPS$, slope $sZdr$ [2] and two parameters which correspond to mean velocity (spatial $\Delta\langle v_s \rangle$ and temporal $\Delta\langle v_t \rangle$ mean velocity changes) [3]. There are five classes of turbulence to be detected: negligible, light, moderate, heavy and severe. Training data were taken from fuzzy logic scheme [6].

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The results of the signal processing procedure are shown in Fig. 2 for both hydrometeor type and turbulence classifiers.

Fig. 2. Outputs of neuron network classifiers for hydrometeor type (left panel) and turbulence intensity (right panel).

Drz=drizzle; Rn=rain; Lds=low density snow; Hds=high density snow; Ws=wet snow; Dg=dry graupel; Wg=wet graupel; Sh=small hail; Lh=large hail; R+h=rain+hail mixture.

4. Conclusion.
The neural network classifier scheme provides good results. The main its advantage in comparison with fuzzy logic is the adaptability; the architecture of neural network can be easily reorganized to satisfy the new requirements. This neural network technique has a good opportunity to be implemented in airborne applications. Kind of Doppler spectrum processing with neural network can be realized in hardware and probably will work faster than classical method due to parallel parameters calculation.

References
The next 9 figures show examples of measurable variables time-height distributions got as results of sounding the widespread rain of September 19, 2001 in Cabauw. One can see the following parameters:

1) Differential Doppler Velocity $DDV$
2) Differential Reflectivity $ZDR$
3) Eddy Dissipation Rate $EPS$
4) Slope Spectral Differential Reflectivity $slp\,sZdr$
5) Specific Differential Phase $Kdp$
6) Correlation Coefficient $\rho$
7) Linear Depolarization Ratio $LDR$
8) Mean Velocity
9) Mean Velocity Difference averaged over 10 profiles for 2 neighboring profiles
10) Mean Velocity Difference for 2 neighboring profiles, each couple was analyzed first, and then the results were averaged over 10 profiles.

The results of the neural network signal processing procedure as color images for both hydrometeor type classifier (upper panel) and turbulence intensity classifier (lower panel) are shown in the following two figures.

Drz=drizzle; Rn=rain; Lds=low density snow; Hds=high density snow; Ws=wet snow; Dg=dry graupel; Wg=wet graupel; Sh=small hail; Lh=large hail; R+h=rain+hail mixture.