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Characterisation and Classification of Natural Transients

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***Abstract*— Monitoring lightning electromagnetic pulses (sferics) and other terrestrial as well as extraterrestrial transient radiation signals is of considerable interest for practical and theoretical purposes in astro- and geophysics as well as meteorology. Managing a continuous flow of data, automisation of the detection and classification process is important. Features based on a combination of wavelet and statistical methods proved efficient for analysis and characterisation of transients and as input into a radial basis function network that is trained to discriminate transients from pulse like to wave like.

***Keywords*— natural transient signals, statistics, wavelets, neural networks

I. Introduction

ATMOSPHERIC electromagnetic pulse radiation (shortly sferics) related to thunderstorms and tornados is a subject of continuous monitoring within worldwide networks for some decades with purposes going from early warnings for severe weather conditions via geophysical research to psychobiological studies [1], [2], [3]. But there is a lot more natural transient electromagnetic activity from terrestrial as well as extraterrestrial sources [7]. In the last years transient radiation on different time scales from earth crust zones under severe pressure is under consideration in the context of earthquake precursors [4],[5],[6]. Characterising, discriminating and classifying natural transient signals therefore is a task with possibly far reaching applications in very different disciplines.

Amplitude thresholding and exact correlation with time of a properly identified pulse at various receiving places is sufficient for localising the signal source. For sferics automated location and intensity logging is practised successfully with increasing accuracy within networks.

Automatic discrimination of transient signal shapes for further investigations needs some more envolved methods we want to discuss in this paper.

We concentrate upon typical transients received in the VLF range (very low frequency, here used as: 300Hz .. 30kHz). These are: unipolar pulses (from very different sources, partly man made, but also possible earthquake pulse precursors Fig. 1), sferics (lightning radiation with ionospheric echoes, Fig. 2), slow tailed sferics (presumably caused by lightnings followed by a continuous current flow; these events are suspected to cause sprites, i.e. voluminous discharges above a thunderstorm up to the lower ionosphere, Fig. 3), tweaks (prolongued, ionospherically dispersed sferics, Fig. 4) and damped oscillations (Fig. 5).

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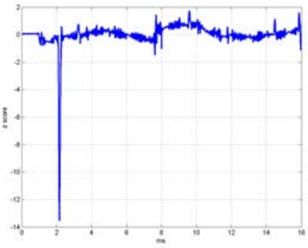

Fig. 1: Unipolar pulse

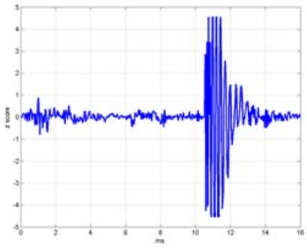

Fig. 2: Sferic: lightning transient with ionospheric echoes

II. Shape features of transients

A. Statistics based features

Usually amplitude thresholding is the first step filtering out strong signals. After that, some information about the transient shape can be quantified using the signal value distribution. For further processing, the signal $y(i)$ is normalised, i.e. its z-scores are calculated:

$$z(i) = \frac{y(i) - \mu}{\sigma} \tag{1}$$

Normalised signals of different sources can be compared more easily. Together with the mean μ and the standard deviation σ the signal $y(i)$ can be reconstructed from the $z(i)$. $z(i)$ is the dimensionless deviation of $y(i)$ from the mean as a multiple of the signal standard deviation. Fig. 6 shows the corresponding z-score histogram to fig. 2.

For shape characterisation we use the 3rd and 4th moments of the distribution, i.e. skewness sk and kurtosis ku:

$$sk = \frac{1}{n} \sum_{i=1}^{n} z(i)^3 \tag{2}$$

$$ku = \frac{1}{n} \sum_{i=1}^{n} z(i)^4 - 3 \tag{3}$$

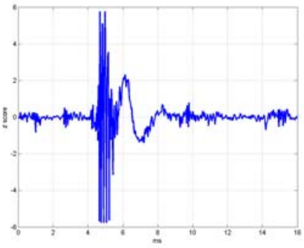

Fig. 3: Sferic with slow tail

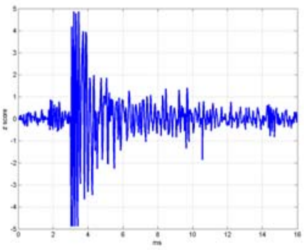

Fig. 4: Tweak: ionospherically dispersed sferic

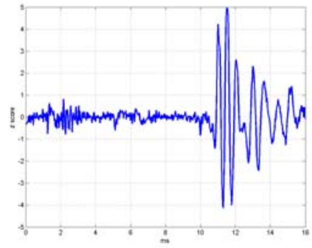

Fig. 5: Damped oscillation

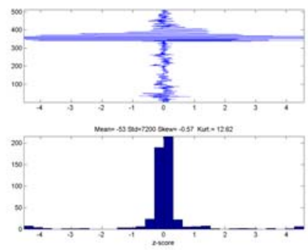

Fig. 6: Normalised signal value distribution (Fig. 2)

Skewness is sensitive to unipolarity of the signal. For example a large negative skewness usually is a consequence of a large negative pulse. Kurtosis is a measure of how tailed the distribution is. A large positive value indicates a strongly 'leptokurtic' distribution shape i.e. values are concentrated around the mean with large (but rare) outliers produced by bipolar pulses in the signal - in contrast e.g. to a gaussian bell shaped distribution with about zero kurtosis as we have with oscillations and noise. A broadened ('platykurtic') histogram shape is characterised by negative kurtosis.

B. Wavelet transform based features

Discrete wavelet transformations (DWTs) have proved to be a valuable tool for transients characterisation.

Fig. 7 shows a signal train ($2^9 = 512$ components, 16ms at 32kHz sampling rate) containing a sferic (cp. Fig. 2) with its DWT sum and detail coefficients with respect to the highly localised Daubechies (DAUB4) wavelets [11]. For the detection of the relevant signal features the energies in the different DWT scales have been proved to be useful. The energy $e(s)$ on scale s simply is the squared sum of the DWT coefficients of that scale.

Filtering out the slow components of a signal is an efficient way to find out its pulse characteristics - in contrast to other applications, where the fast varying part is unwanted 'noise'.

Looking at the frequency domain, zeroing more and more of the less detail ('slow') coefficients increasingly attenuates the lower frequency amplitudes - fig. 8.

The main advantage of wavelet transforms over Fourier and related transforms however is its locality. So by transforming back only those DWT coefficients localised near the time event of interest isolates just the transient under investigation. Because of taking into account local coefficients on the scales with the highest energy, more details of the pulse are reconstructed as with a simple fast component filtering using only the coefficients of the most detailed scale or a high pass Fourier filter.

Fig. 9 shows the relevant part of the locally filtered signal above a threshold containing the pulse wave packet. The time distance of the ionospheric echoes converges to $\Delta t = 2h/c$, with h the height of the reflecting lower ionospheric boundary and the velocity of electromagnetic radiation, c. With $\Delta t = 1/3\ ms$ for this wave packet, $h = 50km$.

III. Classification with a radial basis function neural network

Signal skewness and kurtosis, i.e. the 3rd and 4th moments of the value distribution together with the energies of the wavelets scales form a feature vector suitable for classification. In our example each signal has $512 = 2^9$ components (using 32000 samples/sec this results in a duration of 16ms). The energies of the DWT scales 2..9 are used for the feature vector that in total has 10 components as inputs for the classifier. The task of the classifier using this feature vector is to discriminate unipolar pulses (output center value $y = +1$), sferics ($y = 0.5$), slow tailed sferics ($y = 0.0$), tweaks ($y = -0.5$), and oscillations ($y = -1$), so that events can be automatically sorted and saved for further analysis. The sequence of transients as just indicated can be characterised by a continuous classification parameter going from 'pulse like' to 'wave like'.

A radial basis function network (RBFN, [12]) with a 10 parameter feature input and a single output parameter is trained with a set of training vectors (see Fig. 10).

Each training vector consists of 10 features and a classification value y. The matrix of training vectors is

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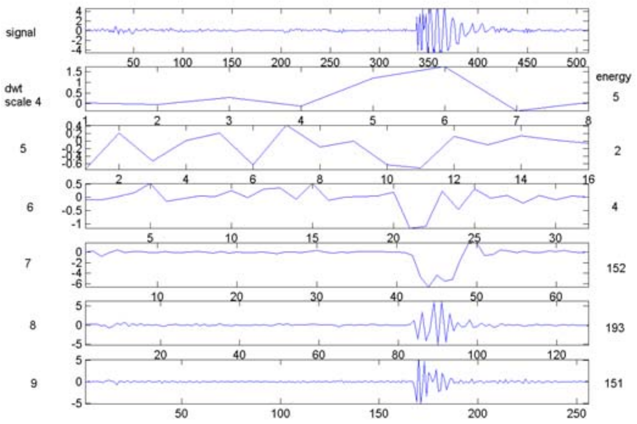

Fig. 7: Input signal and discrete wavelet coefficients from large (slow) to small (fast) scale and the scale energies (right).

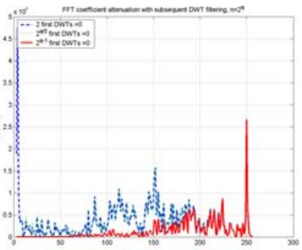

Fig. 8: Subsequent attenuation of low frequency amplitudes with DWT fast component filtering

normalised with respect to the mean and the standard deviation of each component. With normalised feature vector $\vec{x}$, K weights w_j, basis function centers $\vec{t}_j$ and width parameters c_j the normalised classification output $y^{(n)}$ for a (normalised) input $\vec{x}$ is

$$y^{(n)}(\vec{x}) = \sum_{j=1}^{K} w_j e^{-c_j(\vec{x}-\vec{t}_j)^2} \tag{4}$$

As starter parameters for a training process we randomly select K basis function centers $\vec{t}_j$ from the training set and define constant width parameters

$$c_j := \frac{K}{d_{max}^2} \tag{5}$$

with the maximum center distance

$$d_{max} = max_{i,j}|\vec{t}_i - \vec{t}_j| \tag{6}$$

The initial weight matrix we get from

$$w_j := \sum_{i=1}^{m} g_{ji}^{+} y_i^{(n)} \tag{7}$$

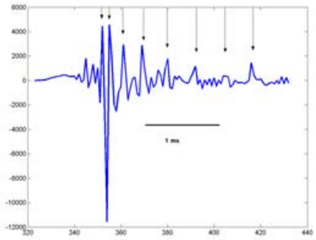

Fig. 9: Locally component filtered signal and identification of ionospheric echoes.

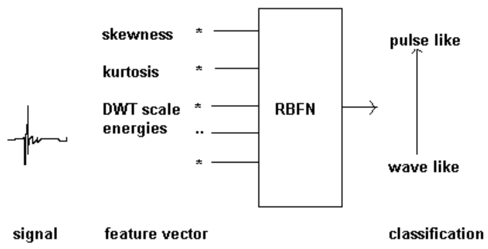

Fig. 10: Signal classification scheme

with m training vectors $(\vec{x}_i, y_i^{(n)})$, and g^+ being the pseudoinverse matrix of $g_{ij} := e^{-c_j(\vec{x}_i-\vec{t}_j)^2}$.

Weights, centers and width parameters are then optimised (trained) using a Nelder-Mead-simplex algorithm [11] with respect to the mean squared classification error.

We currently use $K = 10$ basis functions with $m = 200$ training vectors. m will be increased as soon as more reliably classified examples are available. In a VLF monitoring system the RBFN is successfully used to automatically sort the flow of incoming amplitude thresholded signal chunks into the mentioned transients classes. The fuzzy transition between the transients is satifactorily reflected by the continuous output parameter. Wrong classifications (i.e. with an y-error > 0.5) occur in less than 5 % of the received samples.

A reason for choosing a RBFN was, that it has a structure allowing a straightforward Takagi-Sugeno fuzzy rule interpretation [13],[14] for each member function:

(if $\vec{x}$ is in the domain of basis function j, then $y^{(n)} = w_j$)

allowing some more direct insight into the classification process, than e.g. backpropagation networks. In this way domain analysis of the basis functions using the trained centers, widths and weights reveals correlations between feature combinations and transients characteristics.

IV. Conclusion

A sequence of statistics and wavelet transform based features proved useful with automating transients signal

detection, classification and analysis. Whereas the moment parameters skewness and kurtosis characterise global signal distribution statistic properties, the wavelet scale energies represent information about the behaviour at different time scales.
Using a radial basis function net, the features successfully discriminate transients received in the VLF frequency range from 'pulse like' to 'wave like'.
The sets of the wavelet coefficients with the highest energy contents additionally provide the information to locally reconstruct the most relevant part of the transient for further analysis.

The transients shown in this paper have been monitored with an E-field receiver, the signal then fed into the sound card of a notebook and digitally processed with the described algorithms in this paper - thus providing a mobile VLF monitoring, discrimination and analysis system. We believe that the discussed methods are valuable beyond this example.

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