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POSITIVE POLARITY: MISCLASSIFICATION BETWEEN INTRACLOUD AND CLOUD-TO- GROUND

DISCHARGES IN THE SOUTHERN AFRICAN LIGHTNING DETECTION NETWORK

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1. INTRODUCTION

Lightning detection networks measure the radiated impulse from the discharge; and report the stroke in terms of: the time, a computed stroke location, a measure of confidence often in the form of an ellipse, a measure of fit quality, and stroke type classification. Network performance is often assessed by two metrics: location accuracy and detection efficiency.

Location accuracy is often assessed by computing the mean of the major confidence ellipse length, although ground truth verification studies have determined that the location error may be less than the mean length. Ground truth studies include rocket triggered work by Jerauld et al. (2005), video work by Biagi et al. (2007), and still camera work by Liu et al. (2011). Similarly detection efficiency is often assessed through video studies, for example the work of Biagi et al. (2007).

Type classification is a parameter assigned to a detected lightning stroke, and indicated if the stroke is intracloud (IC), or cloud-to-ground (CG). Unlike the measure of position, peak current and type classification are not assigned any measure of confidence. An error may be assigned to the estimation of peak current, which is estimated from the range normalised signal strength of the peak of the vertical component of the electric field (Cummins et al. (1998), Orville (2008)): the error in position does contribute to the error in the estimation, but this contribution is very small. The type classification assigned to a stroke is derived from the rate of change of the electric field (Rakov and Uman (2003)), but no account of channel geometry is made.

a. Misclassification

The misclassification problem is well understood and much work has been done since the problem was first noticed in the 1995/1994 upgrade of the U.S. National Lightning Detection Network (Cummins et al. (1998); Wacker and Orville (1999a,b); Jerauld et al. (2005); Orville et al. (2002); Cummins et al. (2006); Biagi et al. (2007)). The problem is that small peak current positive strokes are often assigned the type classification of cloud-to-ground when in fact these are more likely to be intracloud discharges. In 1998 it was proposed that positive cloud-to-ground strokes with peak currents less than 10 kA are discarded, or at least reclassified as intracloud strokes.

A video study by Biagi et al. (2007) a decade later formed the basis of increasing the positive cloud-to-ground reclassification limit by 5 kA to 15 kA. A lower theoretical limit for peak current positive discharges has not yet been established and while various video studies have confirmed the presence of misclassified strokes, correctly classified strokes below either of the reclassification limits are also found.

The presence of misclassified strokes in other data sets (negative cloud-to-ground, and intracloud; and positive intracloud) has not been directly assessed.

b. Southern African Lightning Detection Network

The data in this paper are from the Southern African Lightning Detection Network (SALDN). This IMPACT (Cummins et al. (1998)) type network consists of 25 LS7000 and LS7001 sensors distributed throughout the Republic of South Africa, and the Kingdom of Swaziland. The locations of the sensors is shown in Figure 1.



Figure 1: Political map of southern Africa, showing the location of the SALDN sensors

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Figure 2: Discrete probability density functions computed from the cloud-to-ground data set.

The period of the data is from August 2007 to March 2010; a period before the sensors were moved or added to the network. The 2010/2011 upgrade to the SALDN consisted of adding several sensors and moving others to reduce the baseline distances between the sensors.

2. STATISTICAL DISTRIBUTION OF LIGHTNING STROKES

Histograms for the four polarity-type data sets ([negative; positive] \cap [intracloud; cloud-to-ground]) are computed in 2 kA bins from the peak current estimate of every stroke in each data set. The notion of a direct measurement of peak current of intracloud discharges is absurd, and in this analysis peak current data is from the magnitude of the vertical component of the electric field that has been converted to a peak current estimate (by the network) using the range normalised signal strength method.

The histograms may be converted to probability density functions by dividing each bin of the histogram by the total number of strokes in each data set. No strokes have been reclassified or discarded.

a. Cloud-to-ground

The cloud-to-ground histograms are shown in Figure 2, along with the 1998 and 2009 reclassification limits. Current literature suggests that the reclassification limits should only be applied to the positive cloud-to-ground data set, and through inspection of the resulting probability density function it is obvious that the most probable peak current assigned a type classification of positive cloud-to-ground should be reclassified.

Unlike the negative cloud-to-ground data set, which is unimodal at 10 kA, the positive cloud-to-ground data set is bimodal: the first and most significant mode occurs at 6 kA (below both reclassification limits) and the second mode occurs at 18 kA (above both reclassification limts).



Figure 3: Discrete probability density functions computed from the intracloud data set.

b. Intracloud

Both of the intracloud distributions are unimodal, with the positive distribution mode at 6 kA and negative distribution mode at 8 kA. The region of the positive intracloud distribution between 2 kA and 10 kA has the same shape as that of the positive cloud-to-ground data set. There is also discontinuity in the positive intracloud distribution at 16 kA where the gradient changes abruptly. There are few similarities between the negative distributions, with obvious differences in the kurtosis between the two.

The established fact that the positive cloud-to-ground distribution contains many misclassified strokes in the region below 15 kA and the similarity in the shapes hints at some common underlying process.

3. DECOMPOSED DISTRIBUTIONS

The author has proposed that each distribution consists of the sum of two distinct distributions: that of the correctly classified component and that of an incorrectly classified component (Grant et al. (2012)). These distributions have been shown to vary independently of each other and indeed the components corresponding to intracloud discharges precede (by between 10 to 30 minutes) the cloud-to-ground components (Grant (2010)). The method used to compute the separate distributions is the particle swarm optimisation of the resulting 6 dimensional problem.

a. Cloud-to-ground

Figures 4a and 4b show the fitted distributions describing the misclassified (intracloud) component, which is given by a gamma distribution; and the correctly classified (cloud-toground) component, which is given by a Cauchy distribution.

Particularly in the case of the unimodal negative cloud-toground distribution, the sum of the two distributions provides a better description than a single classic log-normal distribution (Grant (2010)).











Figure 6: Type classification confidences for cloud-to-ground data sets.

b. Intracloud

Figures 5a and 5b show the fitted distributions to the intracloud data set. In these cases the misclassified component is the cloud-to-groud component given by the Cauchy distribution, and the correctly classified component is given by the gamma distribution.

4. ASSESSING MISCLASSIFICATION

A confidence for the type classification assignment may be computed by comparing the contribution, at a particular current, of the correctly classified component to the measured probability mass function:

$$c(i) = \frac{p(i)}{T(i)} \tag{1}$$

Where c(i) is the confidence at a particular current, i, p(i) is the contribution of the correctly classified component, and T(i) is the probability mass function.

The resulting type classification confidence functions for



(b) Negative intracloud

Figure 7: Type classification confidences for intracloud data sets.

cloud-to-ground discharges are shown in Figure 6, and intracloud discharges in Figure 7. The reclassification limits have been included for reference.

For the positive cloud-to-ground data set, there is almost complete confidence in the type classification assigned to strokes with peak currents above 15 kA. The 50% confidence level corresponds to the 10 kA reclassification limit. There is almost an inverse function for the positive intracloud data set, where strokes with peak currents above 15 kA are almost certainly misclassified. The 10 kA reclassification limit roughly corresponds to a 60% confidence.

The negative cloud-to-ground confidence function is similar to the positive cloud-to-ground function in that there is decreasing confidence below the reclassification limits. However the function is much wider with a longer tail. Therefore for currents with peak currents between 15 kA and 30 kA There is still some doubt about the type classification assigned. The intracloud function is not the inverse of the cloudto-ground function, but is still long tailed. The region of high classification confidence is small (between 2 kA and 18 kA).

5. CONCLUSION

The simple reclassification of strokes with small positive peak currents below a threshold does discard some correctly classified strokes. The application of this hard limit ultimately results in some information loss, and in order to better understand the extent of this information loss type classification performance must be assessed. The results in this paper show that there is no sudden cut off of the misclassification problem, nor is the problem only confined to the positive cloud-to-ground data set.

A new measure, that of type classification confidence, has been introduced. This measure provides a means to select data above a certain confidence level; instead of applying a hard limit. It is also proposed that this method is also applied to the other three data sets, where the misclassification problem has not been addressed.

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