Implementation of convolutional neural networks to determine lightning location

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Abstract. Lightning produces not only electromagnetic signals but also thunder sound signal. A new method was proposed to determine lightning location by measure time of arrival (TOA) of lightning electromagnetic signals and thunder sound signal to get lightning distance using Convolutional Neural Network (CNN). These signals were caught by using a set of cell phones. These cell phones collect three main data i.e. the TOA of lightning electromagnetic signals, the TOA thunder sound signal, and the coordinates obtained from Global Positioning System (GPS). In this study, CNN determines thunder sound signal pattern which is recorded by certain cell phone. More than one hundred samples of thunder sound signals were used as data set. Whole data set divide into three categories i.e. training data, validation data, and testing data. The model runs few hours to train the network and then produce a confusion matrix. The matrix consists of several column represents a set of samples that previously predicted by their labels and several rows represents actual labels. The labels are thunder sound and the other sound. After the model created, it is exported to the cell phone so that every time cell phone record a sound signal, the model will predict whether the thunder sound or not. When the model predicts the sound as thunder sound, the cell phones save the exact occurrence time. This determination is very important when the cell phone is going to measure lightning distance between lightning location and cell phone location.

1. Introduction

Lightning is a natural phenomenon which is produced by clouds called cumulonimbus. Sometimes the lightning strikes are accompanied by rain. This phenomenon is associated disasters in field electric power, aviation, public health etc. Most people concern about the weather but they don’t know exactly where dangerous area is. The dangerous area means the area on the surface of the earth which is impacted directly by cloud to ground lightning. It can destruct everything on it and interfere human activities [1]. Many researches have been done to determine lightning location. Han et. al. (2019) proposed a new technique called direction of arrival (DOA). He used a compact acoustic array which consists of 19 microphones placed on a 3-D steel frame. The system detects both the thunder signal and electromagnetic signal [2]. In 2012, Qiu designed a compact synchronized observation system combined VHF broadband interferometer with broadband acoustic array. She investigated different VHF and acoustic behaviours in lightning processes and study the physical mechanism involved the generation of acoustic and VHF emissions [3].
In this research, the thunder sound produced by lightning is used to determine lightning location. A new approach is introduced using trilateration method which using either three or more cell phones. These cell phones catch the thunder sound and their location using global positioning system (GPS). Both the time of arrival (TOA) of electromagnetic wave and thunder sound produced by lightning were noted and calculated. So that the distance between cell phones and lightning position can be obtained. Obviously, these cell phones record everything not only thunder sound but also other noise sound. The cell phones use Convolutional Neural Network (CNN) model to ensure the wanted sound is thunder sound.

2. Methods

This work used 102,109 sound samples dataset which is divided into three classes i.e. 101,949 samples of random sound, 153 samples of thunder sound and 7 samples of background noise sound. Furthermore, this work used only one second clip duration of each samples. Each sample has 16,000 sample rates. The whole recorded sounds were converted to spectrogram as image. The spectrogram was produced by breaking the sound signal into millisecond pieces of sound signal as a result of the division between thunder sound duration and sample rates. Each pieces of sound signal were computed by discrete fourier transform (DFT). DFT uses the sample transformation $x = [x_0, x_1, \ldots, x_{N-1}]$ into a vector $z = [z_0, z_1, \ldots, z_{N-1}]$ which represents numerical values of a signal, where the values are the complex and can be written as $z_i \in \mathbb{C}$. The formula of DFT proposed in Ref. [4] as follows:

$$z_k = \frac{1}{N} \sum_{n=0}^{N-1} x_n \exp \left( -\frac{2 \pi i n k}{N} \right)$$

The information obtained from spectrogram is the amplitude spectrum signal over time. The power at certain frequency can be seen from the colour. The colour has range from dark blue to bright yellow. The darker blue corresponds lower value and the brighter yellow corresponds higher value. The high frequency is on higher points of the figure. The purpose of this conversion to spectrogram is to determine the pattern of the thunder sound. From fig. 1 below, four samples of the thunder sounds dataset have similar pattern in spectrogram. This image pattern can be used as main data in CNN.

![Figure 1. Four samples of thunder sound have similar pattern in spectrogram.](image-url)
CNN are hierarchical neural networks whose convolutional layers alternate with subsampling layers, reminiscent of simple and complex cells in the primary visual cortex [5]. The CNN algorithm has several layers as shown in flowchart below:

![Flowchart of CNN Layers](image)

**Figure 2.** Flowchart of CNN Layers

CNN uses fingerprint input to obtain audio feature vectors. Each of neurons of CNN layers has weight, bias, and activation function. Feature extracting layer consists of convolutional layers and pooling layers. The convolutional layers consist of neurons forming a filter which has length and width. This filter will be shifted over all the whole image. Every shift uses dot operation between the input and the filter so that produces an output called feature map. After convolved, the image is pooled by pooling layer. Most commonly pooling used is max pooling and average pooling. Fig. 2 shows us the CNN layers use max pooling.
3. Result and Discussion
The dataset was trained in several hours depending on PC performance. After training finished, it produced CNN model and confusion matrix as shown in fig. 3 below:

\[
\begin{bmatrix}
2 & 0 & 0 \\
0 & 2 & 0 \\
2 & 1 & 13
\end{bmatrix}
\]

**Figure 3.** Confusion Matrix

As mentioned, previous, the dataset was divided into three classes and each name of classes are labelled as “silence”, “unknown”, and “thunder”. The silence label is for background noise sound, the unknown label is for the other sounds. Each column corresponds a set of samples that were predicted to be each label, so the first column corresponds all the samples that were predicted to be silence, the second all those were predicted to be unknown sounds, and the third column corresponds all the samples that were predicted to be thunder sound. In other hand, each row corresponds samples by their correct, ground truth labels. The first row is all the samples that were silence, the second sound that were unknown sounds, and the third sound that were thunder sound. This matrix can be more useful than just a single accuracy score because it gives a good summary of what mistakes the network is making. Fig. 3 shows that the majority values at first row are zero, except the first value at the first row which all the clips are actually silence, this means that none of them were mistakenly labelled either as unknown sound or thunder sound, so we have no false negatives for silence. It indicates the network is good at distinguishing silence from other sounds. There are two non-zero values at the first column of the matrix. The column represents all the sounds that were predicted to be silence, so positive numbers outside of the first cell are errors. This means that some thunder sounds are actually being predicted to be silence.

![Thunder 1](image1.png)
![Thunder 2](image2.png)
![Thunder 3](image3.png)

**Figure 4.** Three samples of thunder sound recorded between November 4 and November 7

![Rain droplet 1](image4.png)
![Rain droplet 2](image5.png)
![Rain droplet 3](image6.png)

**Figure 5.** Three samples of rain droplets sound recorded

Three samples of different thunder sound outside the thunder sound training dataset have been tested by the model created to obtain data validation from the model. Fig. 4 shows that each sample has different sound wave but they look similar in pattern of spectrogram. The brightest yellow indicating the higher value is in the lower frequency. It means that the majority of thunder sounds are in low frequency. Other samples are rain droplets sound labelled as unknown have been tested by the model as
well. From fig. 5, the rain droplets sound spectrogram patterns are different with the thunder sound spectrograms. The frequency of rain droplet sound has wider range than the frequency of thunder sound.

| Table 1. The comparison of the three samples of the thunder sound and the three samples of the rain droplets sound |
|---------------------------------------------------------------|
| Silence label | Unknown label | Thunder label |
|----------------|--------------|---------------|
| Thunder 1      | 0.00001      | 0             | 0.99999       |
| Thunder 2      | 0.0001       | 0.00035       | 0.99964       |
| Thunder 3      | 0.00001      | 0.00621       | 0.99378       |
| Rain droplet 1 | 0.23520      | 0.41579       | 0.34901       |
| Rain droplet 2 | 0.52735      | 0.42556       | 0.04709       |
| Rain droplet 3 | 0.67428      | 0.25789       | 0.06783       |

After the samples have been tested, both thunder sound and rain droplets sound have final scores respectively. The score is always between zero and one. The higher score represents more confidence in the result. Table 1 shows us that thunder 1 – 3 has high score almost one at thunder label. It means that the model predicts the thunder sound very confidence. In other hand, the rain droplets sound mostly get high score at unknown label except the rain droplets 3 which predicted as silence label.

4. Conclusions
The CNN model has succeeded to predict thunder sound with high score nearly one. From this research, we can analyse that thunder sound and rain droplets sound have different pattern in spectrogram respectively. The CNN model can be exported to cellular phones so that the thunder sound caught by cellular phone, its time arrival, and the cellular phone coordinate can be computed to get the thunder location.

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