

Laguerre-Gauss Preprocessing: Line Profiles as Image Features

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Introduction

An image preprocessing methodology based on Fourier analysis together with the Laguerre-Gauss Spatial Filter (LGSF) is proposed. **It reduces the feature space significantly, preserving enough information for classification tasks.** It is called Laguerre-Gauss Preprocessing.

Given the reduced feature space, a simple learner should be able to perform well on image classification tasks. k-Nearest Neighbors (k=1) and a Multilayer Perceptron are employed. They are compared with a Convolutional Neural Network, which is a model appropriate for image classification but expensive during training and inference.

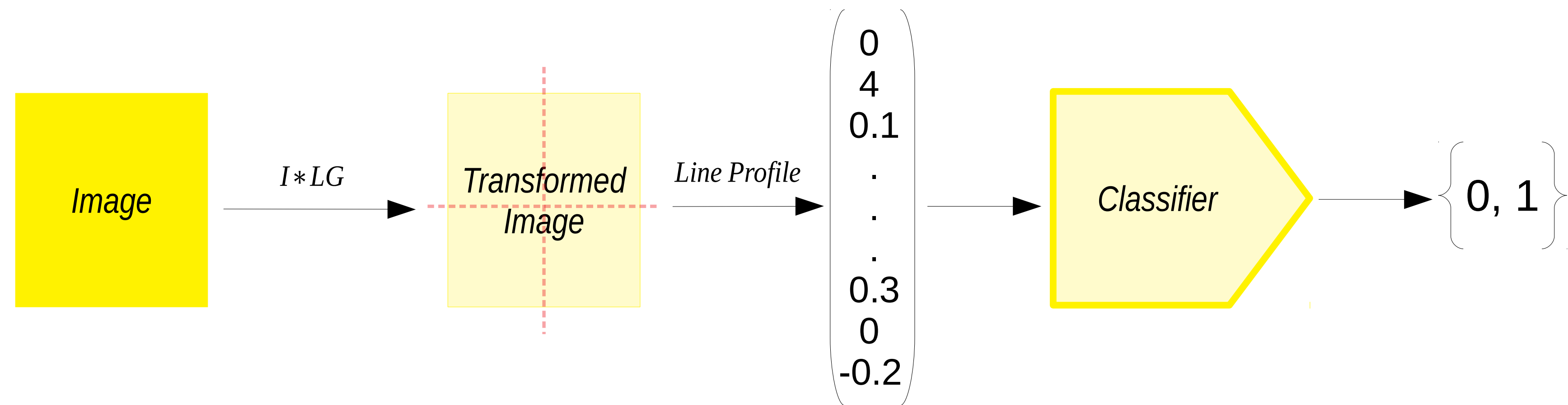


Figure 1: Laguerre-Gauss Preprocessing Pipeline.

Also, this work aims to successfully apply Laguerre-Gauss Preprocessing to classify aerial images. The data set was collected to identify illegal mining and deforestation in large areas. The images come from multiple news agencies. The idea is to classify an image in the class 1 if it contains something of interest (i.e., heavy-equipment, boats, deforestation, etc.); or as class 0 if it does not (i.e., forest, rivers, populations, etc.).

Preliminaries

- The **LGSF** was proposed by Guo *et al.* [1]. In the spatial domain it is given by [2]

$$LG(x, y) = (i\pi^2\omega^4)(x + iy) \exp \{-\pi^2\omega^2(x^2 + y^2)\} \quad (1)$$

where ω is a parameter that controls the bandpass filter size. As ω approaches 1 it favors higher frequencies, that is, thinner edges.

- The **Line Profile** of a matrix is the sampling of its values along a path (usually across the origin and parallel to the x - and y -axis).
- The **Shift** function centers the zero-frequency components of the spectrum.

Laguerre-Gauss Preprocessing

Algorithm 1: Laguerre-Gauss Preprocessing

```
Data: image,  $\omega$ 
s ← size(image);
filter ← LaguerreGaussFilter( $\omega$ , s);
imageFT ← FourierTransform(image);
filterFT ← FourierTransform(filter);
convolved ← imageFT · filterFT;
shifted ← shift(convolved);
x-profile ← LineProfile(shifted, axis = x);
y-profile ← LineProfile(shifted, axis = y);
return x-profile, y-profile
```

Conclusions

This work introduced Laguerre-Gauss Preprocessing. It was shown that it can be successfully applied to learn to classify aerial images with simple models. As a result, the model's size footprint is reduced, as well as the training and inference time. The LGSF enabled edge enhancement and reduced the low- and high- frequency noise. This resulted in characteristic frequencies that allowed learning special/relevant shapes within an image.

Results

The main challenge posed by the Aerial Images data set is the infinite number of possible camera angles and altitudes from which the images are taken. Also, the noise added by images from moving cameras, fog, clouds and changing climates. Note that not all images come from the same distribution, since they are taken in different locations with different kinds of sensors.



Figure 2: Aerial Classification classes. Source: *Noticias Caracol, 2019. Noticias RCN, 2019. Revista Semana, 2019.*

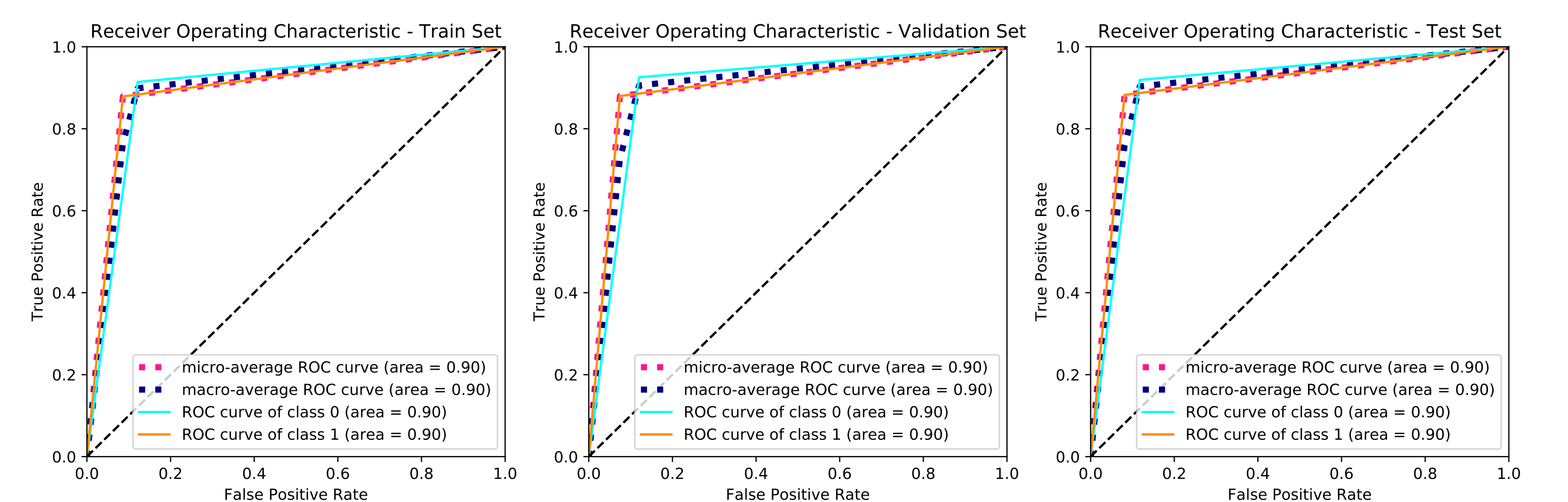


Figure 3: ROC curve for a kNN trained to classify Aerial Images.

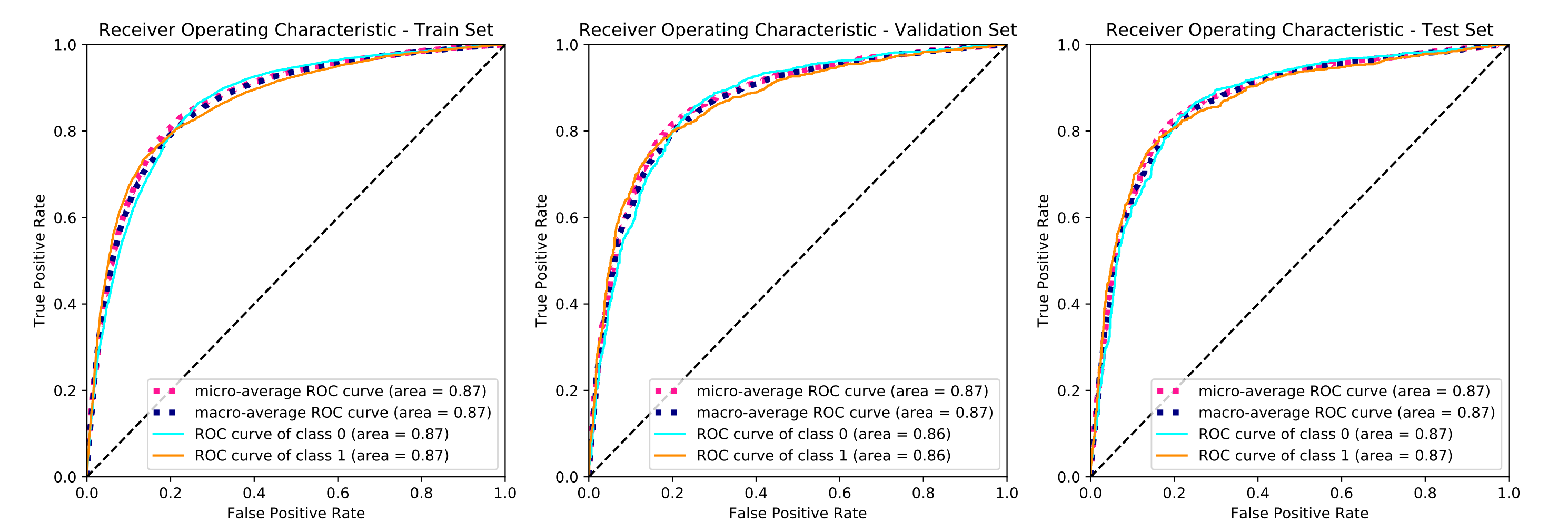


Figure 4: ROC curve for a MLP trained to classify Aerial Images.

| Model | Data | Size | Train | | Validation | | Test | |
|-------|-----------|-----------------|---------------|-----------|---------------|-----------|---------------|-------------|
| | | | Accuracy | F1 | Accuracy | F1 | Accuracy | F1 |
| kNN | Flattened | 951.2 MB | 0.9257 | 0.93/0.91 | 0.9286 | 0.93/0.91 | 0.9183 | 0.92/0.90 |
| | LP | 30.0 MB | 0.9030 | 0.91/0.88 | 0.8900 | 0.90/0.86 | 0.9046 | 0.9151/0.89 |
| MLP | Flattened | 4.4 MB | 0.5747 | 0.72/0 | 0.5720 | 0.72/0 | 0.5730 | 0.72/0 |
| | LP | 376.4 kB | 0.8012 | 0.82/0.76 | 0.8116 | 0.83/0.77 | 0.7990 | 0.82/0.76 |

Table 1: Results of Aerial Images classification.

| Model | Data | Size | Train | | Validation | | Test | |
|-------|-----------|-----------------|---------------|----------------|---------------|----------------|---------------|----------------|
| | | | Accuracy | F1 | Accuracy | F1 | Accuracy | F1 |
| kNN | Flattened | 750.8 MB | - | - | 0.9513 | 0.94/0.94/0.96 | 0.9601 | 0.95/0.95/0.97 |
| | LP | 23.7 MB | - | - | 0.9832 | 0.97/0.98/0.99 | 0.9880 | 0.98/0.98/0.99 |
| MLP | Flattened | 4.4 MB | 0.9661 | 0.95/0.95/0.98 | 0.9311 | 0.93/0.90/0.95 | 0.9066 | 0.90/0.88/0.94 |
| | LP | 374.7 kB | 0.9770 | 0.96/0.97/0.98 | 0.9563 | 0.94/0.95/0.97 | 0.9563 | 0.95/0.95/0.96 |
| CNN | Image | 15.5 MB | 0.9819 | 0.98/0.97/0.98 | 0.9550 | 0.95/0.93/0.97 | 0.9584 | 0.96/0.94/0.96 |

Table 2: Results of Geometric Shape classification. Classes: Circle/Square/Triangle.

References

- [1] Cheng-Shan Guo, Yu-Jing Han, Jian-Bo Xu, and Jianping Ding. Radial hilbert transform with laguerre-gaussian spatial filters. *Opt. Lett.*, 31(10):1394–1396, May 2006.
- [2] Juan Paniagua and Olga Quintero. Attenuation of reverse time migration artifacts using laguerre-gauss filtering. 06 2017.