Laguerre-Gauss Preprocessing: Line Profiles as Image Features

Alejandro Murillo-González [1] **José David Ortega Pabón** [2] **Juan Guillermo Paniagua** [1] **Olga Lucía Quintero Montoya** [1]

Abstract

An image preprocessing methodology based on Fourier analysis together with the Laguerre-Gauss Spatial Filter is proposed. This is an alternative to obtain features from aerial images that reduces the feature space significantly, preserving enough information for classification tasks. Experiments on a challenging data set of aerial images show that it is possible to learn a robust classifier from this transformed and smaller feature space using simple models, with similar performance to the complete feature space and more complex models.

1. Introduction

Machine Learning (ML) methods have been solving more and more problems each day. Consequently, they are being used in a larger number of platforms. One of those are Unmanned Aerial Vehicles (UAVs). These are still resource constrained platforms. So, when a ML solution is required to run on one of these, such models must guarantee a low energy, memory and compute consumption. That is the case of this work, where an image classification model is to be deployed on an aerial vehicle. Here, a video stream is recorded live from the UAV, and the model must provide fast execution to keep up with the constantly incoming video while generating accurate results.

Therefore, an image preprocessing methodology based on Fourier analysis together with the Laguerre-Gauss Spatial Filter (LGSF) is proposed. It reduces the feature space significantly, by sampling the line profiles of a transformed image, preserving enough information for classification tasks. It is called Laguerre-Gauss Preprocessing.

[1]Mathematical Science Department, Universidad EAFIT, Medellín, Colombia [2]CETAD, Fuerza Aérea Colombiana, Rionegro, Colombia. Correspondence to: Alejandro Murillo-González <amurillog@eafit.edu.co>.

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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.

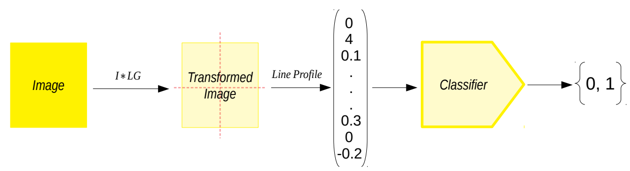

Figure 1. Overview of Laguerre-Gauss Preprocessing.

Furthermore, the proposed methodology is successfully applied 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.).

The code implementation of Laguerre-Gauss Preprocessing and the presented results are available on GitHub [1]; a deeper dive onto the methodology is available on arXiv [2].

2. Related Work

Line Profiles. Sierra-Sosa (Sierra-Sosa et al., 2016) use Fourier analysis on spectrograms of audio recordings to identify the speaker's emotions using the spectrum's line profile. In (den Hollander & Hanjalic, 2003) multiple line profiles, whose position are based on maxima in the Hough transform space, are used to recognize logos (classification over invariant classes). In (Raffei et al., 2014) the authors employ line intensity profiles to identify reflections in eye images, which are then classified as reflections or non-reflections using a suport vector machine. Bhan (Bhan et al., 2016) use feature line profiles from preprocessed ra-

[1]https://github.com/AlejandroMllo/Laguerre-Gauss-Preprocessing

[2]https://arxiv.org/abs/1912.06729

diographic images to detect dental caries and their severity.

The works described above, specially those on images, work over very restricted spaces. In the Aerial Images classification task the environments and elements of each class have higher variation.

3. Preliminaries

- The **Laguerre-Gauss Spatial Filter** (LGSF) is the kernel employed during preprocessing to enhance the edges and reduce low- and high- frequency noise (Guo et al., 2006; Castrillón et al., 2018).

  The filter, proposed by Guo (Guo et al., 2006), in the spatial domain is given by (Paniagua & Quintero, 2017)

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

  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. This work uses the line profiles taken along a line segment that crosses the origin and is parallel to the $x-$ and $y-$axis, respectively.

- The **Shift** function centers the zero-frequency components of the spectrum.

4. Proposed Method

Figure 1 is an overview of classification using the Laguerre-Gauss Preprocessing procedure. The methodology involves obtaining the Fourier components of the image $\hat{I}$ weighted by the Fourier components of the LGSF $\hat{LG}$ filter. The resulting analytic image is arranged such that the zero-frequency components are at the origin (center). Finally the **line profiles** are sampled along the $x-$ and $y-$axis.

This procedure means that if an image of size $n \times n$ is being classified, the classifier will only need $2 \times n$ features, reducing significantly the feature space.

Algorithm 1 presents the pseudocode of the procedure.

Algorithm 1 Laguerre-Gauss Preprocessing

Input image, ω
s ← `size`(image);
filter ← `LaguerreGaussFilter`(ω, s);
$image_{FT}$ ← `FourierTransform`(image);
$filter_{FT}$ ← `FourierTransform`(filter);
convolved ← $image_{FT} \cdot filter_{FT}$;
shifted ← `shift`(convolved);
x-profile ← `LineProfile`($shifted, axis = x$);
y-profile ← `LineProfile`($shifted, axis = y$);
return x-profile, y-profile

Table 1. **Results of Aerial Images classification**. The F1 score is reported for each class in the next order: (0) No object of interest / (1) object of interest. The *Flattened* data type means images whose pixels were transformed to a column vector, which will later be used as input to the model. The *LP* data type represents the image features (line profiles) obtained using Laguerre-Gauss Preprocessing.

			Train		Validation		Test	
Model	**Data**	**Size**	**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	0.91/0.89
MLP	Flattened	4.4 MB	0.5747	0.72/0.0	0.5720	0.72/0.0	0.5730	0.72/0.0
	LP	**376.4 kB**	**0.8012**	0.82/0.76	**0.8116**	0.83/0.77	**0.7990**	0.82/0.76

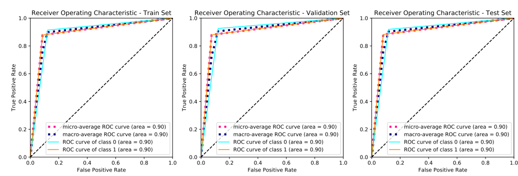

Figure 2. ROC curve for a kNN trained to classify Aerial Images.

5. Results

The **Data Set** contains 5707 instances (resized to 64×64 pixels) of which 3297 (57% of the total) images are samples of class 0 and the remaining are samples from class 1. The data was augmented to 20000 instances through random rotations ($\pm 20°, 90°, 270°$), left-to-right and top-to-bottom flips. The data set is considered challenging since all images were not taken with the same sensor, nor at the same altitude or orientation. On top of this, there is noise from moving cameras, fog, clouds and variable weather.

The results of the **classification** of the aerial images are reported on Table 1. Figure 2 shows the Receiver Operating Characteristic (ROC) curve of the kNN employing the LP feature space. The results displayed are a good indication of the combined precision and recall of the models.

From Table 1 it is possible to see that doing a small tradeoff with accuracy it is possible to use a model that is way smaller. Empirically, the smaller model (kNN) was also found to be faster during execution

6. Discussion

- The introduced methodology can learn a robust classifier for Aerial Images (see Table 1 and Figure 2). It also guarantees the fulfillment of the energy, memory and compute constraints.

- Upon inspection, most classification errors occurred on images taken from high-altitudes, meaning that the classifier is constrained to certain heights.

- The use of features from the frequency domain might lead to generalization to diverse environments, where it highlights relevant shapes regardless of background noise (i.e., deserts, oceans, jungle, etc.).
- The LGSF distributes homogeneously and smoothly the intensity in the Fourier spectrum due to its isotropic feature. This resulted in characteristic frequencies that allowed learning relevant shapes within an image.
- Using line profiles it is possible to obtain peaks and valleys of varying amplitudes and at different frequencies. Since the synthesized profiles obtained in this work always lied in the axis, it remains necessary to study how sampling profiles from other paths within the spectrum might help to obtain a richer feature space.
- This methodology could be successfully applied is finding regions of interest within large images.

7. Conclusion

This work introduced Laguerre-Gauss Preprocessing. It was shown that it can be successfully applied to robustly 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. The LGSF distributes homogeneously and smoothly the intensity in the Fourier spectrum due to its isotropic feature. This resulted in characteristic frequencies that allowed learning special/relevant shapes within an image. In addition, The LGSF can enhance any small changes in the image according to small changes in frequency.

The parameter ω tends to one in order to preserve the spatial frequency distribution in the image and perform the band-pass filter component from the LGSF, but it is important to analyze and propose a methodology to select the appropriate value depending on each data set.

This feature selection technique achieves models with a lower complexity (measured in terms of the VC dimensionality) and introduces a tool to develop a robust, quick, simplified and low-cost solution which can be deployed in aerial vehicles.

Future work could focus on extending this method for classification tasks with more categories where the shapes have high variance between elements of the same class.

References

Bhan, A., Goyal, A., Harsh, Chauhan, N., and Wang, C. Feature line profile based automatic detection of dental caries in bitewing radiography. In *2016 International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE)*, pp. 635–640, Los Alamitos, CA, USA, sep 2016. IEEE Computer Society. doi: 10.1109/ICMETE.2016.59. URL https://doi-ieeecomputersociety-org.ezproxy.eafit.edu.co/10.1109/ICMETE.2016.59.

Castrillón, J. G. P., Montoya, O. L. Q., and Sierra-Sosa, D. Laguerre-gauss filters in reverse time migration image reconstruction. *Brazilian Journal of Geophysics*, 35(2): 81–93, 2018. ISSN 1809-4511. doi: 10.22564/rbgf.v35i2.822. URL https://sbgf.org.br/revista/index.php/rbgf/article/view/822.

den Hollander, R. J. M. and Hanjalic, A. Logo recognition in video by line profile classification. In Yeung, M. M., Lienhart, R. W., and Li, C.-S. (eds.), *Storage and Retrieval Methods and Applications for Multimedia 2004*, volume 5307, pp. 300 – 306. International Society for Optics and Photonics, SPIE, 2003. doi: 10.1117/12.525025. URL https://doi.org/10.1117/12.525025.

Guo, C.-S., Han, Y.-J., Xu, J.-B., and Ding, J. Radial hilbert transform with laguerre-gaussian spatial filters. *Opt. Lett.*, 31(10):1394–1396, May 2006. doi: 10.1364/OL.31.001394. URL http://ol.osa.org/abstract.cfm?URI=ol-31-10-1394.

Paniagua, J. and Quintero, O. Attenuation of reverse time migration artifacts using laguerre-gauss filtering. 06 2017. doi: 10.3997/2214-4609.201700678.

Raffei, A. F. M., Asmuni, H., Hassan, R., and Othman, R. M. Fusing the line intensity profile and support vector machine for removing reflections in frontal rgb color eye images. *Information Sciences*, 276:104 – 122, 2014. ISSN 0020-0255. doi: https://doi.org/10.1016/j.ins.2014.02.049. URL http://www.sciencedirect.com/science/article/pii/S0020025514001558.

Sierra-Sosa, D., Bastidas, M., P., D. O., and Quintero, O. Double fourier analysis for emotion identification in voiced speech. *Journal of Physics: Conference Series*, 705:012035, apr 2016. doi: 10.1088/1742-6596/705/1/012035. URL https://doi.org/10.1088%2F1742-6596%2F705%2F1%2F012035.