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Synthetic Images Generation for Deep Learning Assessment Towards the Inflow Forecast for Power Systems Operation

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Abstract. This paper presents the reasons and the means to work with synthetic images sequences to assess Deep Learning (DL) Artificial Neural Networks (ANN), aiming a better technology for water inflow forecast to base the operations of wide power systems. We developed a computer program that efficiently generates the images and the respective numeric data series, allowing the training of ANNs. As the program includes an user-defined displacement between the image and the numeric values when it creates the sequences, the prediction ability of DL ANNs can be evaluated over temporal data series in several fields, even in noisy scenarios. We ended up with a powerful software tool, extensible and portable, able to incorporate more image generators algorithms. Our main contributions are exploring the DL potential to make predictions in temporal image data series and developing a tool for this purpose.

Key-words. Hydroelectric plants, Temporal data series, Climate forecast, Image analyses, Data assimilation.

1 Introduction

The water inflow forecast is the main factor in the operation of hydroelectric plants, specially to base dispatchment decisions in large integrated systems. It is not the same as rainfall forecast and there is a complex hydrological dynamic acting in the natural environment that has leaded to several mathematical, stochastic, and hydrological models designed to predict the inflow on the rivers. However, although the efforts toward an accurate prevision, deviations still persist between the predict and the observed inflow, as reported by [10, 20].

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In [22], we applied *Soil Moisture Model Accounting Procedure* (SMAP) [14], a deterministic model of hydrological simulation of the type rainfall-runoff transformation, to analyse the the inflow forecast in Tietê basin (Brazil) according to three indicators recommended by [17]: Nash-Sutcliffe efficiency (NSE), percent bias (PBIAS), and ratio of the root mean square error to the standard deviation (RSR). We found out better results than those produced by PREVIVAZ [15], that is the forecast model used by the local companies.

We have looked for further improvements in our work and we have noticed that Artificial Neural Networks (ANNs) are also employed in the inflow forecasts for river basins, on the following examples: [3, 4, 8]. The use of ANNs in this problem was demonstrated by [1], that reached acceptable accuracy for a horizon up to 10 days in River Ganges (India). It have been showed that remote sensing techniques and data driven modeling can be combined to build an ANN for flow forecasting of large-scale river basins.

In Nigeria, [19] explored the potential of satellite radar altimetry, getting NSE above 0.70 for an horizon of 5 days. In South Asia, [11] found NSE about 0,80 and concluded that satellite-based flow estimates are a useful source of dynamical surface water information, adding that they could be used for model calibration and data assimilation purposes. The use of thermal infrared imagery feeding hydrological models was investigated by [9], combined with other data sources and calibrations in Africa. We highlight the application of Multilayer Perceptron (MLP) ANNs by [6] with good results. In an effort to make monthly average forecasts, [25] selected an ANN with 3 normalized data inputs, one intermediate (hidden) layer of 16 neurons, and the sigmoid logarithmic function, reaching an efficiency level about 77%. Also using ANNs, [8] got better performance than PREVIVAZ in a certain scenario.

Thus, ANNs can be considered an established resource in the water inflow forecast. Nevertheless, the models and tools still require long data series to operate properly, usually collected in the field, from meteorological stations. Often the series have inconsistencies, errors, and disruptions, especially in case of manual collections. Because a river basin spreads for a wide terrain, the measurements taken by a station are considered representative of a large territory as showed in [21], where a single station covers about 3,000 Km^2.

On the other hand, images taken by satellites are very useful in several fields, particularly in the meteorological forecast, as illustrated by [16, 23]. We highlight the use of satellite imagery by [20] to estimate the river flow under 15% of error and overcoming the reliability of the forecasts made from data series collected by terrestrial measurement stations.

The image processing with ANN is reviwed by [7], showing that the approach is valid, but there is no discussion in that paper about the temporal displacement which we face trying to forecast river flows.

We intend to combine temporal data series and satellite images as input to deep learning (DL) ANNs, a promising approach as discussed by [13, 24]. We are going to investigate the performance of DL ANNs in the inflow forecast using images from Geostationary Operational Environmental Satellite (GOES) plus the data series from Brazilian National Agency for Waters (ANA) and National [Electric] System Operator (ONS).

The satellite imagery and historical data are too complex to the first evaluation of the DL algorithms. Image databases usually considered for tests, as IRIS from UCI [4], are not suitable for our purposes, mainly because we can not define patterns nor the temporal shift of data series. The use of synthesized images to train ANN was successfully demonstrated by [18], whereas [2] presents it as a cheaper solution for the production of large training sets for ANNs. Then, we decided to use synthetic sequences, in which we have total control, to verify the settings of DL tools and to take insights about the difficulties we will face with. Our image sequences are *not* videos, but individual pictures.

2 Purposes

The goal of this research is to understand the behavior and limitations of DL ANNs in a predictive task of processing images sequences to extract underlying patterns. As each individual image pixel is an input to the ANNs, it is reasonable to employ DL techniques to the data set, once the amount of information is very large. DL has showed good results in problems like image classification, social network analysis, knowledge extraction, items recommendation, and others. A review about DL ANNs can be found in [24].

Briefly, we first train a DL ANN feeding it with images and the expected data that would result of the images processing; after the training period, unknown images are presented to the ANN and the DL algorithms return their answer about that image set. Our work started with an evaluation phase of the DL ANNs, designed to support the set up process of our investigation.

3 Methods

In order to obtain the synthetic sequences of images, we implemented the *Fast Image Series Generator* (Fisgen) sofware, which requirements included a high level of user customization, extensibility, and portability. We used the following resources: general use microcomputers; Linux operating system (actually Fedora Core 25); Eclipse Neon.3 (4.6.3) platform; and Java JDK 1.8. Fisgen efficiently produces large amounts of synthetic images and their associated data, supporting the insertion of a user-defined level of noise in each image. The program was written in Java to be portable and easily accommodate new extensions. The latter is an important feature because there are countless patterns and parameters sets that can be designed. The same feature helps Fisgen tool to be successfully applied to other problems and fields.

Whereas other parameters may be accepted for specific generators algorithms, the software allows the user to choose at least the following values from the command line: a) Series Name: the user-friendly name of the files; b) Series Size: the number of images to be generated; c) Data Offset: the temporal shift between the image and data; d) Horizontal Resolution: pixels in the horizontal side; e) Vertical Resolution: pixels in the vertical side; f) the class that effectively implements the generator; g) Noise: the rate of random noise to embed in the image as a fraction of total pixels.

[4]http://archive.ics.uci.edu/ml/datasets/Iris

All generators must be derived of the *AbstractGenerator* class, whose method *abstract void doGeneration()* must be implemented. Currently, the following concrete generators (CGs) are in place: *CGMovingPoint*, *CGRotatingPoint*, *CGFloodingArea*, and *CGSplashingArea*. The CGMovingPoint generator outputs image sequences where a single square moves linearly from the center to the border and records numerically the coordinates of the square center and its euclidean distance to the starting point. CGRotatingPoint moves cyclically a small square around the image center, recording the same data. CGFloodingArea grows a centered circle along the image sequence and write down the circle radius and area. The CGSplashingArea implementation splashes pixels randomly in the images according to an increasing coverage rate, keeping track of its value. The images are actually stored as individual *jpeg* files.

The Data Offset integer parameter allows a displacement between an image and its related data. Though this ability is of little use in other scenarios, here it is mandatory, once we intend to make predictions. For a positive offset, the images are advanced in relation to the numeric data. It means that, in the series, each image anticipates the future numeric values, as in the case of the rainfall forecast, where one has the satellite imagery some time *before* the actual rain.

4 Results

As there is no graphical user interface, the program is uniquely controlled by command line and it had allowed us to write small *scripts* that can order the generation of thousands images without any further intervention.

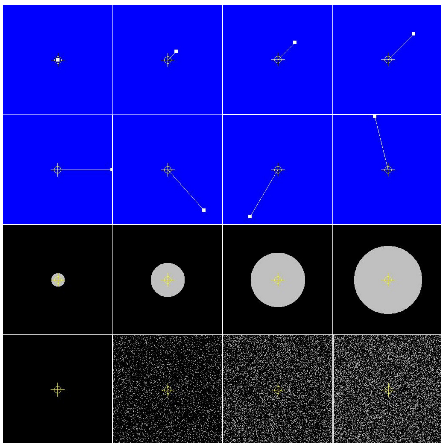

Figure 1: Samples of image sequences generated by Fisgen.

In Fig. 1, outputs samples of the four implemented concrete generators are shown. In the first line, the moving point traverses the images towards the left upper corner. The second line presents different instants of the rotating point. The third line illustrates the increasing flooded area and the last one shows samples of the splashed pixels along the time. Each individual image has 256 x 256 pixels, 24 bits for color depth, and no noise.

They are four out of 256 images generated by each algorithm. The complete series has 1,024 images, took 2.89 seconds to be produced and used about 11.3 MB of storage. The real images we have from GOES are 1,870 x 1,714 pixels sized. Figure 2 presents samples of images of each algorithm with 0.05 of noise.

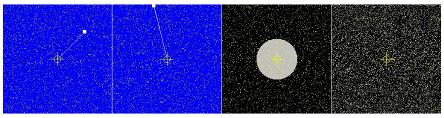

Figure 2: Individual images with 5.0% incorporated noise.

5 Discussions

Fisgen was able to produce images and data according to our expectations. New generators are planned, but we found in [26] motion detection results in pictures that resemble those generated by classes *CGMovingPoint* and *CGRotatingPoint*. The method we described is according to the directions pointed by [7, 18] and is cheap as indicated by [2].

The limitations of standard image collections about pattern controls and time displacement were fully overcome. We have inputs to evaluate the predictions capabilities of DL algoritms. If we confirm our prognosis about the performance of DL ANNs in our sets of synthetic images, we can move ourselves to real satellite imagery and we count on a large amount of works to make comparisons and validate our results, as [1, 3, 4, 8, 11, 19].

6 Conclusions

This research is an intermediate step in the investigation of the still unexplored possibility of the combined use of DL ANN, temporal data series databases and satellite imagery to improve forecasting models and techniques and to overcome some limitations of the input data series which feed the different models of flow forecasting.

Fisgen is our tool for synthetic images sequence generation. These sequences will allow us to assess DL ANNs under very strict control, testing the ability of them in making predictions from displaced series of data and images. If this ability could be confirmed and moved to the water inflow forecast, a new robust and accurate technology could be developed, leading to the increase of the quality of hydroelectric system planning, resulting in meaningful economic gains. Furthermore, this research explores the capabilities, limitations, and performance of DL ANNs in Big Data analysis.

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