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DE-striping Augmented Images of Blood Cells using Deep Convolutional Neural Network

Atheel Sabih Shaker

Computer Engineering Techniques, Baghdad College of Economic SciencesUniversity, Baghdad , Iraq, .Email: atheel.sabih@baghdadcollege.edu.iq

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ABSTRACT

The aim of this biomedical image processing-based research paper is to use augmented images of blood sample and Deep Convolutional Neural Network (DCNN) for the purpose of de-striping on Hyperion data to de-stripe on multicore platforms GPU. In order to reach our goal, we have started by analyzing the challenges associated with de-striping, Hyperion data and DCNN. A novel implementation pipeline of training, validating and evaluating stating from input an augmented blood image sample with the help analyzing the Hyperion data leading to the de-striping of augmented image blood sample by removing all the kernel black. What is clear is the high importance of applying the adequate pre-processing on Hyperion data because of low signal-to-noise ratio. By comparing the known layers of DCNN model for de-striping augmented images. The results obtained by applying the mentioned methods, it is revealed that all the higher stripes in an image as well as black color has been reduced and entirely associated with the Hyperion data alteration, and in contrast, the Hyperion imagery successfully corresponds to the de-striping of augmented image with an accuracy of 91.89% using DCNN model. The proposed DCNN is capable of reaching high accuracy within 150s after the launch of the evaluation phase and never reaches low accuracy. The pre-trained DCNN model approach would be an adequate solution considering de-striping as its high inference time is lower compared existing available methods which are not as efficient for de-striping.

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1. Introduction

From the biological perspective, this research introduces an algorithm for the processing of Hyperion data including all necessary de-striping steps in logical order. The literature, in most of the previous studies, the results are not satisfactory mainly due to the noisy nature of the Hyperion data. Therefore, the main contribution of this study is

∗Corresponding author: Atheel sabih shaker.

Email addresses: *atheel.sabih@baghdadcollege.edu.iq*.

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expected to introduce a comprehensive application that aims to increase the accuracy of the de-striping images and removing all the black from an image as much as possible.

After the correction, the inversion of the calibrated image data into different classes or deep learning proportions will applied. First of all the images of interest need to be identified through a process called neural network endmember identification. There are two general inversion types that may be utilized: augmented image de-striping or augmented image unmixing for striping. While de-striping methods assign a single, unique image endmember to each pixel in an augmented image, unmixing methods are more sophisticated and assign a proportional amount of each augmented image endmember to each pixel. To speed up calculations, focus the problem and simplify the analysis, a subset of the image feature space is often. This is called feature selection process and involves selecting a subgroup of image bands or re-projection and simplification of the feature space for de-striping using deep learning.

The augmented image vector space for de-striping over all of the augmented image bands is called feature space. Feature selection and feature extraction are methods for selecting or extracting a subset black color of the feature space for processing. Imaging spectrometer data are, in general, over determined with high band-to-band correlation. The feature selection problem may be approached in a couple of ways. If the hyperspectral sensor has some reported defects on certain bands it is wise to eliminate those bands using DCNN. The simplest approach is to apply knowledge of what parts of the spectra are important for a specific problem and use only those selected regions, like for augmented image absorption features are in the DCNN part of the spectrum. The more general approach involves orthogonalization of the augmented image vector space and the use of sub-space projections for de-striping. While technically elegant, orthogonalization can propagate noise and stripes through the augmented image vector space. While it may be used for noise reduction, this is only feasible in the case of a augmented image de-striping model.

1.1 *Research Problem*.

The following section presents the primary and secondary questions that this paper aims to answer.

- Is it possible to de-stripe images by using a Deep Convolutional Neural Network (DCNN) and a measured ground truth of conversion percentage?
- Does the approach of deep learning techniques as a way of automating de-striping process with Augmented Images of blood cells?
- Do Augmented Images of blood cells are necessary to obtain good results?
- What should be an implementation pipeline for efficiently process the Augmented Images of blood cells for de-striping using DCNN classification?
- What aspects need to be considered if further work on the subject is to be performed?

1.2 *Aim of Study.*

This assignment aspires to propose a fully functional de-striping method composed of the following elements:

- Provide an overview of previous works and achievements on de-striping on images.
- Apply DCNN methods Augmented Images of blood cells to the unified database of striping scans to perform de-striping of images which potentially contain stripes.
- Evaluate and compare used DCNN, as well as compare with other studies from the literature.
- Develop a novel methodology with good results for de-striping.

2. Literature Review

Author in article [1] conduct research on de-striping process using gradient magnitude histograms with image texture and data analysis in subset an MR image. The learning approach used unsupervised k-means clustering learning and achieved a sensitivity and specificity of 87.98% respectively.

Author in article [2] show that image texture analysis and de-striping of images in different scans using data mining with machine learning and gray level gradient co-occurrences are valuable techniques that achieve good results. They compare several machine learning classification methods including Neural Networks, Support Vector Machines and k-Nearest Neighbor that all perform well.

Authors in article [3] use image features based on ANN for de-striping an image and gray level histograms to de-stripe image regions. The optimal features are found using a genetic algorithm inspired by the principle of biological evolution. The optimized feature vector is fed to a neural network and they achieve a de-striping pixel classification accuracy of 79.6%.

Author in [4, 5], looked at de-striping and striping separately in 2 studies. Both studies involved multi-spectral images FFT trained using features selected using forward stepwise selection. When compared using different methods to a number of scoring approaches the FFT models were shown to be superior. The best of these models was found to outperform score-based approached by up to 69% with an absolute conversion of 83.45% [6].

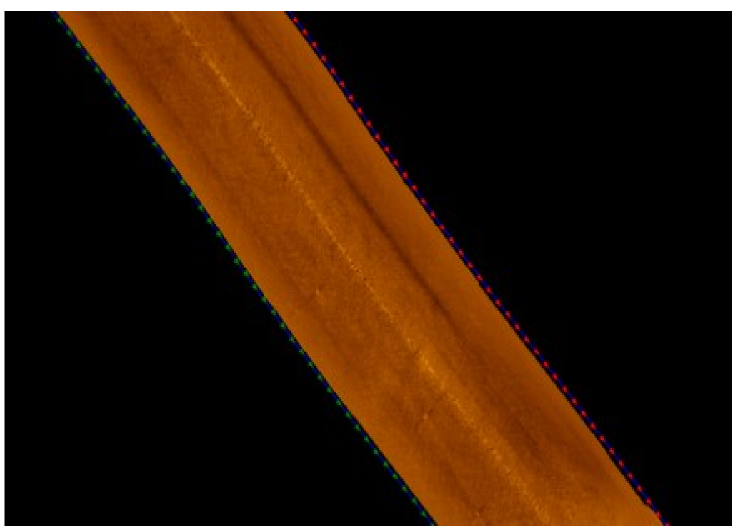

Figure 1: An image containing stripes with regularized low rank representation [7],

With a growth and evolution of deep learning many new models' architectures appear. It is, thus, important to evaluate which of them give best performance in terms of the number of produced false positives, as well as time consumption with low rank representation [7]. Sometimes, very deep neural networks are actually an overkill for a particular task, while usage of the less complex methods can preserve similar outcome, in the same time, save some resources [8]. Each specific problem, hence, needs the complete and detailed studies, which would compare different approaches and provide a report on their effectiveness.

To increase the accuracy of a full end-to-end de-striping system, separate models are used for this purpose, which learn to de-stripe between stripes and non-stripes. The received probability for each striping process, then, is used to filter out all the stripes which certainly do not enclose any black kernel, leaving a smaller number of images for Hyperion data [9]. Many techniques have been used for the de-striping. Some approaches perform feature extraction using classical computer vision approaches followed by any kind of machine learning classifier (decision trees, k-Nearest Neighbor, Support Vector Machine, artificial neural network etc.) [10].

3. METHODOLOGY

Deep learning models merged with Hyperion data are known to have a number of potential advantages over traditional statistical models. In particular, their ability to learn complex non-linear relationships can lead to better predictive accuracy [11]. They are also able to handle large numbers of input variables with ease and tend to be more robust to missing data for de-striping. Finally, since they are driven primarily by the data, they can be easily trained and validated for a specific population and kept up to date as new survival data becomes available.

Deep Convolution Neural Network (DCNN) is a class of neural work that becomes hot in recent years because of the huge success in lots of task across from classification, image segmentation, object tracking has been used solely for the modeling of this research work. DCNN was inspired by the connectivity pattern of the neurons in the brain. As the name indicates, the main portion in DCNN is deep convolution operation.

The process described as deep convolution here is just by convention in deep learning. Mathematically, it is a cross-correlation. In computer vision application, convolution is always done between kernel (filter) and the image. The main purpose of these operations is extracting the features. The pre-processing required in DCNN is much fewer than other traditional methods.

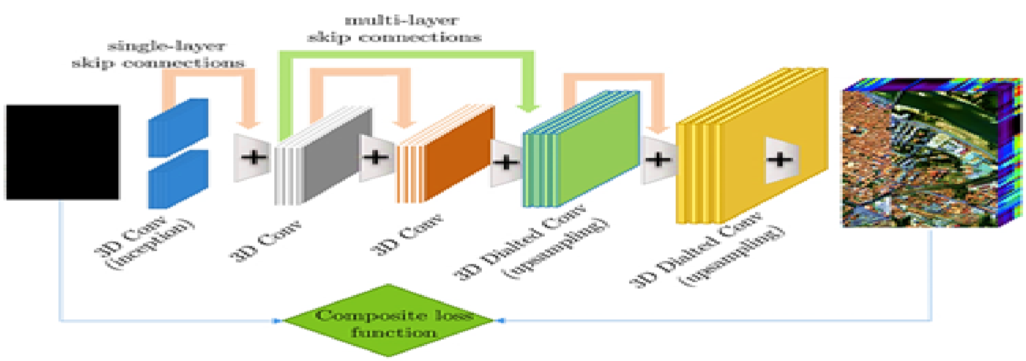

Figure 2: Each layer contains a set of functions that can be plugged together to convolute and finally leading to the de-striping.

With enough training, DCNN can learn those filters that were hand-engineered in traditional methods for de-striping on Augmented Images of blood cells. This main advantage of DCNN is that there is no need to extract the matrix and design the formula to extract the features manually. The learnable weights and bias in DCNN are a more powerful alternatives than human effort and knowledge in feature design.

Frankly, the purpose of the paper is to provide a model or formula that can be easily inserted and adapted to de-stripe augmented images. Instead of providing formula, the model adapted to Hyperion data, a model procedure is provided using DCNN that everyone can follow in order to de-stripe Hyperion data and images in the result. The performance is quite promising within the Hyperion data that comes from the same source.

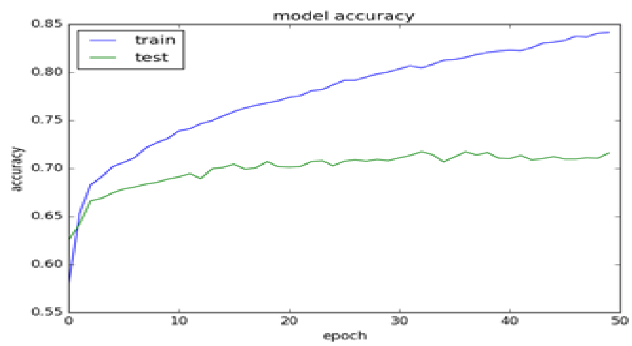

Figure 3: The DCNN model accuracy for training and testi

As expected, the DCNN model allows for an interesting increase in performance over other baseline models. However, the training time required to fit a model is more consequent for the DCNN than other available existing models for de-striping. This enhancement of performance among the de-striping is particularly visible for the DCNN models. The DCNN, on the other hand, is capable of handling most subjects with smaller variations in performance. We distribute the Hyperion data into 85% for testing and 15% for the purpose of testing. Regarding the misclassified trials, a quick augmented image analysis of the matrices reveals that DCNN tends to exactly de-stripe. This robustness can be an advantage of Hyperion data partially distributed for de-striping images. The DCNN approach don not seem to suffer from any issue. Training the DCNN took 179.85 seconds and 26.78 seconds for testing each augmented blood cells image for a nice performance while reducing the average training time.

4. Results

This paper is deemed a necessity in order to achieve a fully automatic method for de-striping of Augmented Images of blood cells. Below are results of de-striping on some images with improved DCNN methods discussed in this paper. Hyperion data is available foe the level of correction, thus tests using Hyperion data have been performed to achieve de-striping of images as given below:

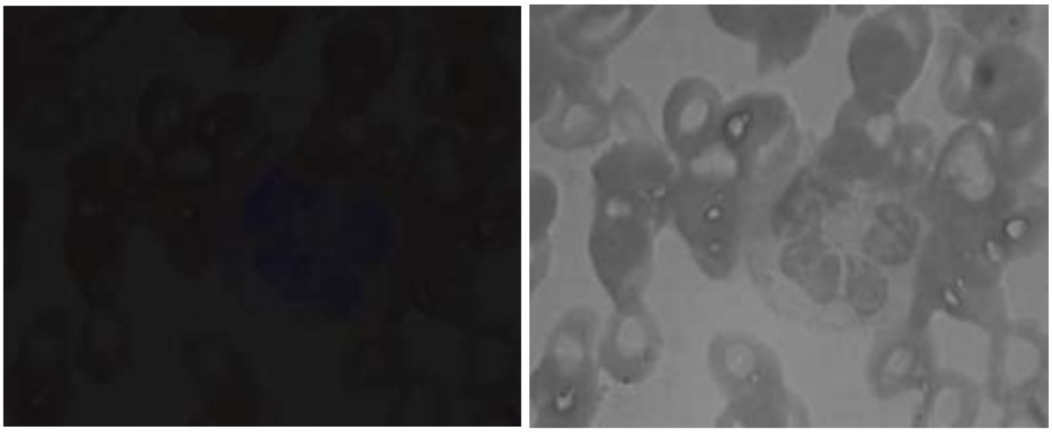

Figure 4: De-striping kernel black from augmented blood cells images using DCNN.

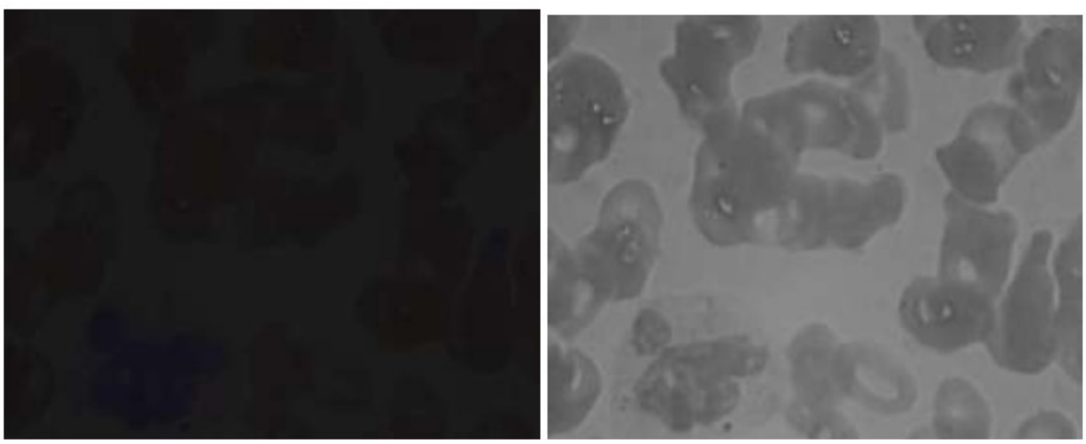

Figure 5: De-striping kernel black from augmented blood cells images using DCNN.

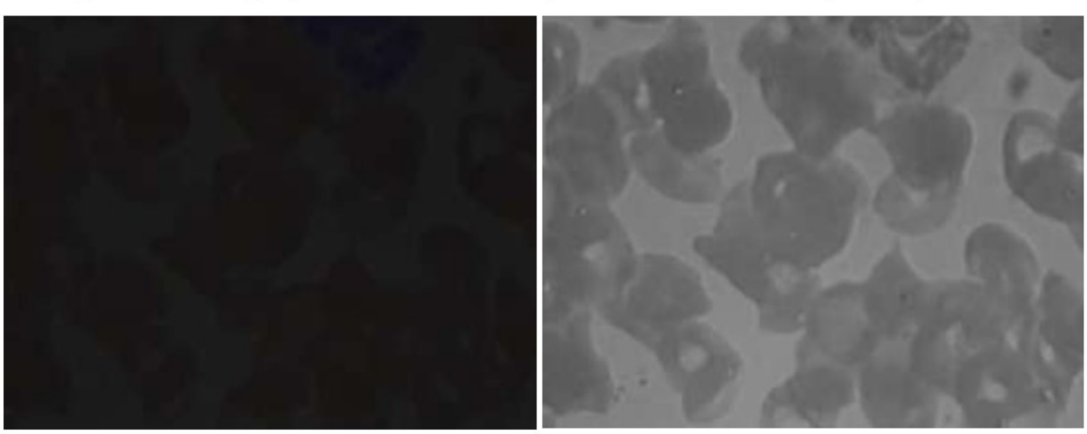

Figure 6: De-striping kernel black from augmented blood cells images using DCNN.

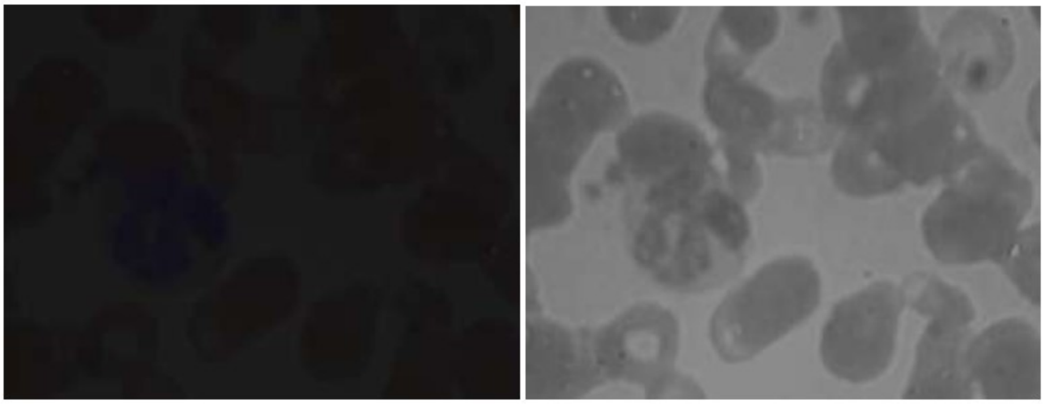

Figure 7: De-striping kernel black from augmented blood cells images using DCNN.

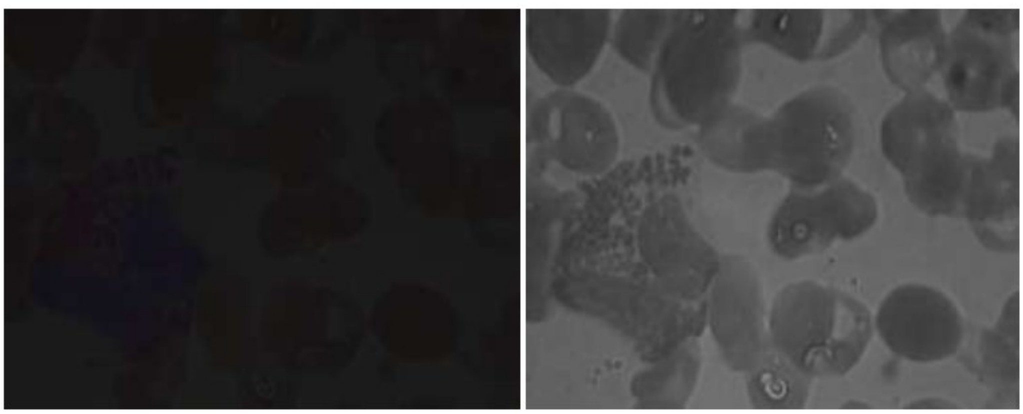

Figure 8: De-striping kernel black from augmented blood cells images using DCNN.

For DCNN architecture and de-striping the augmented images while removing kernel black, we have written a module on MATLAB using the open-source deep learning toolbox and sinal processing toolbox for modeling. Therefore, it is possible to train models in different environments: with installed toolboxes with necessary pre-defined filter and kernels. This allows us to compare the frameworks' performance and be more flexible in the process of building new networks.

5. Discussion

The result shows that advance methods with automatic feature extraction and deep learning methods work better than any existing methodology for de-striping. Apart from the other methods based on signal-noise ratios, DCNN with augmented images method do not depend on human judgment no matter which blood cells sample is chosen. This characteristic has both advantage over other existing system. The advantage is that the de-striping can be staged automatically and the result can be treated as coming from another aspect which the blood sample can take into account and conclude a final de-striping. The system is working as a black box. This problem is more serious in deep learning and imaging, in which the features of the model extraction are not even known. Although the intermediate features that the model produce will not be shown, some straight forward interpretation of the model is provided in this work.

6. CONCLUSION

This paper showed that deep learning was a viable approach to automatically de-striping augmented image blood cell samples. It was also shown that given augmented images with Hyperion data fractions and training data set can be generated from large quantities of augmented images. It was shown that de-striping using local image intensity features combined with features calculated from a wavelet decomposed image region of Hyperion data resulted in the extra-ordinary de-striping of images and removing all the kernel black. We applied DCNN methods on Augmented Images of blood cells to the unified database of striping scans to perform de-striping of blood cells image which potentially contain stripes. Pre-trained model for each input trial from which we extract de-tripe augmented image data with an accuracy of 91.89%. The processing operations consist of different layers of DCNN. All other parameters remain identical to the de-striping of Hyperion data-based image. The proposed DCNN is capable of reaching high accuracy just in 150s after the launch of the evaluation phase and never reaches low accuracy. The pre-trained DCNN model approach would be an adequate solution considering de-striping as its high inference time is lower compared existing available methods which are not as efficient for de-striping.

6.1. Future Recommendation

• In future, the ultimate goal for de-striping is replacing the invasive existing staging methods and reducing complexity. The purpose of this paper is not provide a model in the shelf that everyone just pick and plug in to their data set, instead, this paper is trying to figure out a procedure or a set of features that might suitable for de-striping on any data set with deep convolutional neural network.

• The progress of the deep learning technique now is not enough for one model to fit in every data set which might never be possible since there truly is no difference between different imaging methods.

• The main thing that should be improve in future is merging deep learning method DCNN with combined LTSM and RNN model which are useful for classifying due to low complexity.

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