Improving accuracy of automatic fracture detection in borehole images with deep learning and GPUs

Rommel Anatoli Quintanilla Cruz*, Diego Carriço Cacau*, Renato Moraes dos Santos†,
Evandro Jose Ribeiro Pereira† Fabiana Rodrigues Leta† and Esteban Walter Gonzalez Clua*
*Computer Science Institute, Medialab
Universidade Federal Fluminense, Rio de Janeiro, Brazil
Email: rquintanillac@ic.uff.br, dc_cacau@id.uff.br, esteban@ic.uff.br
†Engineering School, LMDC
Universidade Federal Fluminense, Rio de Janeiro, Brazil
Email: rmoraes@lmdc.uff.br, evandropereira@id.uff.br, fabianaleta@id.uff.br

***Abstract*—The logging and further analysis of borehole images is a major step in the interpretation of geological events. Natural fractures and beddings are features whose identification is commonly performed using acoustic and electrical borehole imaging tools. Such identification is a tedious task and is made visually by geologists, who must be experts on classification. The correct identification of planar features, represented as sinusoids into an image projection, depends on the quality of the images. Due to the distortions and noises of the images, known as artifacts, the automatic features detection is not trivial through conventional image processing methods. Since the identification process has to ensure that the marked events are true with minimal inconsistencies, we propose a pioneering approach to improving the quality of the results by applying deep neural networks to confirm or exclude candidate features extracted by a regular Hough transform. This is the first approach in literature to improve the quality of geological auto-detected marks by applying deep learning techniques for borehole images where our implementation is able to exclude most of the false positive marks.**

I. Introduction

Analysis of borehole images is the main method used by geologists to detect several weak points in wells. Some patterns, like fractures and breakouts, can prevent a possible collapse of wellbores, being an important analysis for geologists. Our work deals only with natural fractures and beddings, which are planar features, but are presented in the images as sinusoids due to the cylindrical geometry of wells projected into a 2D image as can be seen in Figure 1. While in this work we analyze only images acquired by electrical and acoustic tools, the proposed method can be easily extended to other sources.

Electrical tools use the resistivity of the borehole to generate the image. They are based on pads with electrodes, which in an oil-based-mud, apply a voltage that is partially reflected at a borehole wall and captured back at the upper part of the tool [2], [3].

Acoustic tools are based on a rotating transducer that emits acoustic energy in a mud-filled borehole, which is partially reflected at the walls and received by the transducer. This kind of tool uses the amplitude of reflected energy (pulses) to create an image of the borehole wall [4].

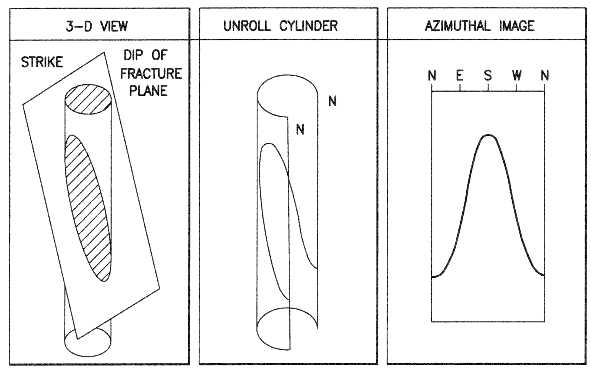
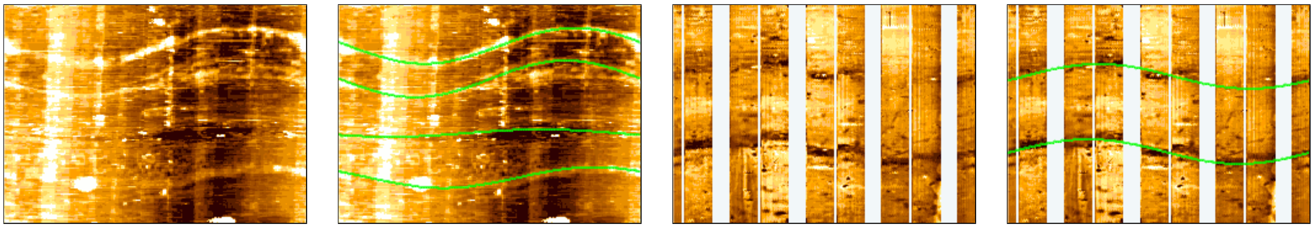


Fig. 1. **Plane crossing a borehole:** shows the corresponding sinusoidal pattern at the projected image. Image extracted from [1].

The images generated by these tools usually have artifacts, which interfere in the features detection [5]. While the analysis of these artifacts is fundamental for the borehole pre-analysis, the complexity of the images can increase the time spent for this task by geologists, which in some cases can lead to human failures. Figure 2 shows sample images of both acoustic and electrical borehole images presenting several sinusoids. Figures 2a and 2c illustrate the input images that geologists will analyze. Figures 2b and 2d depict the result of the manual feature identification process.

Aiming to help geologists, this work presents a new automatic detection approach of sinusoids in borehole images. We first clean up the image with traditional image processing and correction strategies [6]. Next, we apply traditional Hough transform [7] to select possible beddings and fractures. Finally, we apply deep learning algorithms to fine-tuning the results and arrive at a more precise classification. In order to have a higher computational performance, our methods are fully based on GPU Computing, making all results for big images available in a few seconds of processing [8].

The remainder of this paper is organized as follows. Section 2 briefly exposes related works for automatic curves classification. Section 3 presents our deep learning identification



(a) Original acoustic (b) Manually marked (c) Original electrical (d) Manually marked

Fig. 2. **Sample images:** Example of original images (a,c), and sinusoids manually marked (b,d) of acoustic and eletrical wellbores.

process, starting from the pre-processing stage. Section 4 presents our experiments and results. Finally, we present our conclusions and future works.

II. Related Works

In the last 30 years, several works proposed new methods for detection and characterization of borehole image features. The most common methods for detecting sinusoidal shapes are based on Hough [9] and Radon transforms [10].

Hall [7] proposed a methodology for automatic extraction and characterization of features in borehole images combining edge detection, Hough transform, and an unsupervised neural network called Competitive and Selective Learning. Thapa [11] used a more simple method based on Hough transform. After selecting the 10% darkest pixels, a 3D search finds the amplitudes, phases, and offsets of the possible sinusoids. Due to the computational limitation of their times, both methods were not practical to be used in production stages. Similar methods were proposed by Glossop [12] and by Zhang [13]. While the first uses a Laplacian of Gaussian (LoG) filter, the second combines an adaptive histogram equalization with a direction filtering, before applying the Hough transform.

Ginkel [10] presented an approach for curve detection using Radon transform on a 3D orientation space, which the authors acknowledge as having a poor performance.

Assous [14] combined gradient and phase-based approach to validate congruence and amplitude, using Log-Gabor wavelets for validating detected edges and then sinusoidal detection and estimation. The authors claim a false positive rate between 2% and 5%.

Wang [15] developed a methodology for rock fracture detection using edge detection and Support Vector Machines (SVM). After the edge detection, 11 parameters were extracted from the image, for fracture detection using SVM with the Gaussian kernel. Although it seems to be a promising approach, the authors noticed that it did not achieve the expected performance.

Al-Sit [16] proposed a method for detecting planar discontinuities in borehole digital images using Gabor filters to extract features and Hough transform to detect sinusoidal forms and planar discontinuities. The authors achieved high detection rates with only 1% of false positives.

Most of the previously published experiments were made using modeled data or low noise level images, usually acoustic images. When used with real images, extracted from acoustic and electrical images of public borehole data, most with high levels of noise, these methods fail and bring a considerable amount of false positive results.

Compared with the state-of-the-art approaches, our method presents a way to make effective analysis in real acoustic and electrical images, with high performance due to the GPU optimization, making possible the interactive analysis during perforation in such a way that the extraction process is improved and the risks are reduced.

III. Method

Our proposed method is composed of 4 steps (see Figure 3). At the preprocessing stage, the colored image is filtered to select the most relevant pixels and reduce noise artifacts. In the Identification process, the binary image will be filtered with a Hough transform, in order to identify all possible candidates of senoids. The postprocessing step involves reducing the set of identified senoids removing those that are very close, with high probability to be the same feature at the borehole. Finally, all the remaining senoids are considered as feature candidates, and they go through a convolutional neural network confirmation process for validation or exclusion. Only the senoids with a high likelihood of being real planar fractures are held and shown to the user.

Figure 3 presents a more detailed description of each stage.

A. *Preprocessing*

Black pixels typically indicate the presence of fractures and breakouts. However, several other gray pixel patterns may appear due technical inaccuracies regarding data acquisition and also be part of breakouts. It is desirable, therefore, to minimize the set of pixels that may not represent any relevant borehole feature. In this sense, the image is first converted to grayscale, and then the extra noise is removed by applying quantization and the median filter. Following, all pixels greater than a threshold are removed.

To minimize user intervention, we select a fixed fraction of the darkest pixels based on the image histogram; their value was experimentally determined to be 25% since such value obtained clear contrasts on most of the input images. Therefore, the threshold is automatically set by traversing the histogram bins until the intended fraction of the pixels is reached.

B. Identification

In order to select the pixels that likely form part of planar fractures, we use the Hough transform [9] [11] due to the robustness of the method for detecting lines, circles and even arbitrary shapes with noise or pixel discontinuity [17].

The sinusoidal curve is represented mathematically as:

$$y = A\sin(\omega x + \theta) + y_0 \tag{1}$$

where A is the amplitude, θ is the phase, ω the angular frequency, and y_0 the baseline position. Since ω can be considered a constant, for each position y_0 this method makes use of an auxiliary 2D parameter space, where each point denotes a specific curve represented as the pair (A, θ). For each pixel from the binary image, a new vote is accumulated in the parameter space.

Next, we select the most voted curve in the space, since it has the biggest amount of pixels composing it. This procedure is repeated varying the y-coordinate with a fixed step size. Finally, each selected curve is characterized by retrieving their main features such as depth, amplitude, and phase.

C. Postprocessing

At this stage, depending on the step size, the number of senoids identified could be impeditive. Also, several nearby curves could be representing the same planar feature. Nevertheless, a bigger step size could make the procedure overlook some curves with perhaps more probability of being right marks. So, regarding this trade-off, we chose to set a step size that allows us to achieve a performance as close as possible to real-time while removing the curves with fewer votes by grouping them according to their y-coordinate.

D. Classification

In the previous stage, the step size is determined in order to guarantee that all candidates of fractures will be selected. However, doing so, many false positives will be selected. In fact, this strategy will generate a huge amount of senoids. While this is a common problem in numerous previous works, our solution uses this big dataset in order to apply the deep learning strategies for filtering the correct results.

Since each identified sinusoidal curve has an associated voting weight, with the criteria given by the user, it is possible to select a threshold to show just the most voted curves. However, because of the presence of noise, many of them should not have been marked automatically. We abstract this problem as an image classification problem which aims to select those candidates that have a high probability of being a real planar fracture and exclude any other.

We adopt deep learning strategy due to its ability to overcome human performance regarding object recognition in different scenarios, such as those presented at the ImageNet challenge [18].

Inspired by biological processes, convolutional neural networks (CNN) are composed of multiple layers to learn representations of data with several levels of abstraction. Each layer transforms the input volume into an output volume where the final layer is often a function that outputs a probability value for classification problems. Internal layers such as convolution, pooling, and fully connected layers complete the CNN architecture.

For the neural network strategy, we use the AlexNet model [19]. Alexnet is an architecture composed of 5 convolutional layers, three fully-connected layers, and three max-pooling layers for a total of 8 weight layers. Although it is not as deep as other popular convolutional networks solutions, Alexnet is good enough to learn the basic edge features even up to intermediate cases between the raw pixels data and the high-level curve classification [20].

We perform that classification by training separately electrical and acoustic models. Following the supervised learning techniques strategy, borehole experts should first mark by hand senoids of differents boreholes images.

IV. Experimental Results

We performed several experiments using real data in order to evaluate our proposed method. In this section we first introduce our dataset, then we discuss the results.

A. Dataset

Our data is composed of two types of images, classified as positive and negatives. Positive images are those where a planar event exists, and their mark was visually made by specialists. Each sinusoidal curve defines a separated slice of the image with fixed size. Conversely, negatives images do not contain any event, and random sections are extracted from the corresponding log image. They also are divided into slices. Figure 2 shows five positive and five negative slices of images that belong to an acoustic image log.

Due to the deep learning limitations, it is necessary to have a huge amount of samples. Since the datasets of boreholes are

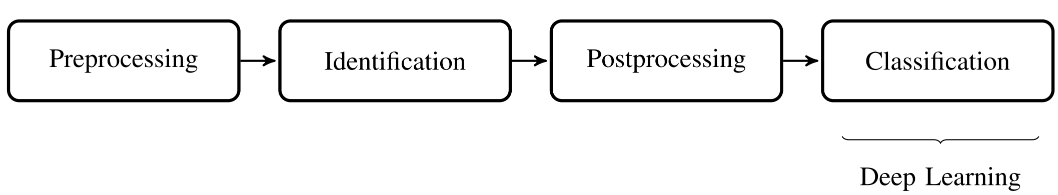
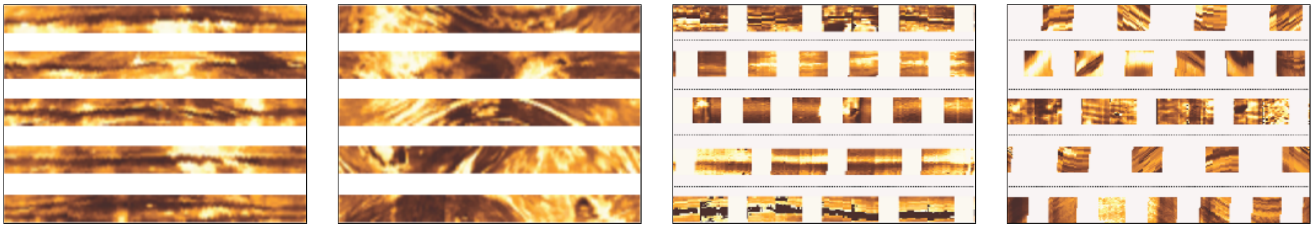
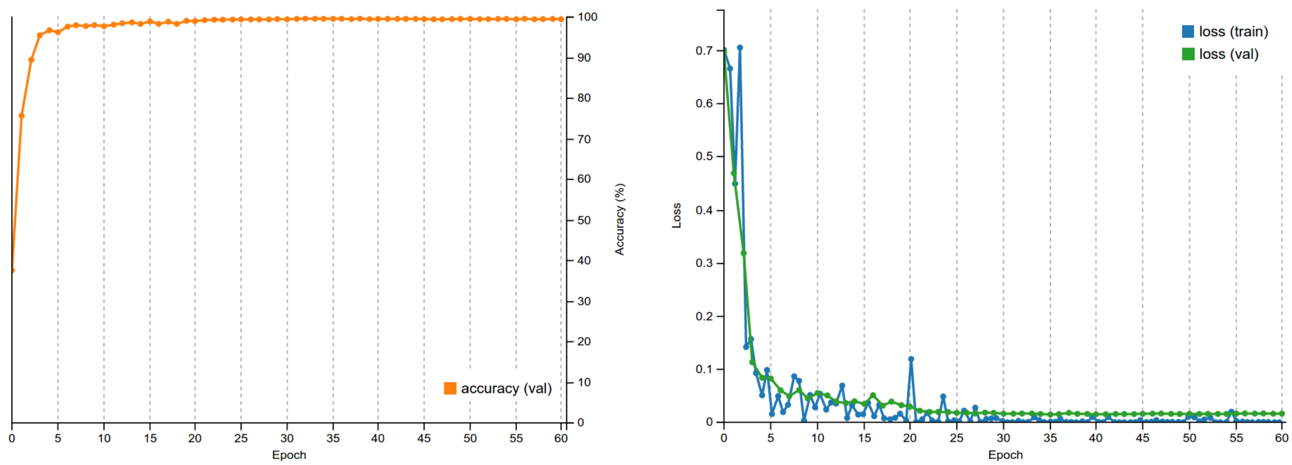


Fig. 3. **Method flowchart:** Our proposed method has four main phases. Preprocessing is where we reduce the number of pixels in an image to 25% of them. In Identification, we apply the Hough transform to identify the possible sinusoids. Postprocessing is where we remove the sinusoids that have greater possibilities of being false. Finally, in Classification, we apply deep learning and remove all but the true positives sinusoids.



(a) Positive acoustic (b) Negative acoustic (c) Positive electrical (d) Negative electrical

Fig. 4. **Dataset samples:** example of acoustic and eletrical sinusoids in wellbores.



(a) Accuracy (b) Loss

Fig. 5. Results of the training phase

Image Type	ID	Senoids Detected by Hough Transform	Senoids Classified as Real by Deep Learning method	Ratio of false positives removed
Acoustic	Well A	855	33	96.14%
	Well B	778	35	95.50%
Electrical	Well C	901	411	54.38%
	Well D	364	2	99.45%

TABLE I
COMPARISON RESULTS OF THE HOUGH TRANSFORM AND DEEP LEARNING METHOD

limited in number, we successfully used data augmentation techniques, which is a common approach for deep learning solutions [21]. We implement this augmentation within horizontal and vertical mirroring transformations, resulting in four times the number of the original images.

Considering the augmented data, in the case of acoustic image logs, we used 7750 images for training and 2600 images for testing. For the electrical image logs, the dataset contains 18500 images for training and 6250 images for testing. As pointed previously, each subset is categorized into two classes, positive and negatives.

In this work, we used two datasets and trained two different networks for the deep learning approach for automatic detection of sinusoids, one for each dataset. The datasets were divided according to the type of tools: electrical and acoustic. We train our CNN model over a GPU-based environment using the deep learning framework Caffe, considering 60 epochs for achieving good results. The total training time using two NVIDIA GPUs (GeForce GTX 980 and Quadro K2200) took approximately 45 minutes and 120 minutes respectively. Figure 5a shows the accuracy reported when the model was trained with the training dataset. The loss rate is shown in figure 5b and suggests that the model trained does not overfit the training dataset when using different data.

B. Results

We define precision and recall as:

$$Precision = \frac{TP}{(TP + FP)} \tag{2}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{3}$$

The confusion matrix for the acoustic dataset returns 99% of accuracy, where 103 of 104 features where correctly classified.

The results were TN = 64, FP = 1, FN = 0, TP = 39. This resulted in 97.5% of precision and 100% of recall.

The confusion matrix for the electrical dataset returns 100% of accuracy for 250/250 corrects. The results were TN = 175, FP = 0, FN = 0, TP = 75, suggesting 100% of precision and 100% of recall.

Once the models are trained, the automatic identification of senoids on new borehole images is real time, allowing the operational process to be interactive. The number of false positives was remarkably reduced from both electrical and acoustic images. Figure 6a shows a sample of an acoustic image used as input. Figure 6b is the result of the preprocessing step where some enhancing filters are applied. Then, by means of the Hough transform, as shown in figure 6c, red marks represent senoids with a high probability of being false positives, and the green marks represent those that were classified as real fractures. In figure 6d, green marks represent those events identified by specialists. Just like the acoustic image log, figure 7 shows the process when we apply our method to an image acquired with an electrical tool having similar results. Table I presents numerical results about the quantity of false senoids removed by our method in four wellbore samples.

V. Conclusions and Future Work

In this research, we used two different trained neural networks, one for each type of drilling tool (electrical and acoustic) in separated datasets. Our results show considerable improvements when compared with traditional image segmentation techniques and show close matches when compared with human based detection.

The main achievement of the presented method compared with the available literature is that we were capable of excluding most of the false negatives senoids detected by the Hough transformation. Another important characteristic of our work is the initiative of using deep learning to improve the precision of the results and using GPUs to optimize our algorithm achieving near real-time processing, reducing the costs and time for borehole image analysis and making easier the geologists' classification work.

As future works, we intend to test the method using larger datasets of borehole images, so our neural network knowledge can be naturally incremented. A possible network variation would be mixing the different types in only one dataset and train a new neural network to compare two approaches: using two networks (specific) against using one network (generic). We also intend to extend this experiment to including the automatic detection of breakouts in the borehole images.

Acknowledgment

We would like to thanks NVIDIA, Petrobras and CAPES for the financial support and incentive received.

References

[1] N. F. Hurley and T. Zhang, "Method for characterizing a geological formation traversed by a borehole," Oct. 22 2009, uS Patent App. 12/384,945.

[2] P. Gaillot, T. Brewer, P. Pezard, and E.-C. Yeh, "Borehole imaging tools-principles and applications," *Scientific Drilling*, vol. 5, pp. 1–4, 2007.

[3] M. Tingay, J. Reinecker, and B. Müller, "Borehole breakout and drilling-induced fracture analysis from image logs," *World Stress Map Project*, pp. 1–8, 2008.

[4] A. Hayman, P. Parent, P. Cheung, P. Verges *et al.*, "Improved borehole imaging by ultrasonics," *SPE production & facilities*, vol. 13, no. 01, pp. 5–14, 1998.

[5] J. Lofts and L. Bourke, "The recognition of artefacts from acoustic and resistivity borehole imaging devices," *Geological Society, London, Special Publications*, vol. 159, no. 1, pp. 59–76, 1999.

[6] F. R. Leta, E. Clua, M. Biondi, T. Pacheco, and M. d. S. de Souza, "An automatic process to identify features on boreholes data by image processing techniques," in *Experimental and Numerical Investigation of Advanced Materials and Structures*. Springer, 2013, pp. 249–262.

[7] J. Hall, M. Ponzi, M. Gonfalini, G. Maletti *et al.*, "Automatic extraction and characterisation of geological features and textures front borehole images and core photographs," in *SPWLA 37th Annual Logging Symposium*. Society of Petrophysicists and Well-Log Analysts, 1996.

[8] G.-J. van den Braak, C. Nugteren, B. Mesman, and H. Corporaal, "Fast hough transform on gpus: Exploration of algorithm trade-offs," in *International Conference on Advanced Concepts for Intelligent Vision Systems*. Springer, 2011, pp. 611–622.

[9] J. Illingworth and J. Kittler, "A survey of the hough transform," *Computer vision, graphics, and image processing*, vol. 44, no. 1, pp. 87–116, 1988.

[10] M. van Ginkel, M. Kraaijveld, L. J. van Vliet, E. Reding, P. W. Verbeek, and H. Lammers, "Robust curve detection using a radon transform in orientation space," in *Scandinavian Conference on Image Analysis*. Springer, 2003, pp. 125–132.

[11] B. B. Thapa, P. Hughett, and K. Karasaki, "Semi-automatic analysis of rock fracture orientations from borehole wall images," *Geophysics*, vol. 62, no. 1, pp. 129–137, 1997.

[12] K. Glossop, P. J. Lisboa, P. Russell, A. Siddans, and G. Jones, "An implementation of the hough transformation for the identification and labelling of fixed period sinusoidal curves," *Computer Vision and Image Understanding*, vol. 74, no. 1, pp. 96–100, 1999.

[13] X. Zhang and X. Xiao, "Detection of fractures in borehole image," in *Sixth International Symposium on Multispectral Image Processing and Pattern Recognition*. International Society for Optics and Photonics, 2009, pp. 749 541–749 541.

[14] S. Assous, P. Elkington, S. Clark, and J. Whetton, "Automated detection of planar geologic features in borehole images," *Geophysics*, vol. 79, no. 1, pp. D11–D19, 2013.

[15] W. Wang, H. Liao, and Y. Huang, "Rock fracture tracing based on image processing and svm," in *Third International Conference on Natural Computation (ICNC 2007)*, vol. 1. IEEE1, 2007, pp. 632–635.

[16] W. Al-Sit, W. Al-Nuaimy, M. Marelli, and A. Al-Ataby, "Visual texture for automated characterisation of geological features in borehole televiewer imagery," *Journal of Applied Geophysics*, vol. 119, pp. 139–146, 2015.

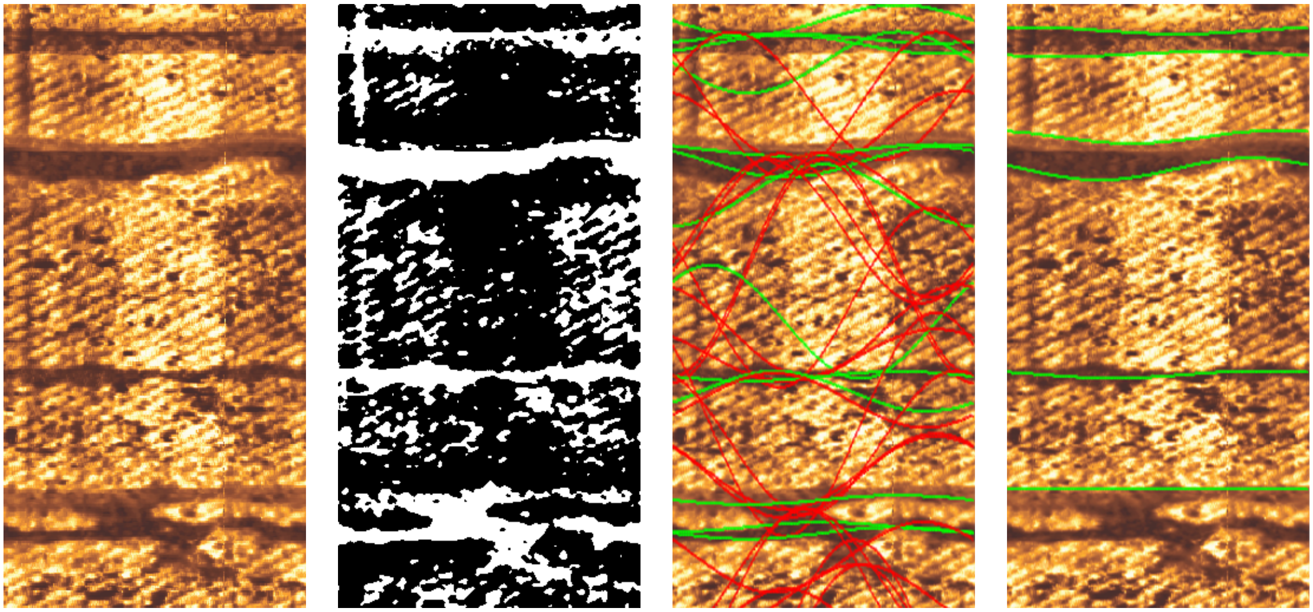
[17] Z. Changchun and S. Ge, "A hough transform-based method for fast detection of fixed period sinusoidal curves in images," in *Signal Processing, 2002 6th International Conference on*, vol. 1. IEEE, 2002, pp. 909–912.

[18] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein *et al.*, "Imagenet large scale visual recognition challenge," *International Journal of Computer Vision*, vol. 115, no. 3, pp. 211–252, 2015.

[19] P. Ballester and R. M. Araujo, "On the performance of googlenet and alexnet applied to sketches," in *Thirtieth AAAI Conference on Artificial Intelligence*, 2016.

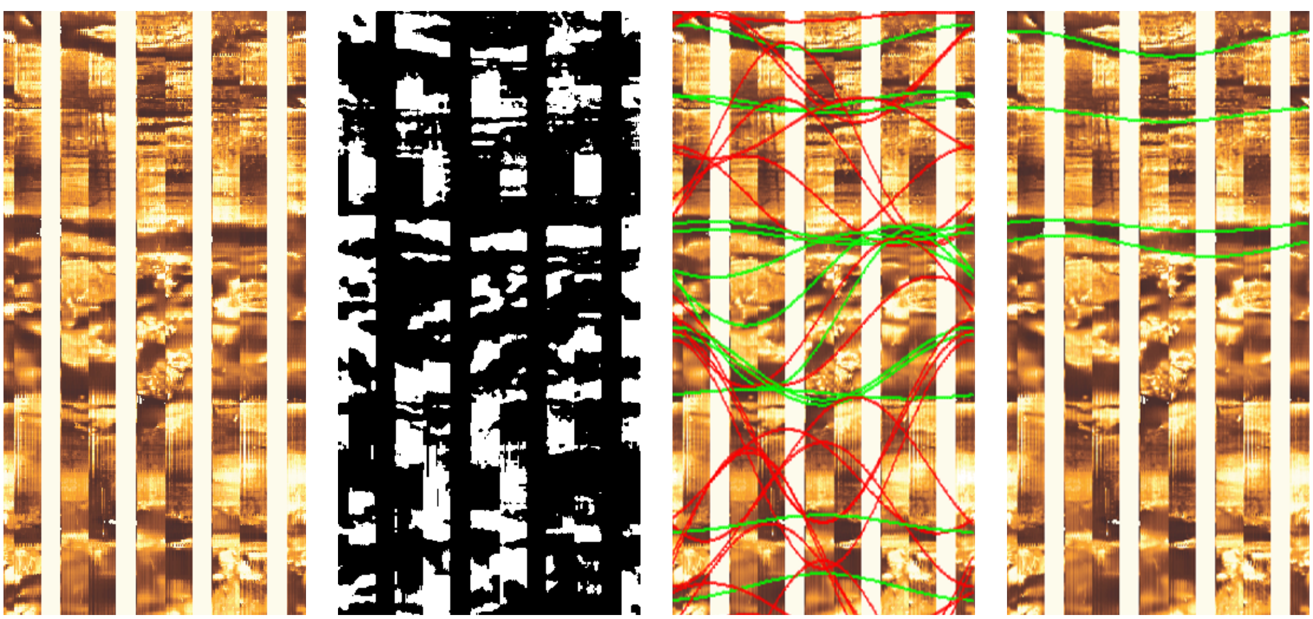
[20] W. Yu, H. EDU, K. Yang, C. Y. Bai, T. Xiao, and C. H. Yao, "Visualizing and comparing alexnet and vgg using deconvolutional layers," in *Proceedings of the 33 rd International Conference on Machine Learning*, 2016.

[21] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097–1105.



(a) Original (b) Filtered (c) Automatic marks (d) Manual marks

Fig. 6. **Process of detection in accoustic images:** Shows original wellbore image (a), filtered image (b), the automatic marked image (c) and the original image manually marked. The green sinusoids, in (c), indicate the true positives and the red are false positives, detected by the Hough transform and removed using deep learning.



(a) Original (b) Filtered (c) Automatic marks (d) Manual marks

Fig. 7. **Process of detection in electrical images:** Shows original wellbore image (a), filtered image (b), the automatic marked image (c) and the original image manually marked. The green sinusoids, in (c), indicate the true positives and the red are false positives, detected by the Hough transform and removed using deep learning.