Automatic detection of fibers orientation on composite laminates using convolutional neural networks

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Abstract. The mechanical behaviour and failure of the composite materials are highly influenced by the fibre’s orientation. It is important to decide which type of layers and orientations to use for the layup sequence such that the composite laminate is as light and/or cheap as possible while being capable to carry the load for which it is designed. During the production process it is critical to cut and lay the composite woven according to the optimal layup sequence resulting from the optimization process. Therefore, it is important to develop an automatic system which is capable to accurately detect the fibres orientation from a material picture. In our previous work we proposed such a system based on image processing and computational geometry. The main disadvantage of this system is that it has a lot of parameters which need to be manually tuned for each material. In this paper we propose a simple system which doesn’t need any parameter tuning. It is based on convolutional neural networks and we demonstrate with a lot of examples that it is very accurate, stable and insensitive to image variations. The method was tested on diverse composite laminates and woven with different chromatic and morphological properties.

1. Introduction

Advanced composite materials represent one of the biggest innovations of the last decades in the material science. A lot of industries adopted composite materials – ranging from sports [1-3] and music to automotive and aerospace industries [4-7]. The great success associated with composites is mainly due to their physical properties such as strength-to-weight ratio, high stiffness-to-weight ratio, low density, wear resistance, chemical environment stability and long fatigue life [8].

When we bring into question the fiber reinforced plastic materials (FRP) it is important to discuss about their anisotropic behavior. Because of the layer’s reinforcement (unidirectional, bidirectional, etc.) FRP materials do not exhibit the same properties in all directions and their mechanical behavior and failure are determined by the orientation of the fibers and implicitly by the orientation of the layers [9-10]. For this reason, it is important to find a layup sequence such that the material can carry the load that it will encounter. Also, it is desirable for the material to be cheap, light or maybe both. Finding an optimal layup or a pareto-optimal front is a combinatorial problem with a huge, noisy, multidimensional and multimodal solution space. For this reason, brute force search is not reliable and heuristic methods such as genetic algorithms [11-14] are used to explore and exploit the solution space.

It is critical to supervise the production to ensure that the composite laminate is build according to the optimal stacking sequence provided by the layup optimization. Therefore, it is important to evaluate the orientation of the fibers during certain production processes such as preparing and laying
the composite woven or cutting the composite laminate. A fast and accurate automated methodology to detect fibers orientation not only contributes to a high quality of the products but also it will reduce the production time and human involvement and implicitly it will reduce the costs.

The purpose of this paper is to provide a completely automated model capable to accurately detect the fibers orientation based on a material image. Our previous work in this direction [15] is based on a complex method combining traditional image processing with intensive computational geometry techniques such as luminance computation, mean filtering, edge detection, flood fill, minimum area enclosing rectangle, clusterization and linear regression. This previous method was specially designed for a CF/PPS material and with a lot of parameters tuning it can be used on other materials as well. The main disadvantages of this method are that it is restricted to a relatively small class of materials and the tuning of the parameters might be a time-consuming task. Also, it is sensitive to image variations such as intensity and contrast which can induce instability and evaluation errors. Other previous work related to automatic detection of fibers orientation can be found in [16-21] where different methods based on traditional image processing are presented.

In this paper, we propose a quite simple method which does not require any parameter tuning. The proposed method is fully accurate and stable, and it can be used on a large class of materials having different chromatic and morphological properties. To demonstrate the strength of our method we tested it with a lot of materials. The results were particularly good for all materials and a complete report can be found in this paper. Also, we demonstrate that the proposed model remains stable for image intensity and contrast variations. We accomplish this performance by taking the advantage of the new advances in the computer vision by the deep convolutional neural networks (CNN) as part of deep learning. CNN achieved outstanding performance over traditional image processing technics and already replaced them in a lot of computer vision applications. Among our examples we present some difficult materials where our model performs very well using the same CNN architecture and we postulate that models based on traditional image processing techniques would have serious difficulties in achieving the same results even with a lot of parameters tuning.

2. Deep convolution neural networks

Neural networks (NN) are artificial intelligence models which are intended to replicate the high-level structure of different parts of the brain. The NN units (neurons) are organized in layers and the connections between neurons from different layers can be compared with brain synapses. NN were introduced few decades ago and at that moment they were considered a breakthrough. However, their popularity dropped after a while mainly due to the difficulty to train complex neural architectures. For that period, it was unusual to develop a NN with more than two hidden layers and such a reduced capability makes impossible to model some complex functions (e.g. object recognition from images). Few years ago, the popularity of NN explodes due to the new hardware capabilities - graphics processing units (GPU) with tremendous parallel computation facilities - and due to the huge datasets available for training. These make it possible to efficiently train NNs with tens or even hundreds of layers capable to model incredible complex problems from computer vision, speech recognition, natural language processing, etc. The multi layers NNs such as deep neural networks (DNN), convolutional neural networks (CNN) and recurrent neural networks (RNN) are integrated in a new research area called deep learning (DL) having impressive results and a promising evolution.

In this paper, we propose a very slim CNN architecture for automatic evaluation of the fiber orientation for composite materials/woven using an image as input. The development of our method was driven by the following goals:

- Accuracy - the model inference error should be less than 0.5°;
- Universality - outstanding performance for a large class of materials;
- Automation – once put in place the model should be capable to run independently without the cumbersome process of parameters tuning;
- Stability – the ability to perform well when image perturbations like intensity and contrast variations occur;
- Simplicity – the model should be a plain replacement for the complex and convoluted available methods based on traditional image processing techniques.

3. CNN architecture
The estimation of the fiber orientation is obviously a regression task and implicitly our CNN is a regressor. The input layer is a tensor containing the material image. For the hidden layers, we have used a single convolutional layer (1) to capture the relations induced by the local connectivity exhibited by the input image and two fully connected layers with rectified linear unit (ReLU) activation (2) which became a very popular choice among other nonlinear activations like sigmoid and hyperbolic tangent

\[ C = K_{(d_x, d_y)} \ast X \]  

\[ \text{ReLU}(x) = \max(0, x) \]  

where \( X \) is the input tensor and \( K_{(d_x, d_y)} \) represents the convolution kernel with dimensions \((d_x, d_y)\).

In the CNN terminology, the result of a convolution represents a feature map.

The output layer consists of a single neuron giving the estimation of the fiber’s orientation. The cost function to be minimized is the Euclidean loss

\[ E = \frac{1}{2N} \sum_{i=1}^{N} ||\hat{y}_i - y_i||^2_2 \]  

where \( \hat{y}_i \) is the model estimation of the fibers orientation and \( y_i \) is the target value. Both input images and target values are normalized.

The minimization of the cost function is performed using minibatch stochastic gradient descent (mSGD) with momentum

\[ V_{t+1} = \mu V_t - \alpha \nabla \theta L(x, \theta) \]  

\[ W_{t+1} = W_t + V_{t+1} \]  

where \( \mu \) is the momentum parameter, \( \alpha \) is the learning rate, \( L(x, \theta) \) is the cost function (Euclidean loss) and \( W \) are the model parameters (weights and biases).

The number of observations in the minibatch \( N \), the number of neurons per hidden layer, the dimension of the convolution kernel \((d_x, d_y)\), the number of feature maps, the momentum parameter \( \mu \) and the learning rate \( \alpha \) are hyperparameters and their values and policy will be discussed in the subsequent sections. The proposed CNN were implemented using Tensorflow with GPU. The computer used to run the training and inferences has the following specifications: i7 6700HQ CPU, 16 Gb RAM, nVIDIA 950M GTX GPU.

4. Datasets generation
For the training and evaluation of our CNN model we used three disjoint datasets: train dataset, validation dataset and test dataset. This is a quite common setup in machine learning. The model is trained with the train dataset and evaluated against validation dataset. If necessary, some hyperparameters are tuned and the model is retrained and evaluated again using the validation dataset. This process repeats until satisfactory results are obtained for the validation dataset. Because validation dataset is used multiple times and to avoid reporting generalization performances biased toward hyperparameters tuning it is used a third dataset, namely the test dataset.

For a composite material, the raw input is a set of images of that material with known fibers orientation. The first step in obtaining the train, validation and test datasets is to randomly split the set
of raw images in three, keeping 80% of the images for training, 10% for validation and 10% for testing. The sample images are the images used by the CNN model for training and inference and they have equal width and height \( (sz_{\text{width}} = sz_{\text{height}} = sz) \). To generate a sample image for a specific dataset (train, validation or test) we used the following procedure:

- Randomly select a raw image from that specific dataset split;
- Denoting by \( sz_{\text{width}}^{\text{raw}} \) and \( sz_{\text{height}}^{\text{raw}} \) the width and height of the selected raw image and by \( m = \lceil sz/\sqrt{2} \rceil + 1 \) the margin, then generate a random center \( (c_{\text{width}}, c_{\text{height}}) \) with \( c_{\text{width}} \in [1 + m, sz_{\text{width}}^{\text{raw}} - m] \) and \( c_{\text{height}} \in [1 + m, sz_{\text{height}}^{\text{raw}} - m] \):
- Select a sub-image from \( c_{\text{width}} - m \) to \( c_{\text{width}} + m \) and from \( c_{\text{height}} - m \) to \( c_{\text{height}} + m \):
- Randomly generate a rotation \( \text{rot} \in [-\pi/2, \pi/2] \):
- Rotate the sub-image according to \( \text{rot} \);
- Obtain the sample image \((x)\) of size \( sz \) by selecting the central area of the rotated sub-image;
- Compute the target value/label \((y)\) from the fiber orientation in the initial raw image and the value of \( \text{rot} \) – using addition.

The above procedure is illustrated in figure 1.

5. Results

The method proposed in this paper was tested on 15 composite materials and woven. Sample images of these materials are presented in figure 2.
To highlight the robustness and feasibility of our approach we used the same CNN architecture with the same hyperparameters for all the materials. Here is a list of important settings:
- Sample images size $s = 256$;
- 1 convolutional layer with kernel dimensions $(d_x = d_y = 3)$, stride equal to 1, no pooling, 16 feature maps;
- 2 fully connected layers with 128 hidden units and ReLU activation;
- Minibatch size $N = 32$;
- Learning rate $\alpha = 0.01$ and momentum $\mu = 0.9$;
- Train for 1500 iterations (minibatches);
- Test on 1000 sample images.

Table 1 summarizes the results obtained after running this experiment. Obviously, the results are reported for the test dataset. We define the deviation as the difference between the target value and the estimated value, measured in degrees. In table 1, the “Min. dev. [°]”, “Max. dev. [°]”, “Mean. dev. [°]” and “Std. dev. [°]” columns represent the minimum, maximum, mean and standard deviation values for the deviations. “Min. 95% dev. [°]” and “Max. 95% dev. [°]” are computed by subtracting/adding 2 standard deviations from/to the mean. The worst results per column are bolded.
Table 1. Experimental results.

| Material | Min. dev. [°] | Max. dev. [°] | Mean. dev. [°] | Std. dev. [°] | Min. 95% dev. [°] | Max. 95% dev. [°] |
|----------|---------------|--------------|----------------|---------------|------------------|------------------|
| 1        | -0.248194     | 0.616353     | -0.002663      | 0.046028      | -0.09472         | 0.089393         |
| 2        | -0.225210     | 0.410692     | 0.003792       | 0.030931      | -0.05807         | 0.065654         |
| 3        | -0.194172     | 0.235903     | 0.004052       | 0.026803      | -0.04955         | 0.057658         |
| 4        | -0.138827     | 0.096944     | -0.001038      | 0.023102      | -0.04724         | 0.045166         |
| 5        | -0.124708     | 0.354199     | -0.004424      | 0.027153      | -0.05873         | 0.049882         |
| 6        | -0.189086     | 0.357724     | 0.010576       | 0.037412      | -0.06425         | 0.0854           |
| 7        | -0.224843     | 0.461284     | -0.000389      | 0.032776      | -0.06594         | 0.065163         |
| 8        | -0.369612     | 0.532309     | -0.028948      | 0.048464      | -0.12588         | 0.06798          |
| 9        | -0.171772     | 0.341477     | -0.066447      | 0.032636      | -0.07172         | 0.058825         |
| 10       | -0.148813     | 0.265767     | 0.004124       | 0.028149      | -0.05217         | 0.060422         |
| 11       | -0.122648     | 0.241198     | -0.010698      | 0.026532      | -0.06376         | 0.042366         |
| 12       | -0.238160     | 0.402457     | -0.002402      | 0.035262      | -0.07293         | 0.068122         |
| 13       | -0.105128     | 0.257522     | 0.005988       | 0.025219      | -0.04445         | 0.056426         |
| 14       | -0.230663     | 0.326572     | 0.006471       | 0.032103      | -0.05774         | 0.070677         |
| 15       | -0.203069     | 0.556202     | -0.011854      | 0.050458      | -0.11277         | 0.089062         |

The deviations have a normal distribution almost centered in 0 and the biggest standard deviation is about 0.05° (material 15) which means that the model error is ±0.15° at a confidence level of 99.8%. Also, the biggest absolute deviation is 0.61° (material 1) which is obviously an outlier. The results are very stable and accurate even for difficult materials like material 6, 10 and 15. These are low contrast materials with diluted motifs, a lot of irregular shadows and light reflections. From our experience, we postulate that solving the fiber orientation problem for these materials using traditional image processing techniques is particularly challenging and unstable even with a lot of parameters tuning.

We also analyzed the impact of image variations such as intensity and contrast regarding the performance of our proposed method. We artificially inject such image variations into our training and test datasets. Few corrupted images are shown in figure 3 for material 1.

For this experiment, we kept the same minimal network architecture and hyperparameters, but we extended the training for 3000 iterations because the input space is a lot bigger. The results remain very stable and accurate with the following statistics shown table 2.

Table 2. Experimental results for image variations: intensity and contrast.

| Material | Min. dev. [°] | Max. dev. [°] | Mean. dev. [°] | Std. dev. [°] | Min. 95% dev. [°] | Max. 95% dev. [°] |
|----------|---------------|--------------|----------------|---------------|------------------|------------------|
| 1        | -0.248194     | 0.616353     | -0.002663      | 0.046028      | -0.09472         | 0.089393         |
| 1 - corrupted | -0.326223 | 0.583172     | 0.036299       | 0.051552      | -0.06681         | 0.139403         |

From table 2 it can be easily observed that the performance of our model doesn’t degrade even if high image variations are present.
6. Conclusions
In this paper, we presented an end-to-end framework for estimating the fiber orientation of the composite materials or woven given an image as input. Our method is based on convolutional neural networks and represents an example of practicability of artificial intelligence techniques in engineering. The model is very accurate (with inference errors smaller than $\pm 0.15^\circ$ at a confidence level of 99.8%), applicable for a large class of materials, fully automated (eluding the cumbersome process of parameters tuning) and stable when image perturbations occur. Also, the model is very light, simple and easy to reproduce opposite to the complex methods based on traditional image processing techniques. The results are important for the industry on ensuring a high quality of the products and reducing the production time and human involvement and, implicitly, the costs which are achieved by automated supervision of certain production processes such as preparing and laying the composite woven or cutting the composite laminate.

Figure 3. Addition of image variations: intensity and contrast.
7. References

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