MaLeFiSenta: Machine Learning for Filament S Identification and orientation in the ISM

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ABSTRACT

Filament identification became a pivotal step in tackling fundamental problems in various fields of Astronomy. Nevertheless, existing filament identification algorithms are critically user-dependent and require individual parametrization. This study aimed to adapt the neural networks approach to elaborate on the best model for filament identification that would not require fine-tuning for a given astronomical map. First, we created training samples based on the most commonly used maps of the interstellar medium obtained by Planck and Herschel space telescopes and the atomic hydrogen all-sky survey HI4PI. We used the Rolling Hough Transform, a widely used algorithm for filament identification, to produce training outputs. In the next step, we trained different neural network models. We discovered that a combination of the Mask R-CNN and U-Net architecture is most appropriate for filament identification and determination of their orientation angles. We showed that neural network training might be performed efficiently on a relatively small training sample of only around 100 maps. Our approach eliminates the parametrization bias and facilitates filament identification and angle determination on large data sets.

INDEX TERMS Filaments, Image Processing, Interstellar Medium, Neural networks

I. INTRODUCTION

Filaments are one of the main morphological structures of the baryonic compound of the Universe. They are present over many scales, both in the intergalactic and interstellar medium. The first evidence of the cosmic web structure in the distribution of galaxies was observed almost 50 years ago [1,2] and then reproduced in analytical models and simulations [3,4,5,6] and references therein]. On the contrary, in the interstellar medium (ISM), filaments were first predicted by numerical simulations as elongated structures in density fields. Different authors ascribed their origin to compression and interpreted them as "cuts" through the sheets [7,8,9,10].

The presence of filaments in the ISM became irrefutable after the release of the Herschel telescope images of interstellar dust emission [11,12]. Since then, filament studies constitute a buoyant topic because they coincide with sites of active star formation and act as evidence of the turbulent nature of the ISM and its interplay with the magnetic field and gravity [13,14,15,16,17] to cite a few among many]. In Solar Science, filament studies have also found its application [18,19] because filaments act as means of solar cycle detection [20].

Filament studies require their identification in a map, especially if one is interested in deriving statistical properties. Depending on the purpose, different authors adapted different pattern identification approaches or developed new techniques. Some methods are based on gradients, which are first-order derivatives [21], while other methods use Hessian matrices [22], which involve second-order derivatives, to search for pixels with zero curvature to trace the filaments’ crest. In the work by [23], the author developed the so-called DisPerSE method, which combines the aforementioned approaches to detect voids, walls, and peaks in addition to filaments. This method was initially designed to be used on cosmological data but was further applied in the ISM...
Another example is the \textit{Getsources} method developed by \cite{25} for the \textit{Herschel} data. It constructs filtered decomposition of images over a range of spatial scales to be analyzed separately and reconstructs the filaments. There are also methods based on pattern recognition. The principle is to match a kernel of a given shape, usually a long rectangle, with an original image. Rolling Hough Transform (RHT, \cite{26}), Template Matching (TM, \cite{27}) are such examples.

The methods mentioned above can be virtually divided into two groups, depending on the purpose of the studies. The first group would encompass methods that enable tracing crests of the brightest structures (gradients, Hessian matrices, DisPerSE). The second group aims to identify the spatial extent of structures (filaments having a width), regardless of their absolute intensity (RHT, TM).

Every method uses well-researched image processing techniques and has proven efficiency in specific studies. However, all methods mentioned above are parameter-based and require parameter fine-tuning for every map. Thus, detection of filaments in a large dataset by a given method is usually performed with a predefined set of parameters. The high dependence on a slight change in parametrization may cause bias in filament identification regarding their size or shape. Additionally, the existing methods commonly use advanced image processing procedures applied over the whole image field, which requires ample computational resources. Moreover, a significant amount of time is spent on the parametrization of output maps by visual inspection. We propose a machine learning-based method for filament identification that solves the issue of manual parameter search and visual inspection.

Neural networks are well suited to solve the filament identification problem. Recent developments in the field of deep learning, where object segmentation networks such as U-Net\cite{28}, Mask R-CNN (Region-based Convolution Neural Network)\cite{29}, FastFCN (Fully Convolution Network)\cite{30}, Gated-SCNN (Gated-Shape Convolution Neural Network)\cite{31}, DeepLab\cite{32} provide an efficient and fast image segmentation results. Moreover, neural networks have already showed their efficiency in improving astronomical data and solve the problem of noise \cite{33, 34}.

In astronomy, much effort is dedicated to methods of detection of specific morphological structures. For instance, in solar physics, the detection of bright points has been addressed with a combination of observation and simulation techniques\cite{35}. Analysis of granulation process on solar surface was treated using correlation tracking\cite{36, 37}. Several studies have already used neural networks for filament identification. Authors in \cite{38} proposed a neural network for solar filament segmentation, using a database of filaments detected by alternative methods. Their neural network is based on (R-CNN) model. Additionally, filament identification was researched in other domains, such as microscopy \cite{39}. The authors proposed a densely connected stacked U-Net for filament segmentation in microscopy images. Similar work was performed by \cite{40} for automated and semi-automated enhancement, segmentation, and tracing of cytoskeletal networks in microscopic images.

Our focus is to search for best neural network models that identify filamentary structures and their orientation angles in 2D maps, to apply it to the ISM studies. In particular, we are interested in detecting extended structures of a certain width and their orientation angles. For this purpose, we apply the RHT method to \textit{Planck}, \textit{Herschel} space telescopes, and the Effelsberg-Bonn and Parkes telescope survey data. This data contains a large number of interstellar dust filaments to produce training data sets. Nevertheless, it is worth noting that neural networks can be trained using filament identification methods other than the RHT and different training data sets.

This paper is organised as follows. First, we describe methods in Section \textbf{II} and present the training datasets in Section \textbf{III} We show and discuss our results in Sections \textbf{IV} and \textbf{V} respectively. Finally, we summarise our work and provide quick tips for the network operation in Section \textbf{VI}.

\section{Method}

In this Section, we first outline the existing filament identification algorithm, the RHT, that was used to generate the training samples. Second, we describe the neural networks based on which we constructed our models. Finally, we describe the principle of the goodness-of-fit mathematical measure that we use to assess the effectiveness of our results and during the preparation of the training samples.

\begin{figure}[h]
\centering
\includegraphics[width=0.8\textwidth]{Fig1.png}
\caption{Schematic representation of the RHT kernel scanning in a circular window centered at a pixel $(x, y)$. The blue curve represents the skeleton of the filament in the original image. The green and orange line represent the kernel positions for different orientation angles $\theta_1$ and $\theta_2$ respectively. The width of the orange line is enhanced to show that for $\theta_2$ the histogram value is greater than the fixed threshold.}
\end{figure}
A. THE ROLLING HOUGH TRANSFORM

The Rolling Hough Transform is based on the computer vision algorithm developed by Paul Hough in 1962 [41] to solve the problem of shape identification in 2D images. It employs parametrization from Cartesian coordinates \((x, y)\) to slope-intercept parameter space. Further, Duda and Hart [42] improved the method by replacing the slope-intercept space with angle-radius:

\[
\rho = x \cos \theta + y \sin \theta .
\]

This transformation ensures counting all pixels contributing to a pair \((\rho, \theta)\). Duda and Hart’s representation also facilitated the generalization of the Hough Transform from lines to various shapes such as ellipses, rectangles, or triangles.

More recently, authors in [26] introduced the Rolling Hough Transform. The method consists of applying the Hough Transform at the same location inside a circular area of a fixed diameter, consequently in different directions. The number of pixels that are "on" the rotating rectangular kernel at each rotation position is stored. Thus, a histogram of number of pixels that are "on" the rotating rectangular kernel of a fixed diameter, consequently in different directions. The transformation ensures counting all pixels contributing to a pair \((\rho, \theta)\). Duda and Hart’s representation also facilitated the generalization of the Hough Transform from lines to various shapes such as ellipses, rectangles, or triangles.

Practically, this is performed in the following way. First, a "top-hat" filter is applied on the image. Second, the resulting image is subtracted from the original image which provides skeletons of the structures. Third, a bitmap is created. Finally, image is subtracted from the original image which provides skeletons as output results. Here, we use MSSIM to quantify the results of the neural networks approach to the results of the RHT. We used the publicly available code written in Python. Below we shortly describe the main principles of the similarity index.

C. MEASURE OF THE STRUCTURAL SIMILARITY

Minimization of human bias in filament identification is one of the principal aims of this work. The Mean Structural Similarity index (MSSIM) was introduced by [45] to measure similarity between images. [46] proposed to use MSSIM in filament analysis applied to the results of DisPerSE and FILFINDER filament identification algorithms which yield skeletons as output results. Here, we use MSSIM to quantify and compare the results of the neural networks approach to the results of the RHT. We used the publicly available code written in Python. Below we shortly describe the main principles of the similarity index.

For a given pixel, the relationship between two images, or signals, \(x\) and \(y\), is characterized by "luminance", "contrast", and "structure" [45]. They are denoted as \(l, c\), and \(s\), respectively, and are, in fact, the mean intensity, the standard deviation, and the stored pattern, or the correlation between them:

\[
l(x, y) = \frac{2\mu_x \mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1} ,
\]

\[
c(x, y) = \frac{2\sigma_x \sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2} ,
\]

\[
s(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3} ,
\]

where

\[
\mu_x = \frac{1}{N} \sum_{i=1}^{N} x_i , \quad \mu_y = \frac{1}{N} \sum_{i=1}^{N} y_i ,
\]

\[
\sigma_{xy} = \left( \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu_x)(y_i - \mu_y) \right) ,
\]

\[
\sigma_x = \left( \frac{1}{N-1} \sum_{i=1}^{N} (x_i - \mu_x)^2 \right)^{1/2} ,
\]

\[
\sigma_y = \left( \frac{1}{N-1} \sum_{i=1}^{N} (y_i - \mu_y)^2 \right)^{1/2} ,
\]

are the mean values of signals \(x\) and \(y\) (\(\mu_x, \mu_y\)), their covariance (\(\sigma_{xy}\)), and the variances (\(\sigma_x, \sigma_y\), respectively). The constants \(C_1, C_2, \text{ and } C_3\) are much smaller than 1 and are introduced to avoid division by 0. The local structural

1https://github.com/seclark/RHT, based on [26].

2https://github.com/mubeta06/python/tree/master/signal_processing/sp
similarity index (SSIM) is given by the multiplication of the three above-cited parameters which results in the following expression:

\[
\text{SSIM} = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)},
\]

given that \(C_3 = C_2/2\) for simplification.

Then, the mean value of the SSIM index over an image provides a single value called MSSIM. It appears from [46, 47] that MSSIM primarily reflects the variation of the structure rather than luminance and contrast. For this reason, the metric is efficient for comparing the outputs of filament identification algorithms with the original images.

MSSIM ranges from -1 to +1, where -1 means no similarity while +1 means perfect match. The higher the MSSIM value of the output image containing identified filaments, the better the algorithm identifies critically essential structures of the image.

**III. DATA**

In our work, we collected approximately 506 labelled images to train the neural networks. We generated the datasets from the data from the following telescopes: Planck and Herschel space telescopes and Parkes and Effelsberg ground-based radio telescopes, the data from which is used the most in the analysis of ISM filaments.

We ran each astronomical map through the RHT procedure and obtained the RHT intensity and angle. We then transformed RHT intensity maps to bitmap to obtain a mask. Thus, samples in our dataset contain three 2D maps of a particular region: an original intensity or column density map, a mask of identified filaments, and a map of filament angles. Examples are shown in Fig. 2.

**A. PLANCK-BASED SAMPLE**

Planck filaments are represented in our sample in two ways. The first Planck dataset is taken from the analysis of [44], where RHT was applied over regions where Planck Galactic Cold Clumps are identified [48]. The Cold Clumps are regions that correspond to the coldest ISM, which are generally part of molecular clouds. The dataset contained 137 maps and the associated RHT outputs, such as maps of RHT intensity, angle, and angle uncertainty. The sub-sample will be denoted as "Planck-cc" in what follows. The angular size of the maps in this sub-sample was limited to two-by-two degrees, so we decided to complement it with yet another Planck-based dataset from [49]. The authors designed an algorithm dedicated to filament identification and maps segmentation from large maps. It applies the RHT method on an arbitrarily chosen portion of the large map, labels all the detected structures, chooses the most prominent filament and determines the direction in which the map should be extended to capture the whole filament. As a result, it produces maps (mask and angle) that contain unique entire filaments while more
minor features are masked. Finally, a visual analysis of the maps was performed to pick the most successful selections. The sub-sample will be denoted as “Planck-1”. In total, the Planck-based sample consists of 242 maps.

B. HERSHEY-BASED SAMPLE

We used Herschel maps from the Galactic Cold Cores (GCC) survey [50], which consisted of 116 targets. Herschel telescope’s angular resolution (37") allows us to resolve the intriguing filamentary structures of molecular clouds. Thus, it diversifies our dataset and allows us to test the performance of neural networks at different complexity level because Planck filaments are generally smooth and extended because of the low angular resolution (7′ in our sample) of the telescope. The corresponding column density maps were computed using spectral energy distribution fits with modified black-body law with a given spectral index β = 2 [51]. The advantage of using the column density maps is having more prominent filaments and less marginal features, especially at low sensitivity observations, which is the case for Herschel compared to Planck.

Herschel GCC fields are an example of maps for which using the RHT method may be problematic because each map needs detailed parametrization. This is due to the variety of the shapes of the observed molecular clouds and their morphological complexity. To get the most robust training sample, we ran RHT with different parameters for each map and chose the output maps that gave the best MSSIM result. The kernel parameters, length, and width in pixels, are given in Table I. Their ranges extend from 1 pixel to 7 pixels for the width and from 5 to 31 pixels for the length. These values are motivated by the maps’ size, and the variety of the structures observed in the maps. Thus, each Herschel map was treated with the most appropriate kernel that provided the mask and the angles map used in the neural network training. In general, a Herschel GCC map contains many small structures because each observed structure is resolved and complex. Thus, after the RHT procedure, we additionally perform mask binarization and select only ten largest filaments with respect to their pixel count. This choice is motivated by the necessity to avoid noisy input and non-significant structures, improving generalization.

| l | 1 | 3 | 5 | 7 | 9 | 13 | 15 | 21 | 27 | 31 |
|---|---|---|---|---|---|----|----|----|----|----|
| w | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

C. HI4PI-BASED SAMPLE

We used the all-sky survey of the atomic hydrogen data from the Effelsberg-Bonn and Parkes telescopes which is publicly available as the HI4PI survey [52]. The atomic hydrogen (HI) traces the diffuse gas content and is generally mixed with dust in the ISM. In addition, findings of [53, 54] showed that the HI gas and Planck dust filaments show good agreement. Thus, HI data adds another dimension to the angular scales in our dataset, with 16’ resolution. We ran the RHT procedure through the column density maps of HI at the same positions where Planck filaments were found in the study by [49]. We conducted a visual check-up and obtained 148 maps.

IV. RESULTS

In this Section, we present the results of application of two most efficient architectures for our purposes, although other models were tested and will be discussed in Section V. The first architecture is based on Mask R-CNN model. It is used to identify the location and the shape of the filaments, that is, to produce segmentation masks. The masks give the location and extent of the identified filaments. The second architecture is based on the U-Net model. It is used to determine the filaments orientation angles from the mask.

A. Mask R-CNN LEARNING MODEL

In our study, we use Mask-RCNN network architecture [29] to extract masks of filament structures. Mask R-CNN is a Convolutional Neural Network (CNN) and state-of-the-art in terms of image segmentation and instance segmentation. It generates bounding boxes and segmentation masks for each instance of an object in the image. In other words, it detects each object in an image and provides information about its position. Mask R-CNN is based on ResNet101 backbone and Feature Pyramid Network (FPN).
1) Training

In this work, we decided to train the neural network using training sets of astronomical images and their masks generated by means of the RHT procedure. The training datasets consist of astronomical maps described in Section III and their corresponding masks. The latter are obtained from RHT intensity maps to which we applied binary thresholding. The final objective of the neural network was to identify filamentary structures. All images were resized to $256 \times 256 \times 3$ pixels dimension. Technically, the Mask R-CNN neural network was implemented based on Keras [55] and Tensorflow libraries [56] with the support of the GPU assisted parallel computations. We trained the network for 30 epochs. To improve the process, we applied transfer learning which was enabled based on the COCO data set [57].

We first ran the network on the Planck-1 data set where each map has only one identified filament. However, experimental results showed the critical importance of feeding the neural network with multiple filaments in the target image during the training phase. If the neural network was provided with a single filament for each map at the training stage, as in the case of Planck-1 sub-sample, the network could not detect many significant structures in the test set. This explains low mean Average Precision with increasing training size in Fig. 6. Once the criterion of a single filament is relaxed, there is no critical difference related to the number of input filaments, as we see in the Herschel-based data set. However, increasing the number of significant filaments led to detection of noisy structures that blended the results.

2) Results

We trained the neural network separately on each of the available data sets.

We show in the central column of Fig. 4 sample outputs of the Mask R-CNN, and the corresponding RHT masks in the left column. Qualitatively, Mask R-CNN yields larger and smoother structures than the RHT procedure and detects the most significant structures. Quantitatively, we assess the performance of the neural network compared to RHT using the MSSIM index and the mean average precision score. The MSSIM index, described in Section II, quantifies how the output masks differ in structure compared to the original map. A high score correlates with a high similarity between entities and a low score informs about less significant similarities. The score ranges from -1 to 1. We also assess the results using the mean average precision (mAP). The mean average precision shows the average precision score for the fixed value of intersection over union (IOU) of 0.5, i.e. the proportions of test samples that has higher score than the predefined IOU score. The average precision is computed according to the following equation:

$$AP = \sum_n (R_n - R_{n-1}) P_n,$$  \hspace{1cm} (11)

where $R_n$ and $P_n$ depict the recall and precision values at n-

![FIGURE 4. Examples of obtained filaments: the first column depicts the original intensity maps, the second column shows results of the Mask R-CNN and the last column shows results of the RHT procedure. Numbers in the second and third columns indicate the structural similarity score measured by the MSSIM metric.](image)
Fig. 5 shows the comparison between the RHT generated filament masks and the output masks produced by the neural network based on MSSIM index. For the HI filaments, the larger the training size, the higher the MSSIM value, meaning that the neural network becomes more efficient. As for the Planck- and Herschel-based data sets, the morphological similarity comparison does not show any clear trend with increasing size. We note that the Planck-1 sub-sample shows low performance because maps contain only one, largest filament, by construction.

Fig. 6 shows the accuracy of the filament identification measured in terms of mean average precision score depending on the size of the training sample, normalized to one with respect to the total number, for the Mask R-CNN neural network.
TABLE II

Estimation of performance of the Mask R-CNN training. The mean Average Precision (mAP) score measures the overlap between the neural network result and the RHT result. Difference between the MSSIM from Mask R-CNN and RHT results measures the efficiency of the neural network over RHT regarding morphological structure compared to the original image dataset.

| dataset      | train set sample size | validation set sample size | mAP score | mean(MSSIM\textsubscript{NN} - MSSIM\textsubscript{RHT}) | std(MSSIM\textsubscript{NN} - MSSIM\textsubscript{RHT}) |
|--------------|-----------------------|----------------------------|-----------|--------------------------------------------------------|--------------------------------------------------------|
| Hershel-based| 90                    | 24                         | 0.32      | 0.07                                                   | 0.03                                                   |
| HI4PI-based  | 120                   | 28                         | 0.35      | 0.08                                                   | 0.04                                                   |
| Planck-cc    | 100                   | 37                         | 0.33      | 0.03                                                   | 0.0035                                                 |
| Planck-1     | 85                    | 20                         | 0.37      | 0.037                                                  | 0.004                                                  |

TABLE III

Estimation of performance of the U-Net training. Mean squared error measures the squared difference between the model’s predictions and the desired output across the whole data set. The last column shows the mean difference between derived angles with the U-Net and with the RHT methods.

| dataset      | train set sample size (maps) | validation set sample size (maps) | Mean squared error (MSE) | Mean difference (degrees) |
|--------------|------------------------------|-----------------------------------|--------------------------|----------------------------|
| Hershel-based| 90                           | 24                                | 267                      | 2.68                       |
| HI4PI-based  | 120                          | 28                                | 187                      | 1.35                       |
| Planck-cc    | 100                          | 37                                | 245                      | 2.07                       |

training has been shown to gradually converge after the 100 epochs of training. The total number of trainable parameters of the network was 31,031,685.

2) Results

Results of the U-Net training for identification of orientation angles using three different data sets are presented in the Table III. The mean squared error parameter (MSE) shows the squared difference between the U-Net model’s predictions and the ground truth, averaged across the whole data set. The MSE will never be negative since we always squared the errors. The following equation formally defines the MSE:

\[
MSE = \sum_{i=1}^{D} (Y_i - \hat{Y}_i)^2
\]  

(12)

U-Net allows to predict the orientation angles (see Fig. 7) with an accuracy comparable to RHT. This is confirmed by small average differences across each map. The mean over the average differences is shown in Table III which is of order of 1 to 3 degrees.

V. DISCUSSION

This section first describes the neural network models that we have additionally tested. Second, we summarize and discuss both our models.

A. ALTERNATIVE NEURAL NETWORK MODELS

For orientation angle estimation, we have tried several approaches to test the most widely used models in machine learning. In particular, we compared the regular CNN model, the auto-encoder model, the decision tree regression, and U-Net models.

The advantage of the CNN models is that they can capture spatial features in images, provide masks and perform reliable classification. However, they are not efficient in regression tasks. Thus, this type of neural network is not well suited for orientation angles determination. Hence, alongside CNNs, we used auto-encoder and U-Net models in our study. Due to the specific architecture, these models both use global and encapsulated local features in the images to provide a decoded 2D output with more precision. We also tried decision tree regression as one of the most robust and reliable classical machine learning methods. However, we faced overfitting and poor generalization problem using this method. The sample variation significantly affected the results, in which some samples could reliably estimate the angles while other samples provided orders of magnitude less efficient orientation angle estimates.

B. MASK R-CNN FOR FILAMENT IDENTIFICATION

The Mask R-CNN-based model is used to distinguish filaments in the input maps. It is trained with data sets that contain structures of different sizes and morphological characteristics, with more "blobby", low angular resolution HI4PI...
### C. U-NET FOR FILAMENT IDENTIFICATION

Although the U-Net architecture was previously used for the identification of thin filaments in microscopy, in this study, for the first time, it was used to determine the values of the orientation angle of the filaments.

In principle, U-Net may be used to identify the orientation of filaments in a map containing masks of filaments obtained from any filament identification methods, such as intensity threshold or skeletons, among the most simple. Alternatively, it can be combined with more sophisticated procedures such as DisPerSE.

To find out how U-Net can identify orientation angles from the intensity maps directly, we tested various parameters of the network to estimate the best performance. This procedure was repeated on all data sets. We compared results of the U-Net with the following inputs: mask of the filament or the original intensity map. This allowed us to conclude that the latter gives significantly worse results. Hence, we propose using the architecture consisting of 2 stages: Mask-RCNN followed by U-Net to identify filaments and their orientation angles efficiently.

### VI. CONCLUSION

We applied machine learning approach to filament identification for the studies of the interstellar medium. The approach is based on neural networks and allows us to identify extended filaments of finite width and their orientation angles. To create training samples, we used a machine vision algorithm, the Rolling Hough Transform (RHT), that we applied to the publicly available astronomical data: the *Planck* and *Herschel* telescope and the HI4PI survey, which are the most data or more delicate, higher angular resolution *Herschel* data (ratio of angular resolution of 20). Using different data sets diversifies the learning procedure and ensures reliability. The output of the Mask R-CNN neural network consists of multiple layers, each containing a single filament. Furthermore, we can combine all masks to produce a single mask or perform a sorting procedure to limit the identified filaments in, e.g., a hierarchical order. Although the neural network was trained with maps containing ten filaments, the output contained more or less than ten significant filaments. This concludes that the neural network is able to make autonomous decisions. In addition, we showed that the training on a sample as small as 90 maps already gives results that are at least as reliable as the commonly used automated procedure such as the RHT. A comparison of the neural network results with the classic automated RHT procedure results in terms of morphological similarity showed that the neural networks approach provides outputs that are morphologically more representative of the original image. In addition, once a neural network is trained, the computational time for a single map with around 500 pixels per side is less than 1 second compared to a few dozens of minutes with the RHT procedure on the same machine.

| Original image | Unet | RHT |
|---------------|------|-----|
| ![Original image](image1) | ![Unet](image2) | ![RHT](image3) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image4) | ![Unet](image5) | ![RHT](image6) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image7) | ![Unet](image8) | ![RHT](image9) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image10) | ![Unet](image11) | ![RHT](image12) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image13) | ![Unet](image14) | ![RHT](image15) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image16) | ![Unet](image17) | ![RHT](image18) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image19) | ![Unet](image20) | ![RHT](image21) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image22) | ![Unet](image23) | ![RHT](image24) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image25) | ![Unet](image26) | ![RHT](image27) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image28) | ![Unet](image29) | ![RHT](image30) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image31) | ![Unet](image32) | ![RHT](image33) |
| 0.3001 | 0.2981 | 0.3001 |
| ![Original image](image34) | ![Unet](image35) | ![RHT](image36) |
| 0.3001 | 0.2981 | 0.3001 |

**FIGURE 7.** Examples of filaments obtained using the U-Net model: the first column depicts the original intensity maps, the second column shows results of the U-Net, with the color code corresponding to the orientation angle in degrees, and the last column shows results of the RHT procedure. Numbers in the second and third columns indicate the structural similarity score measured by the MSSIM metric.
used in ISM studies [11, 16, 26, 44, 54, 60, 61, 62, 63]. Our main goal was to find the best neural network architectures that would efficiently identify filaments and primarily estimate orientation angles.

We found that two neural network models satisfy the required tasks: the Mask R-CNN and the U-Net. The first model is the best suited for filament mask construction while the second allows us to estimate the orientation angles of structures in the image. We recommend using a combination of the two models. However, it is worth noting that the U-Net model can be applied directly to the intensity or density image, and can also be used in combination with any mask of filaments.

The main advantage of neural networks approach is that the models can be trained to identify structures of different sizes thus diminishing human bias. Such an approach minimizes parametrization, which facilitates application on large or diversified data sets. It opens an opportunity for neural network applications for relative orientation between interstellar filaments, hubs, and magnetic fields. Upon publication, the models set-up will be available via GitHub (https://github.com/danakz). In perspective, future work might be envisaged to improve the efficiency of the models regarding the set-up and the training samples.

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