Feature Extraction of Scale Pattern in Animal Textile Fibers

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ABSTRACT:

Animal fibers have variety in their longitudinal sections. The main difference of the longitudinal section of these fibers is the geometry and dimension of scale patterns, which with attention to one of the physical fiber detection, one can inspect longitudinal section of fiber images, which determine the fiber characteristics. The method of the determination is image processing which extracting the closed contours and then the chain code algorithm inspected characteristic of fibers. Regularity or irregularity of animal scale patterns can be recognized by feature extraction. As result it can be accompanied with others such as scale length, scale area, etc. for classification of fibers.

Keywords

Scale, Fiber, Chain code, Regularity, irregularity, closed contour, Differentiate Filter, Morphology, Gradient Algorithm

1. Introduction

The views of longitudinal section of animal fibers are very various. Microscope observation clearly shows scale like structure, which depends on the breeds and the growing environment of fiber. Using the image processing for determining the fiber characteristics is significant, as firstly the user with complicated and irregular images is not capable of determining the fiber characteristics or the irregularity percentage of longitudinal section of fibers absolutely and, generally visual observation is accompanied by errors and the individual results are based on the previous presumed principle. Secondly fiber characteristics are determined without the user interference. From above discussion, it can be understood that by the micrograph image processing technique, user is capable of determining the fiber characteristics without any present experts.

Characteristics of animal fiber scale patterns are still served as major evidence in the identification and subsequent classification of animal fibers [Wil54]. Under the microscope observation by using human/eye brain, Wildman [Wil54] classified animal fiber scale patterns in five groups: mosaic, wave or waved, chevron, pectinate and petal patterns and classified these group as regularity or irregularity.

Robson [Rod97] used an objective and repeatable approach to extract scale pattern features of merino and cashmere, and to perform discrimination between these two fibers. However these methods is based on the prior subjectively selected features of scales, such as scale length, scale area, etc., and a linear discrimination function. This method also uses a subsequent sophisticated image processing technique to extract these features. The image processing was not totally automatic, requiring some degree of manual intervention depending on the clarity of captured image features [Rod97].

Kong [Kon01] classified merino and mohair fibers by using a nonlinear artificial neural network (NANN). They used two multilayer networks including one supervised and one unsupervised, with the unsupervised network being used for automatic feature extraction while the supervised network serving as the classifier based on the information extracted from unsupervised network, for classification of these two fibers.

In figure 1, we showed our proposed algorithms for which we used the images given in [Wil54] for the experimental results. In this paper, firstly in several stages that are shown in fig.1, a closed contour is extracted for which the fig.2-i is obtained. Secondly the chain code of animal fiber scale patterns is used to obtain the geometry, regularity or irregularity of scales and the other characteristics of scales that achieved in [Rod97].

2.1. Contour extraction

One image of animal fiber with 400X magnification [Wil54] is shown in fig.2-a. The edges of scales in their boundary zones have more diversity in the slope of brightness levels than other parts of image. Boundary lines can be determined by Edge Detection Algorithm (EDA). [Gon92, Sco98, Can86] In this case,

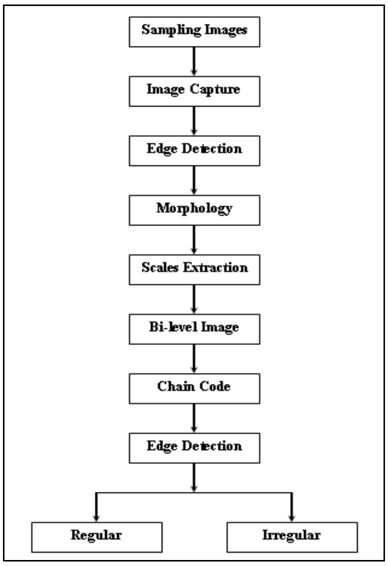
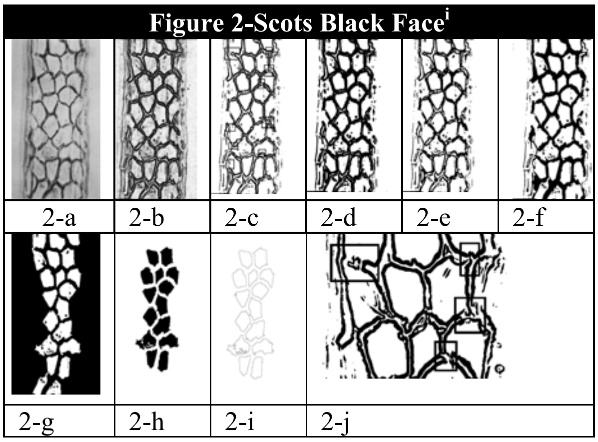


Figure 1: Steps for feature detection

Figure 2-Scots Black Face[i]



2-a Original view, 2-b after EDA, 2-c Threshold, 2-d Dilation, 2-e Erosion, 2-f Remove small particles, 2-g Remove big particles, 2-h Image reject border, 2-i Closed Contour, 2-j Higher scaling of fig.2-c

EDA is applied on an image in four directions (N-W, N-E, S-W, and S-E) so that the ultimate result from each direction with maximum value of brightness levels (255 for 8 bits) for flat levels and minimum value of brightness level (0) for edges are obtained. Ultimately results of the whole edge detection for reconstruction of total edges are logically added together (fig.2-b).

In obtaining edges, the quality of image and characteristics of natural fibers are significant. The difference between the scale edges and other edges is that the former forms a closed contour, but again noises in the image and the probable longitudinal flows, which may form an abnormal edge, prevent formation of closed contour with application of EDA. So it is necessary to perform one stage of smoothing. EDA is the gradient method in this stage with 5×5 window (See Appendix) and smoothing process possesses 7×7 window [Sco98]. The background separates from the edges and other sharp parts of image with using a separation threshold, because of variety in their brightness levels (Fig.3). Brightness levels of edges are higher than 150. Edges and non-edges of an image are separated in two quite distinguishable brightness levels by determining a simple threshold. This action produces a bi-leveled image that facilitates the image processing. (Fig.2-c)

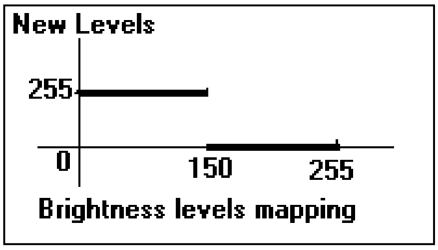


Figure 3: Brightness levels mapping

2.2. Extracting the scale figure

2.2.1 Determining the closed contour boundary of scales:

Determining the boundary of contour edges is impossible just as are shown in fig.2-c and with higher scaling in fig.2-j. Morphology is used for obtaining the boundary contours in such a way that the first dilation and then erosion are used. With using these consecutive processes, at first, fractures in contours are filled, and then with erosion process, the detected edges are returned to the primary thickness extent [Gon92, Sco98]. Structuring element is square during the transformation of morphology. The number of iteration for each of morphology stages is dependent to the magnification and resolution of image and the quality of image capture system. Here the number of iteration for both of them is two. (The images are shown in fig.2-d & fig.2-e).

2.2.2. Separating scales

Limits and dimension of scales must be obtained, because firstly detected edges are not sharp with using of EDA, which means that in the beginning, there is ascending slope, then there is descending slope or vice versa. Accordingly, for determining the boundary of closed contours, wide limits of distances between scales is taken into consideration as boundary which causes the formation of more than one closed contour is possible and consequently the formation of a single closed contour is impossible because of joining boundary of adjacent scales. Secondly, the possibility of studying area and style of

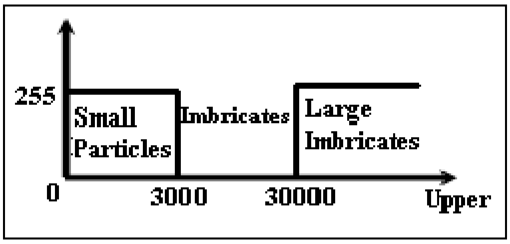


Figure 4: Shown the scales separation thresholds.

variation of each scale is obtained by determining limits of each scale. Particles of image are filtered in such a way that just particles passing from this filter

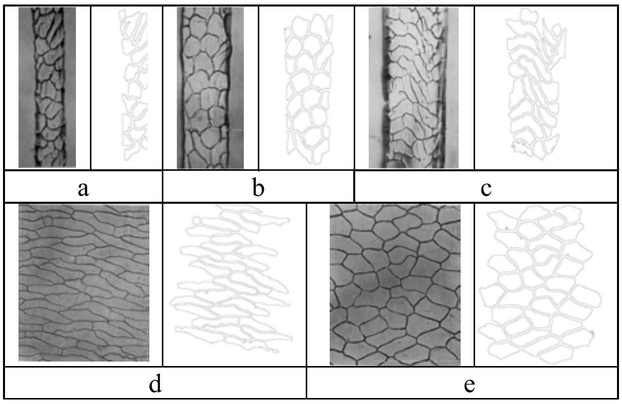


Figure 5: Original view and final image of different fibers

for which the number of pixels are in the range of number of scale pixels. This threshold with attention to 400X magnification of image is shown in fig.4. The scales are transferred to minimum brightness level (0) and other parts of image are transferred to maximum brightness level (255 for 8 bits). Omitting of the useless parts is carried out in two stages: first eliminating small particles, and second eliminating large particles, then scales are filled by filling algorithm monotonously (fig.2-f & fig.2-g). The holes found in contact with the image border are never filled because it is impossible to determine whether these holes are part of a particle. [Sco98]

Some scales are joined to image border; as a result part of characteristic of fiber has been removed. For that reason, particles, which touch the border, are eliminated from image (fig.2-h). Connectivity is taken into consideration for removing of particles and eight-direction are taken into consideration for filling [Sco98]. It means that belonging of each pixel to boundary is studied by eight-direction. Just as shown in fig.2-h, scales are distinguished from background. Scales are discriminated with high percentage (here is higher than 70%) although some scales are eliminated since edges are not recognized well enough. Scales are recognized higher than 95% in images with better quality.

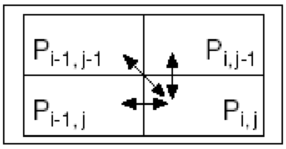


Figure 6: Differentiate Filter

2.3. Determining one-pixel closed contour

Just as known, after segmentation of scales, we obtain a bi-leveled image. We are capable of measuring scale length, scale area, etc but variation of these scales is significant. It is necessary to determine one-pixel closed contour for inspecting the scale movement variation and geometry of scales. EDA, which is used in this stage, is a differentiating filter. The new value of pixel in differentiation filter becomes the absolute value of its maximum deviation from its upper-left neighbors [Sco98]. If the P shows the one pixel, then equation (1) and figure 6 show this operation.

$$P_{(i,j)} = \max\left[\left|P_{(i-1,j)} - P_{(i,j)}\right|, \left|P_{(i-1,j-1)} - P_{(i,j)}\right|, \left|P_{(i,j-1)} - P_{(i,j)}\right|\right] \quad (1)$$

This action is done for extracting one-pixel scale edges. It performed correctly because of formation of bi-leveled image (fig.2-i). The stages are shown in fig.1 are used for several fibers for which the original image and the ultimate result of image are shown (fig.5).

3. Chain code

Chain code used here has four directions. It is extracted by moving on the pathway of one-pixel closed contour. In practice the information, which is extracted from four-directions, is better than from eight-directions. Pathways, which are not in the main directions, are divided into adjacent directions. (Fig.7)

4. Experimental Results

The style of variation of scales can be studied by chain code. The average percentage and the coefficient of variation percentage of information of some fibers that is obtained from chain code are shown in table1. Average percentage is the average of chain codes of scales for each direction. Coefficient of variation for Indian breed and Border Leicester are much more than others that shows irregularity of these fibers. Fibers, which have lower coefficient of variation, are nearer to mosaic scale pattern if they possess nearly the same average percentage in four main directions.

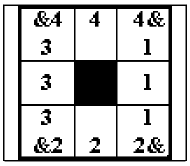


Figure 7: Chain Code Directions

For instance it can be concluded Urial sheep has lower coefficient of variation percentage. As just seen in average percentage of this fiber, the number of closed contours in 1 and 3 directions with respect to 2 and 4, is nearly 2.5.The reason which this fiber is irregular waved mosaic [Wil54], is that it has much more coefficient of variation in 2 and 4 directions than 1 and 3 directions. In this case, this problem is to some extent acceptable because the calculation shows regularity of this fiber in 1 and 3 directions. Scattering information fiber is shown in fig.8. Sum of 2 & 4 directions versus sum of 1 & 3 directions is plotted in this figure. Indian breed has irregular scale pattern and scattering information of this fiber is much more than Root Indian breed that has regular scale pattern. Root Indian Breed is nearer to regular mosaic because of having less scattering information and ratio of their length and width is nearly 1.5. As just shown in fig.8, information group of each fiber scales is overlapped, this case is not important and it is not our aim to separate it. Aggregation of chain code information of scales of each fiber is significant.

Table 1	1	2	3	4	1	2	3	4
Fibers \ Direc	Coefficient of Var. %				Average %			
Scot Black Face	27	21	23	11	20	29	20	40
Border Leicester Fleece	25	33	25	33	21	29	21	30
Swaledate	20	15	20	15	21	29	21	29
Indian Breed	51	53	59	44	23	27	22	29
Urial Sheep	9	21	13	21	37	14	36	14
Root Indian Breed	13	13	14	13	30	20	30	20

Table 1: Compare the C.V.% and Average percentage of Several fibers.

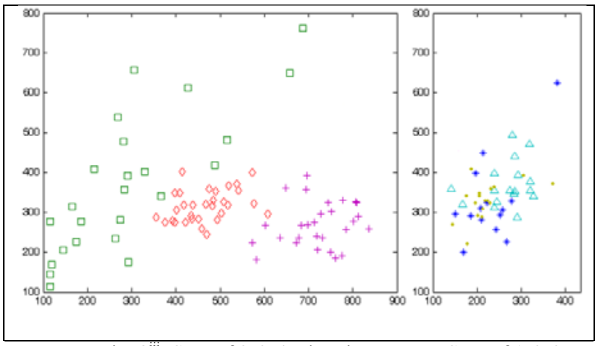


Fig. 8[iii]: Sum of 2 & 4 Directions versus Sum of 1 & 3 Directions

This figure is plotted without intervention of fiber thickness, fiber length, etc.

5. Conclusion

If the resolution of capturing system is good enough, characteristics of fibers can be determined by feature extraction in such a way that the rotation and scaling of images have no effect on the chain code. With using this method, regularity can be used as fiber characteristics in such a way that firstly, animal fiber irregular scale patterns are recognized from regular ones. Secondly, animal fiber irregular scale patterns have classification in which in some directions they are regular, but they are irregular in other directions. For example Urial Sheep has irregularity in directions of 2&4 but Indian Breed has irregularity in all directions.

Our investigation shows that some of the animal fiber scale patterns like Urial Ship cannot be classified in just irregular or regular clusters, since these scales are regular in some directions and irregular in others.

Waved percentage of scales can be calculated by the chain code variation. If the fiber is regular, characteristics of fiber can be recognized by statistical pattern recognition, which in most cases is a linear classification. But if at least one of the fibers that are compared with others has characteristic of irregularity, the classification of fibers encounter with difficulty but the irregularity or regularity can be used as fiber characteristics for the classification of animal fiber scale characteristics.

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Appendix: Gradient 5×5 Kernel

SW/Edge						SE/Edge						NE/Edge						NW/Edge				
0	0	1	1	1		1	1	1	0	0		0	0	-1	-1	-1		-1	-1	-1	0	0
0	0	2	2	1		1	2	2	0	0		0	0	-2	-2	-1		-1	-2	-2	0	0
-1	-2	0	2	1		1	2	0	-2	-1		1	2	0	-2	-1		-1	-2	0	2	1
-1	-2	-2	0	0		0	0	-2	-2	-1		1	2	2	0	0		0	0	2	2	1
-1	-1	-1	0	0		0	0	-1	-1	-1		1	1	1	0	0		0	0	1	1	1

[i] Fig.2) Scots black face from coarse wool fiber is regular mosaic. [Wil54]

[iii] Symbols such as (·)=Fig.2, (*)=Fig.5a, (Δ)=Fig.5b,(□)=Fig.5c,(+)=Fig.5d,(◊)=Fig.5e.