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Identification of Animal Fibers with Wavelet Texture Analysis

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Abstract— **This paper presents the use of the wavelet transform to extract fiber surface texture features for classifying cashmere and superfine merino wool fibers. Extracting features from brightness variations caused by the cuticular scale height, shape and interval provides an effective way for characterizing different animal fibers and subsequently classifying them. This may enable the development of a completely automated and objective system for animal fiber identification.**

Index Terms— **Cashmere fibers, image analysis, Merino fibers, wavelet texture analysis.**

I. Introduction

Cashmere is an expensive and rare animal fiber used to produce soft and luxurious apparel. As cashmere processing capacity outstrips available supplies of cashmere, some cashmere processors use superfine merino wool (19 µm and finer) to blend with cashmere. Cashmere wool blends provide the high quality worsted (twisted and spun from long staple fibers) suiting fabric [1] and produces a lower cost product while exploiting the positive market perceptions associated with the luxury cashmere content. Labeling textiles to indicate their composition in such blends is required from both technical and marketing perspectives.

Current standard test methods for analyzing blends of specialty fibers with sheep's wool are based on scanning electron microscopy (SEM) (IWTO test method 58) [2] and light microscopy (LM) (AATCC test method 20A-2000 [3] and [4] American Society for Testing and Materials (ASTM) method D629-88 [4]). The test accuracy that can be achieved depends largely on the operator's expertise with the visual/microscopic appearances of different fibers. The current operator-based methods are tedious and subjective. It is desirable to develop an objective, automatic method to identify and subsequently classify animal fibers.

A rational descriptive system of classifying the cuticular scale pattern of animal textile fibers was suggested by Wildman [5]. It consists of the following main features: the form of the scale margins, e.g., smooth, crenate (scalloped) or rippled; the distance apart of the external margins of the scales, e.g., close, distant or near; and the type of overall pattern, e.g., regular, irregular mosaic, waved or chevron. To develop an automatic method similar to the above system, various authors have used combinations of microscopy and image analysis together with statistical and neural network techniques [6-10]. Cuticular scale characteristics and scale height have been used as the main diagnostic features to classify wool and specialty fibers.

Scale parameters have been obtained using image processing techniques [10, 11]. They objectively describe the scale interval and scale shape, and form a basis for classification. However, the measurement of the scale parameters is based on a binary skeleton image, which has lost all the information of scale height. Converting the SEM or LM images into binary thin skeleton images needs complicated image processing techniques and loses the important scale height information.

The scale height has been shown to be an important classification parameter for wool/specialty fiber blends [8, 12-15]. By adding scale height to an array of scale pattern parameters [8], Robson greatly improved the accuracy in classifying the wool and cashmere fibers under study. However, as the variation in scale height depends on scale location along the fiber [16], the scale heights depend on the scales selected for measurement. For quantification of fiber blends, which requires a very large number of fibers, the measurement of scale height with techniques described by Robson [8] would be overly time-consuming.

As the scale pattern is determined by the visible shape, height of each scale and the scale interval, changes in scale pattern may occur along the fiber length. The fiber surface texture/overall pattern is actually composed of scale height, scale shape and scale interval. Features of the fiber surface texture would be more useful in distinguishing wool fibers from specialty fibers than parameters based on individual scales. The main objective of this work is to develop a reliable fiber classification system using advanced texture analysis – wavelet texture analysis. Specifically, the discrimination between cashmere fiber and the superfine merino fiber is considered.

II. Sample Image Preparation

Images of cashmere and superfine merino wool fibers were scanned from the reference collection Cashmere Fiber Distinction Atlas [17]. The cashmere fiber collection includes samples taken from 16 main production areas in China. The mean diameter of the cashmere fibers is 14-16 µm and that of the merino fibers is 16.5 µm. Fig. 1 shows

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representative images scanned from the source [17].

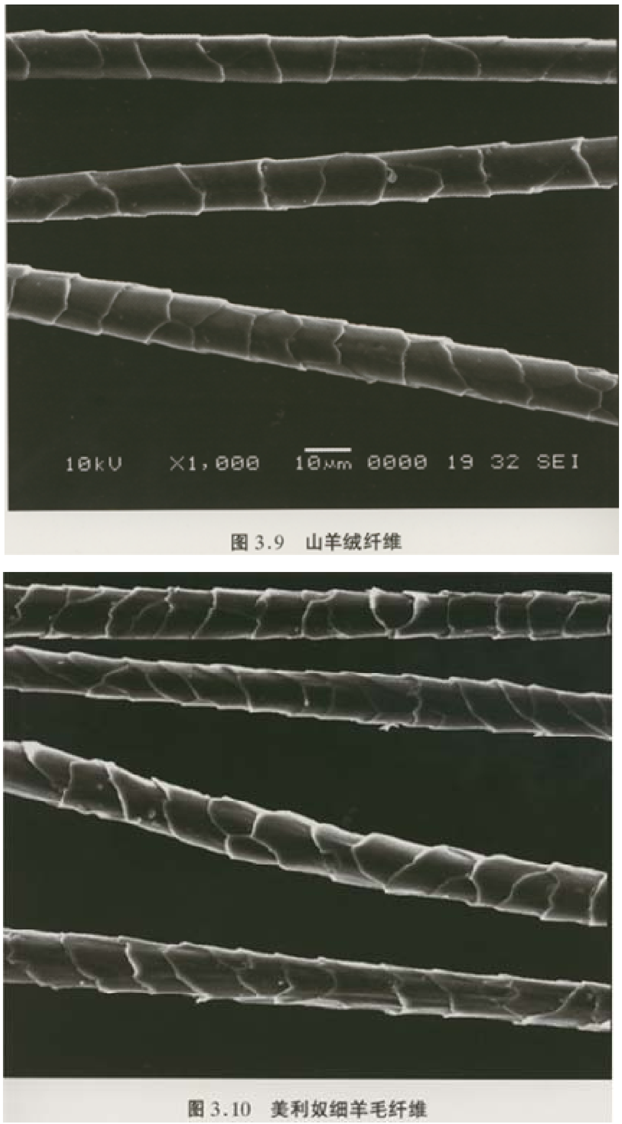

Fig. 1. Scanned images of cashmere fibers (upper) and Merino wool fibers (lower)

Individual fiber images were then cropped from the scanned image and placed in the centre of a 512×512 pixel black background (Fig. 2). All fiber images have been adjusted to the same contrast using Matlab function “imadjust”. From the Cashmere Fiber Distinction Atlas [17], 13 cashmere fiber images and 15 merino fiber images were prepared. The diameters of the cashmere and merino wool fibers range from 7.0 µm to 19.9 µm. The image preparation was performed using the Matlab Image Processing Toolbox [18].

III. Fiber Surface Texture Feature Extraction

Human vision researchers have found that the visual cortex can be modeled as a set of independent channels, each with a particular orientation and spatial frequency tuning [19]. These findings have been the basis for more recent approaches to texture using multiresolution or multichannel analysis such as Gabor filters [20, 21] and the wavelet transform [22-25]. The Gabor transform suffers from the difficulty that the output of Gabor filter banks is not mutually orthogonal, which may result in significant correlation

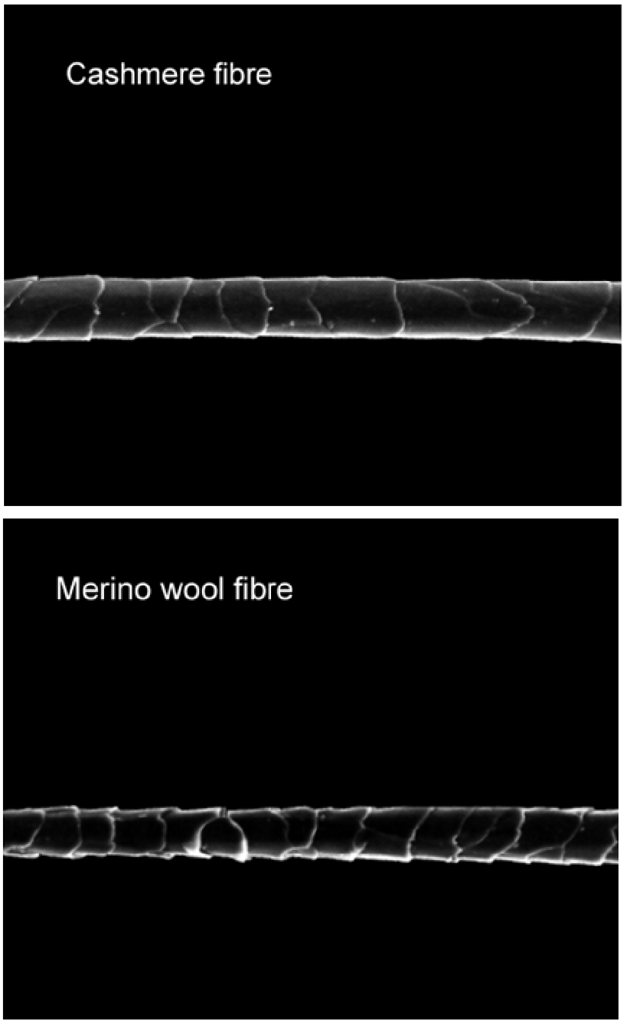

Fig. 2. Prepared sample images of cashmere fiber (11.0-13.9µm) (upper) and Merino wool fiber (7.0-10.9µm) (lower)

between texture features. It is usually not reversible, which limits its application to texture synthesis. Gabor filters require proper tuning of filter parameters at different scales (here ‘scale’ refers to different apparent size ranges in an image). By using the wavelet transform, most of these problems can be avoided. The wavelet transform provides a solid and unified mathematical framework for the analysis and characterization of an image at different scales [26-28]. The two-dimensional dual-tree complex wavelet transform (2DDTCWT) is an enhancement to the two-dimensional discrete wavelet transform, which yields nearly perfect reconstruction, an approximately analytic wavelet basis and directional selectiveness (±15º, ±45º, ±75º) in two dimensions. A detailed definition of the 2DDTCWT is available elsewhere [29]. It has been successfully applied, in a textile texture classification application, to the objective grading of fabric pilling [30].

By using 2DDTCWT, an image can be decomposed and reconstructed into single-scale only detail and approximation images. Fig. 3 displays the reconstructed scales 1 to 4 detail images and scale 4 approximation image from the cashmere fiber image in Fig. 2, where only the section that includes the fiber is displayed. The 2DDTCWT

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was performed using the wavelet software from Brooklyn Polytechnic University, NY [31].

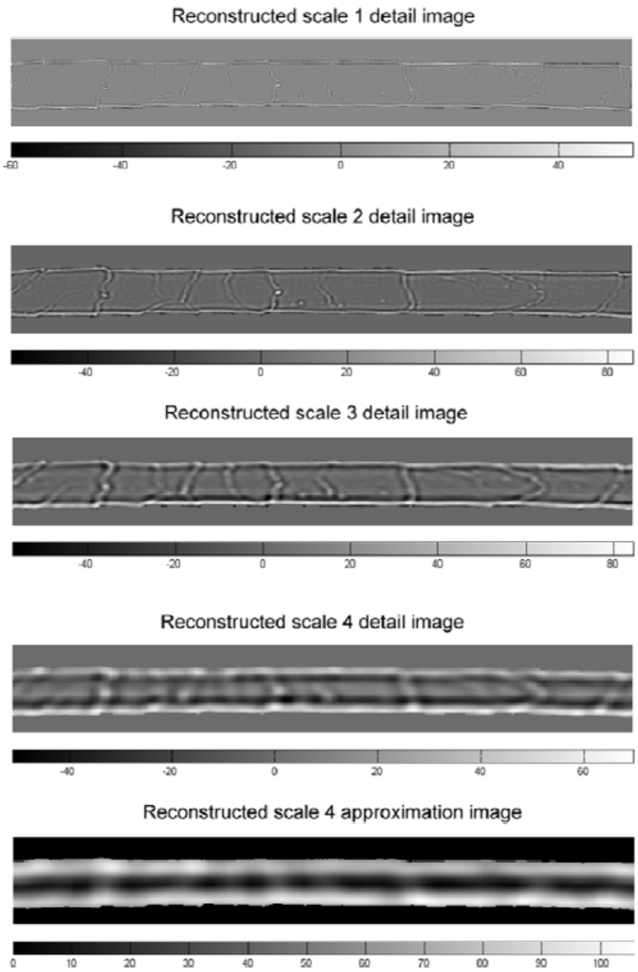

Fig. 3. Reconstructed scale 1 to 4 detail images, and scale 4 approximation image

The wavelet transform measures the image brightness variations at different scales/frequencies [26, 27]. From Fig. 3, it can be observed that the scale 4 (last scale) approximation image represents the lowest frequency brightness variation, that is the lighting or illumination variation, so it is not used to generate a textural feature. The scales 1 to 4 detail images measure the brightness variations of the cuticular scale edges at different scales/frequencies. The cuticular scale's height, shape and interval are directly related to the brightness variation at scale edges, therefore, the texture features extracted from these detail images are intended to be a comprehensive measurement of the scale height, scale shape and scale interval.

Each scale detail image consists of six directional (±15º, ±45º, ±75º) detail subimages, which represent the cuticular scale margins more effectively. Textural features are generated from the six directional detail subimages at scales 1 to 4. A commonly used textural feature is the normalized energy of the detail subimage. In this work, the analysis object is the fiber surface, and the texture feature is defined as:

$$E_{jk} = \tfrac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N} D_s^k(i, j)^2 \left(k = \pm 15°, \pm 45°, \pm 75°\right) \qquad (1)$$

Where $M\times N$ is the size of the fiber surface image, and $D_s^k(i, j)$ are the pixel grey-scale values of fiber surface image in scale *s* and direction *k*.

IV. Results and Discussion

From each of the 28 fiber images, a texture feature vector consisting of 24 (6 orientations x 4 scales) energy features was developed. Principal component analysis [32] was used to reduce the dimension of the texture feature vector. Principal component analysis is a quantitatively rigorous method for achieving this simplification. The method generates a new set of variables, called principal components. Each principal component is a linear combination of the original variables. All the principal components are orthogonal to each other, so there is no redundant information. The principal components, as a whole, form an orthogonal basis for the space of the data. Fig. 4 shows the amount of variance accounted for by each component. Principal components 9 through to 24 explain less than 0.176% of the variance, which is sufficiently close to zero. Thus eight is effectively the actual dimensionality of the 28×24 texture feature vector data. Principal component analysis was carried out using the Matlab Statistics Toolbox "princomp" function [33]. The principal component scores (28×8), which are the original 28×24 data mapped into the new coordinate system defined by the eight principal components, are used as the input of classifier.

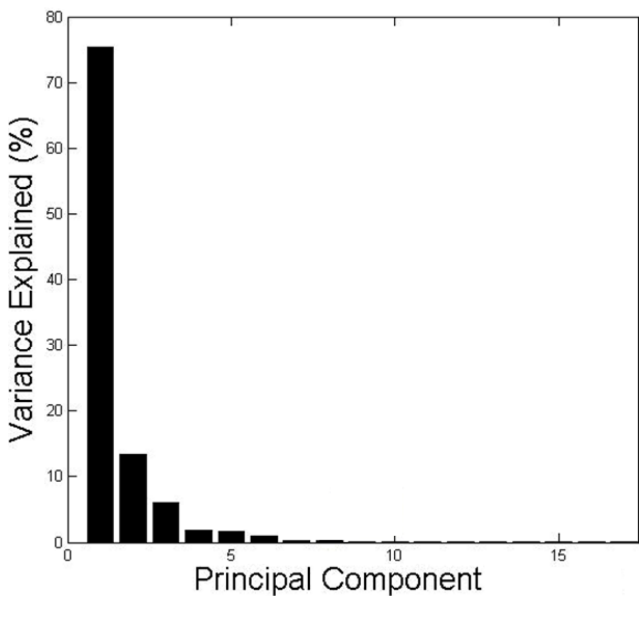

Fig. 4. Variance explained by principal components

Models of data with a categorical response are called classifiers. A classifier is built from training data, for which the classifications are known. The classifier then assigns new data to one of the categorical levels of the response. Parametric methods, like discriminant analysis, fit a parametric model to the training data and interpolate to classify new data. Discriminant analysis was carried out by the Matlab Statistics Toolbox "classify" function [33], which uses quadratic discriminant function.

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Table I tabulates the results from the quadratic discriminant analysis. When the 28 samples are all used as training data, 27 samples out of the 28 samples are correctly classified.

Table I. Discriminant analysis results

Round	**1**	**2**	**3**	**4**	**5**
Training set size	28	26	24	22	20
Training correct no.	27	25	23	22	20
Testing set size	0	2	4	6	8
Testing correct no.	0	2	4	5	6

Fig. 5 shows the misclassified cashmere fiber and a wool fiber with the same range diameter. Based on fiber scale characteristics such as scale frequency and scale length, it is difficult to discern any difference visually. When 4 of 13 cashmere fibers and 4 of 15 merino wool fibers are selected for testing and the rest used for training, the trained classifier with zero misclassification error correctly predicts 6 samples out of the 8 samples. When the selected testing set number decreases, the accuracy of the testing set increases with the training set size.

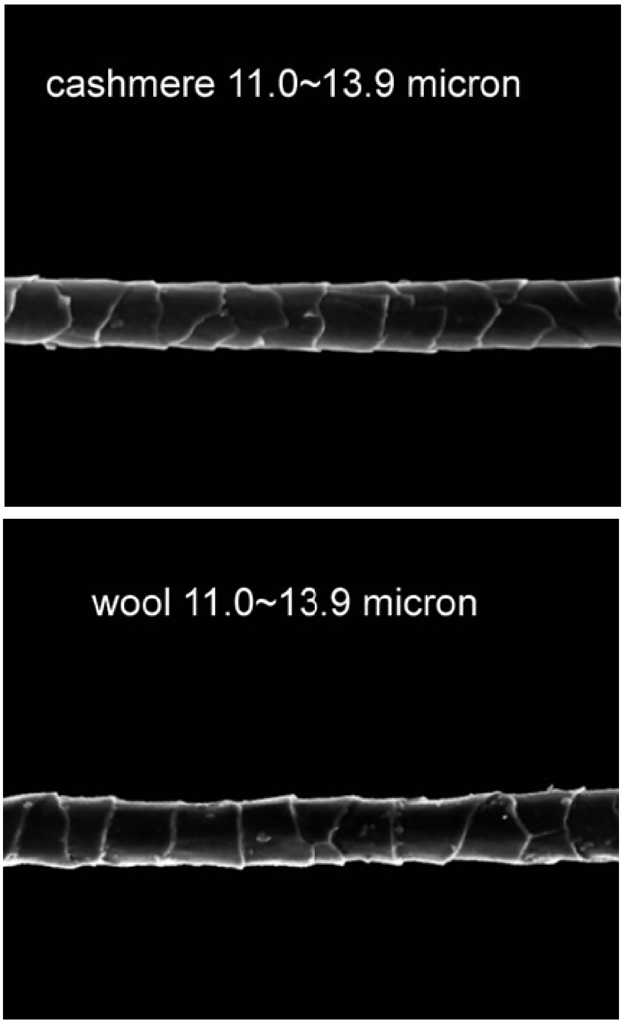

Fig. 5. Misclassified cashmere fiber (upper) and Merino wool fiber with the same diameter (lower) – 1 micron = 1 µm

V. Allied and Future Work

In related work using wavelet texture analysis as the basis for the objective classification of fabric surface pilling (pills are entanglements of fibers that arise from wear that stand proud of the surface of a fabric), it has been shown that the performance of the texture classification method can be significantly improved by using a multilayer perceptron artificial neural network to perform the task of classifying the results of the principal component analysis. Pilling evaluation is traditionally performed manually by an 'expert' comparing a fabric test sample to a set of standard pilling images. The evaluation produces a pilling rating in the range from 1 (heavily pilled) to 5 (no pilling). This expert rating process relies on the subjective experience of the rater.

Using a large set of 203 pilled fabric samples that had been previously rated for pilling intensity by an expert rater, a wavelet texture analysis method was employed to develop an objective pilling rating method. All of the fabric samples were imaged using a digital camera. As described above, the 2DDTCWT was used to decompose and reconstruct the sample images into their single-scale detail and approximation images. It was observed that the pilling features were predominately localized in two detail scales. From each of the 203 fabric images, a texture feature vector consisting of 12 (6 orientation x 2 scales) energy features (using (1)) was developed. Principal component analysis revealed that 87% of the variation in the texture feature vector was contained in the first principal component, and only minor proportions of the variation distributed amongst the remaining components. Based on this result, the single transformed first principal component consisting 12 pilling texture features was used as the basis for classification.

A neural network classifier was constructed comprising 12 linear input neurons (1 for each pilling texture feature), 7 nonlinear (tan-sigmoid) hidden neurons in a single layer, and 1 linear output neuron to provide a floating point pilling rating. Two thirds of the fabric image sample set was used to train the neural network. Following training, the remaining 68 image samples were presented to the neural network as test samples for automatic classification. Fig. 6 gives the test sample rating results from the neural network classifier (in black), paired with the original human expert rating (in white) for the same fabric sample. Note that the result pairs are ordered/grouped using the expert pilling ratings, creating the 'staircase' appearance in Fig. 6 and indicating the relative proportions of the 5 pilling ratings in the fabric sample set.

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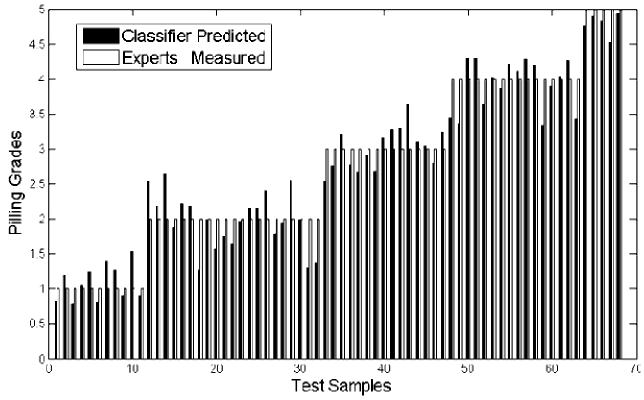

Fig. 6. Artificial neural network pilling classification results

The difference between the classifier test results and the expert measured grades for the test subset samples ranges from -0.81 to 0.69 pilling grades. If the classifier test results are converted to integer values, only a handful of test samples are misclassified, when compared to the expert ratings. As with the misclassified cashmere sample noted previously, it was difficult to visually discern the difference between the pilling ratings of the fabric samples in question. This perhaps raises as many questions about the human expert rating ability as it does about the accuracy of the automatic classification. Many human expert pilling raters claim the ability to interpolate half-interval pilling intensity ratings based on comparisons of fabric samples to a standard pilling image set. The ability of the neural network classifier to produce a floating point output rating can match this purported precision rating precision.

The very good results obtained in the application of automated pilling intensity rating based on wavelet texture analysis combined with neural network classification suggest a number of logical extensions of, and future work for, the application of wavelet texture analysis to the task of automatic identification of cashmere and other specialty fibers, including:

1) the use of a neural network to perform the task of classifying the results of the principal component analysis;
2) the testing of the performance of the wavelet texture analysis method of the fiber identification on a larger set of real cashmere and other fiber samples; and
3) the application of the wavelet texture analysis method to the of task analyzing/assaying blends of specialty fibers – the determination of the relative component fiber proportions in cashmere-merino blends is of particular interest.

VI. Conclusion

This paper demonstrates the feasibility of using wavelet texture analysis in classifying cashmere and superfine merino wool fibers. By using the two-dimensional dual-tree complex wavelet transform (2DDTCWT) decomposition and reconstruction, an effective way to extract features that represent cuticular scale height, scale shape and scale interval is provided, which is needed to develop an automated and objective system for animal fiber distinction. While this preliminary study has used existing SEM images of cashmere and wool for analysis, work is on-going to examine the feasibility of using fiber images from simple optical microscopes for a similar analysis. Further work is also planned to employ an artificial neural network as the classifier element, based on the good performance obtained in a similar textile texture classification application.

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The fiber images presented in Fig. 1, and the source images from which Fig. 2 and Fig. 5 are derived, are the copyright property of Inner Mongolia Erdos Cashmere Group and are reproduced with their permission.

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