A high-precision automatic state monitoring and abnormality alarm technique is proposed to solve the process improvement issues of fiber-optic coil winding and splicing. Industrial cameras are used to capture optical and hot images during the assembly of optical components of a fiber-optic gyroscope. A line and contour analysis technique is used to detect abnormal winding. By analyzing the intensity distribution of transmitted light, the graph cut model and multivariate Gaussian mixture model are used to detect and segment the splicing defects. The practical applications indicate the correctness and accuracy of our vision-based technique.

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The fiber-optic coil is one of the most important components of fiber-optic gyroscopes[1]. Fiber-optic gyroscopes use polarization lights to detect changes in angular rate according to the Sagnac effect. Thus, the fiber-optic coil functions in multiple light transmission[2]. Many studies[3−5] have proven that the winding process of a fiber-optic coil has distinct influences on the output precision of a gyroscope. For example, in Ref. [4], the authors have built the finite element model of a typical coil winding mode to study the effects of structural parameters, thermal parameters, and temperature disturbed parameters on the Shupe error of fiber-optic gyroscope. Thus, the assemblage technique of this coil is an extremely important operation process in gyroscope manufacture.

Currently, at least two kinds of pivotal operation are correlated with this issue, namely, winding and splicing operations. Figure 1 shows the typical optical component diagram of a kind of fiber-optic gyroscope. When assembling the optical module, the fiber-optic coil is firstly wound in a quadrupole symmetrical pattern[3]. The ends of the fiber-optic coil are then spliced with the ends of a Y-junction optical waveguide with a polarization maintaining (PM) fiber splicer. Finally, all other ends such as light source, coupler, and detector are spliced by other single-mode or multi-mode fiber splicer. Traditionally, the winding and splicing operations are all manually completed. The burdensome labor of engineers inevitably brings errors. To address these problems, we use the machine vision technique together with pattern recognition theory to replace people with intelligent machines and improve their working reliability.

Figure 2 shows the winding process diagram of a fiber-optic coil. The winding process involves rolling and wrapping fibers on the surface of a skeleton based on a quadrupole symmetrical pattern. This winding pattern demands fibers to be tidily arrayed with one another without any interspace or interleaving between neighboring wires. Given that the high-output precision of a fiber-optic gyroscope requires a long light transmission distance of a fiber-optic coil (i.e., the length requirement may be more than hundreds of meters), the winding and surveillance processes inevitably consume several hours or days. As a result, abnormal winding occasionally occurs. Figure 2(b) shows the normal winding mode, whereas Fig. 2(c) depicts the result of the abnormal winding mode.

To solve the abnormal detection problem, two kinds of image analysis methods are utilized. Figure 2 (a) shows the section plane image of the winding process. Firstly, we use the parallel detection technique to guarantee accurate orderliness of wound fibers. The image contents within the red rectangle in dashed line show the array of paratactic fibers. Once the parallel mode is broken, an abnormal alert should be reported. The line detection method of Hough transformation[6] can be used to judge the juggling line phenomenon. Secondly, a contour anal-

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ysis method\textsuperscript{[7]} is used to identify the abnormality edge of the fiber-optic coil image. The image included within the green rectangle in dashed line displays the winding edge of fibers. The similar arc and pixel number of each line end can be observed in turns except for abnormal modes.

Figure 3 shows the line and edge contour detection results. Given that the abnormality detection of the winding process has a real-time request, complex processing methods cannot be used. We set the underside region of the winding machine as the region of interest (ROI) to implement the feature analysis task. Figure 3(a) shows that after setting the ROI, the Hough line detection method can be used to identify abnormality: if the slope of line detection result markedly differs from the history value, we conclude the occurrence of abnormality. Figure 3(b) shows the edge contour detection result.

Firstly, the morphological method of the following formula

\[ I_{\text{edge}} = \frac{1}{N} \sum_{i=1}^{N} \{ [(I_{\text{ROI}} \oplus B_i) - (I_{\text{ROI}} \Theta B_i)] \Theta B_{i-1} \} \]

is used to extract contour, where \( I_{\text{edge}} \) and \( R_{\text{abnormality}} \) are the processing results of edge and abnormality detection, respectively. Symbols "\( \oplus \)" and "\( \Theta \)" denote dilation and erosion operations, respectively. \( B_i \) is a morphological rectangle operator with size \( 5 \times 5 \). All its elements equal "1". Then, we compute the contour difference among selected images based on

\[ R_{\text{abnormality}} = \begin{cases} 1 & I(t = t_1) - I(t = t_0) > T_{\text{winding}}, \\ 0 & \text{else} \end{cases} \]

where \( T_{\text{winding}} \) is a threshold, and \( t_0 \) and \( t_1 \) are the specific time points \( (t_1 > t_0) \).

The time-point selection rule of images \( I(t = t_1) \) and \( I(t = t_0) \) should be related to the working speed of the winding machine. This rule guarantees that the increment of edge contour is smaller than a threshold in the time axis. For example, if the fiber-optic coil number appearing in the former image \( (t = t_0) \) is \( n \), a proper capture time \( t_1 \) can be selected only when the coil number in the latter image is \( n+1 \) or \( n+2 \). Finally, once the pixel number of contour difference exceeds this threshold, an abnormality should also be reported.

In this letter, a defect segmentation method with illumination prior is proposed to monitor the process of fiber splicing. Figure 4 shows the splicing sketch map and their image samples, while splicing fibers\textsuperscript{[8]}, we initially peel off the jackets. Then, we place cladding and core into the fiber splicer after the surfaces are cleaned. Next, the splicing machine heats these two fibers by current until a proper polarization observation by lens-effect-tracing.
where \( I_i \) is the gray of pixel; \( x_i = 1 \) or 0 denotes the \( i \)th pixel belonging to the foreground or background; \( \mu \) denotes means; \( \sigma \) denotes variances; subscripts “F” and “B” are the foreground and background, respectively; \( \sigma_n \) is the image noise; and dist \((p, q)\) is a distance metric.

Obviously, \( E_1 \) calculates edge weights between each pixel and terminal points, whereas \( E_2 \) estimates edge weights among neighboring pixels. Although these energy functions can solve the segmentation problem to some extent, more prior information should be considered to improve precision.

The design of \( E_3 \) considers the illumination prior of transmitted light\([10,11]\). Let us take the ellipse-type PM fiber as an example. Figure 4(a) shows that the transmission of light from one side to the other is complex, i.e., reflection, refraction, and intensity distribution of light are all relative to the wavelength, light incident angle, or refractive index and reflectivity of a material \( et al.\)[12]. In Ref. [13], the authors used an analytical method of simulating polarized light transportation in biological tissue samples. The Gaussian function is used to imitate the intensity distribution of laser. Yu \( et al.\)[14] used a Gaussian pulse to test the light propagation characteristic. Without loss of generality, we also take the Gaussian distribution assumption of transmitted ray to be true in this letter. However, different from a laser, the transmitted rays originate from a surface light source. To simulate the surface light source, the complex Monte Carlo method\([15,16]\) is always used to determine its distribution. Fortunately, a fiber can focus surface rays like a convex because of its cylindrical shape. Thus, by considering the intensity distribution of transmitted light as a multivariate Gaussian mixture model (MGMM)\([17]\), we can avoid the complex modeling process of Monte Carlo. Figure 5(a) shows the simplified transmitted light sketch map of fiber splicing implemented with an Ericsson FSU-995PM fiber splicer. Figure 5(b) shows the spliced image samples. Figure 5(c) shows the distribution simulation of two-component MGMM. The intensity distribution shapes of MGMM and spliced fibers are found to be similar to each other.

In this letter, we suppose that the intensity distribution of spliced fibers in normal mode obeys the MGMM form. The intensity distribution shapes of MGMM and spliced fibers are found to be similar to each other.

Table 1. Energy Function \( E_1 \) of GCM

<table>
<thead>
<tr>
<th>Edge Type</th>
<th>Weight</th>
<th>Vertex Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( p, s )</td>
<td>( f_p^f )</td>
<td>( p \notin F \cup B )</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>( p \in F )</td>
</tr>
<tr>
<td></td>
<td>( C )</td>
<td>( p \in B )</td>
</tr>
<tr>
<td>( p, t )</td>
<td>( f_p^B )</td>
<td>( p \notin F \cup B )</td>
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<td></td>
<td>( C )</td>
<td>( p \in F )</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>( p \in B )</td>
</tr>
</tbody>
</table>

Fig. 5. (a) Sketch map, (b) image samples, and (c) intensity imitation of transmitted light.

Fig. 6. Defect segmentation results of GCM. (a) and (e) are the original images. (b) and (f) are the segmentation results of GCM using only \( E_1 \) and \( E_2 \) functions. (c) and (g) are the manually obtained segmentation results. (d) and (h) are the results of GCM using \( E_1 \), \( E_2 \), and \( E_3 \) together.

Thus, \( E_3 \) can be estimated by

\[
E_3 = \begin{cases} 
K & \text{if} \quad I_i - \hat{I}_i > T_0 \\
0 & \text{else}
\end{cases}
\]

(8)

where \( X \) is the image intensity, \( U_i \) and \( \Sigma_i \) are the mean and covariance vectors of the MGMM component, respectively; \( \varpi_i \) denotes weights; \( \sum_{i=1}^{K} \varpi_i = 1, \varpi_i \geq 0; I_i \) and \( \hat{I}_i \) are the original and estimated image intensities, respectively; \( K \) is a constant; \( T_0 \) is a threshold.

Once the defective mode occurs, some bright light spots appear at the center of fiber joint. Thus, when calculating \( E_3 \), we select initial pixels at the outside regions of the spliced image, e.g., pixels within the yellow rectangle in Fig. 5(b), to estimate the MGMM parameters. The expectation-maximization algorithm\([18]\) is used to implement parameter estimation. After calculating the coefficients, we can use this model to compute the intensity distribution \( \hat{I}_i = F(X) \) at the center region of the image where the emergence probability of defects is always high. Finally, we can use the difference between
the actual image intensity $I_i$ and estimated $\hat{I}_i$ to calculate $E_3$.

Figure 6 shows the defect segmentation results. Before we use GCM for elaborated computation, the flood fill algorithm$^8$ is used to identify initial segmentation. The control parameters of flood fill algorithm for guaranteeing a smaller segmentation region than the actual defective region are very easy to set. Figure 6 shows that our proposed method has a better segmentation effect than the traditional method. The highlighted region in the middle axis is always troublesome when segmenting the defective region because they have similar gray values with defective pixels. Thus, with the accessoril constraint of $E_3$, the pixels in the highlighted axis can be classified as the background. Figures 6(e) and (f) also notice some small spots at the right-top and bottom sides. These spots are always the tiny impurities attached onto the surface of fibers. Thus, we do not regard them as defects because of their small sizes.

In conclusion, a high-precision automatic state monitoring and abnomrity detection method for the winding and splicing of fiber-optic coil is proposed. Hough line detection and morphology-based contour segmentation techniques are used to monitor the juggling line issue of fiber-optic coil winding. A GCM with MGMM illumination priors is proposed to segment the defect of a spliced fiber. Many experimental results show the correctness and validity of our techniques.

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References