CHAPTER 6

IMAGE ENHANCEMENT

6.1 GENERAL

In surface roughness studies using machine vision, the material surface is not contacted for making measurement. Only the captured image of the surface is analysed for roughness correlation. Hence, any improvement in the measurement studies can be made on the captured image. Many image-processing algorithms are used in the studies on machine vision to improve the features of the image and retrieve the required information. In this direction, an attempt is made to improve the features of images of the machined surface by applying different edge-enhancing operators.

Most of the machining operations are identified by the tool marks or grooves present on the surface. The tool marks indents are present in the manner the metal surface is being machined. The traditional surface roughness measurement using the stylus instruments is made by moving the tip perpendicular to the lay pattern. The surface irregularities of the tool marks contribute for the $R_a$ – the average roughness. Hence, the tool marks play a major role in surface roughness estimation.

In the image analysis also, the variation in the texture pattern along the tool marks are analysed for roughness correlation. The spatial distribution of the grey level in the region are analysed by different methods and optical features correlated with the stylus roughness. In this work, the variation of the
texture is enhanced by different edge-enhancing operators and the correlation with stylus roughness is studied.

6.2 EDGE OPERATORS

The most important step in image processing is to identify features in images that are relevant in estimating the structures and properties of objects in a scene. Edges are one such feature. Edges are significant local changes in the intensities of the image and are important features for analysing the images (Hedengren 1998, Rosenfeld and Thurston 1971, Tsai and Hsieh 1999). In image analysis, edge detection or edge enhancing is frequently the first step in retrieving information from the images.

In the images of the surface captured by the vision system, the tool marks / lay pattern appear as lines or curves with grey bands. The intensity of the grey level varies with the depth of tool marks. This variation in the intensities over an area / region or along a line is normally studied for roughness correlation. In this study, the changes in the intensity on the neighbourhood are considered as edges and the different edge-enhancing operators are applied on the image. The image-based roughness features are estimated from different edge-enhanced images and analysed. Few of the edge-enhancing operators based on first-order and second-order derivatives such as Sobel, Laplacian, Laplacian of Gaussian and combination of the operators are applied on the image and analysed.

6.3 FIRST-ORDER DERIVATIVES

Edge detection is a context-independent process where the same operation is performed for each pixel, independent of the position. It is
essentially the operation of detecting significant local changes in an image. An image can be considered to be an array of samples of same continuous function of image intensity. In one dimension, a step edge is associated with a local peak in the first derivative. The gradient is a measure of the change in a function. Changes in the grey value in an image can be detected by using a derivative approximation to the gradient. Each pixel is often associated by a weighted combination of the pixels in the local region. A kernel with the size of the local region, is created and filled with coefficients that correspond to the weights. The gradient is the two-dimensional equivalent of the first derivative. Many edge operators for the gradient measurement have been developed in the past. They differ in the use of the computational approach. Some of the edge-enhancing operators are discussed below:

6.3.1 Robert’s Edge Operator

The Roberts cross operator provides a simple approach to the gradient magnitude using a 2 x 2 convolution mask. This becomes

$$G[f(i,j)] = |G_x| + |G_y|$$

where $G_x$ and $G_y$ are calculated using the following masks:

$$G_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \quad G_y = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

The Robert’s operator is an approximation to the gradient at the interpolated point $(i+1/2, j+1/2)$ and not at the point.
6.3.2 Sobel Edge Operator

The sobel operator avoids the gradient calculated at the interpolated point and finds the gradient at the point. In this technique, a 3 x 3 convolution mask / gradient operator is used for the gradient calculation. The assignment of the pixels about the pixels \([i, j]\) is shown in Figure 6.1. This template is then convolved with the whole image to create a new edge-enhanced image.

\[
\begin{array}{ccc}
  a_0 & a_1 & a_2 \\
  a_7 & [i,j] & a_3 \\
  a_6 & a_5 & a_4 \\
\end{array}
\]

**Figure 6.1** Labeling of neighbourhood pixels

The partial derivatives (Jain et al 1995) are computed by

\[
s_x = (a_2 + ca_i + a_4) - (a_0 + ca_7 + a_6) \quad (6.1)
\]

\[
s_y = (a_0 + ca_i + a_2) - (a_6 + ca_5 + a_4) \quad (6.2)
\]

\(s_x\) and \(s_y\) are calculated using equations (6.1) and (6.2) with the constant \(c = 2\). This operator emphasis on pixels that are closer to the centre of the mask. \(s_x\) and \(s_y\) can be implemented using convolution masks shown in Figure 6.2.

\[
\begin{array}{ccc}
  -1 & 0 & 1 \\
  -2 & 0 & 2 \\
  -1 & 0 & 1 \\
\end{array}
\]

(a)

\[
\begin{array}{ccc}
  1 & 2 & 1 \\
  0 & 0 & 0 \\
  -1 & -2 & -1 \\
\end{array}
\]

(b)

**Figure 6.2** Convolution mask for Sobel operator (a) \(s_x\) (b) \(s_y\)
6.3.3 Prewitt Edge Operator

The Prewitt edge operator uses the same equation as the Sobel edge operator, except that the constant \( c = 1 \). The convolution mask for the Prewitt operator is shown in Figure 6.3.

\[
\begin{array}{ccc}
-1 & 0 & 1 \\
-1 & 0 & 1 \\
-1 & 0 & 1 \\
\end{array}
\quad
\begin{array}{ccc}
1 & 1 & 1 \\
0 & 0 & 0 \\
-1 & -1 & -1 \\
\end{array}
\]

(a) (b)

Figure 6.3 Convolution mask for Prewitt operator (a) \( s_x \) (b) \( s_y \)

Unlike the Sobel edge operator, the Prewitt edge operator does not place any emphasis on centre pixels and all neighbouring pixels are given the same weights.

6.4 SECOND-ORDER DERIVATIVES

When the first derivative computed is above a threshold, the presence of an edge point is assumed. This results in detection of too many edges. A better approach will be to find only the points that have a peak in the first derivative and equivalently zero crossing in the second derivative (Jain et al 1995). The edge points are detected by finding the zero crossings of the second derivative of the image intensity.

Considering Figure 6.4, if a threshold is used for the detection of edges, all the points between ‘a’ and ‘b’ will be marked as edge pixels. However, by removing the points that are not local maximum in the first derivative, edges may be detected more accurately. This local maximum is the first derivative corresponding to the zero crossing in the second derivative.
The Laplacian is the 2-D equivalent of the second derivative. The following mask (Figure 6.5) can be used for approximating the Laplacian:

\[
\begin{array}{ccc}
1 & 1 & 1 \\
1 & -8 & 1 \\
1 & 1 & 1 \\
\end{array}
\]

The Laplacian operator signals the presence of an edge when the output of the operator makes a transition through zero.

The edge parts detected by finding the zero crossings of the second derivative of the image intensity are very sensitive to noise. Therefore, it is desirable to filter out the noise before edge enhancement. The Laplacian of Gaussian will be helpful to reduce the effect of noise. In this approach, an image is convolved with a Gaussian filter. This step smoothens the image and
reduces the noise. Isolated noise points and small structures are filtered out. The Laplacian is used as the approximation of the second derivative.

The output of the LoG operator, $h(x,y)$ is obtained by the convolution operation

$$h(x,y) = \nabla^2[(g(x,y) * f(x,y))]$$  \hspace{1cm} (6.3)

Using the derivative rule for convolution,

$$h(x,y) = [\nabla^2(g(x,y))] * f(x,y)$$  \hspace{1cm} (6.4)

where

$$\nabla^2 g(x,y) = \left( \frac{x^2 + y^2 + 2\sigma^2}{\sigma^4} \right) e^{\frac{-(x^2 + y^2)}{2\sigma^2}}$$

6.5 IMAGE ENHANCEMENT

In the field of image processing, no one technique is considered as the best for enhancing the images. A given enhancement task will require application of a specific technique or a combination of several complementary techniques in order to achieve an acceptable result. In this work also, different techniques are combined with the objective of enhancing the image so that the optical features retrieved from the image better correlate with the actual roughness. The strategy followed in this application is to apply the Laplacian operator for highlighting the fine details and the Sobel edge operator for enhancing the prominent edges.

Application of edge operators or combination of different operators for enhancing the images is often tried in the field of image processing.
Kassim et al (2000) in their study on machine tool condition monitoring have utilised the Sobel edge operator, while extracting the edge information from the image of machined surface. The column projection method and run length matrix are used for correlating the tool condition with the stylus roughness. Feng and Chen (2007), on grinding wear measurement, used the Sobel edge operator for finding the edges of the worn out portion. Combining with morphological operation, it was possible to find the area of the worn-out part. Sortino (2003) combined different edge-detecting statistical techniques in the detection of tool wear using machine vision. Sub-pixel edge detection and Zernike moments operator were used along with the Sobel edge operator to locate precisely the edge points in the study made by Dong et al (2005).

The captured images of the milling and the grinding operations are studied for image enhancement. Sub-images of 400 x 400 pixel size are selected for study. The edge operators Laplacian, Laplacian of Gaussian (LoG), Sobel and the combination of different operators are applied on different images. The image-based parameter the arithmetic average of the grey level is estimated from all the images and compared with the stylus roughness.

6.6 RESULTS AND DISCUSSION

The edge operator, the Laplacian filter is an isotropic filter whose response is independent of the derivative of the discontinuity in the image to which filter is applied. They are rotation invariant in the sense that rotating the image and then applying the filter gives the same result as applying the filter to the image first and then rotating the result. Laplacian is a derivative operator and its use highlights the grey level discontinuities in the image and de-emphasize region with slowly varying grey levels. Being a
second-order derivative, it has the advantage of being superior in enhancing the fine detail (Gonzalez 2002).

Figure 6.6 shows the images of a mild steel-milling specimen, before and after applying the different edge-enhancing operators. The variation in the intensities of the tool marks after applying the different edge operators on the original image is shown in Figure 6.6. The variation of the grey level intensity along a line, before and after applying the edge operators are shown in Figure 6.7. Figure 6.7(a) shows the profile of the original image. It can be seen in Figure 6.7(b) that in the positions where there is a peak or valley in the original, there is a sharp transition in the grey level intensity in the Laplacian image. It can be seen in the Laplacian image that there are lot of peaks when compared to the original profile, which indicates that all the variations in the grey level intensities are highlighted after applying the Laplacian operator. When comparing the original and the transformed image, the higher peaks in the original are less disturbed when compared to the slowly varying profile. This indicates that the finer details are taken into consideration in the application of Laplacian operator.

In the application of Laplacian operator, even a smaller noise present in the image will be highlighted. Hence, the noise may also cause peaks and valleys in the image. The response to the noise can be reduced by applying a smoothening filter (Gonzalez 2002). The smoothening operator, the Gaussian operator is applied on the Laplacian image. This operator averages the noise present in the image. Figure 6.7(c) shows the image after applying Laplacian of Gaussian. When compared to Laplacian image, it can be seen that the number of peaks and valleys in the lesser slope region has reduced.
Figure 6.6 Images of the specimen after applying edge-enhancement operation
In image analysis, when the edges are running in different directions, application of rotationally invariant edge operators like LoG or Laplacian will produce the same result. Whereas, rotationally variant edge operators like Sobel operators produce different result.

In this study, the images of the specimen are captured in such a way that the tool marks are parallel to the edges of the image. As the images are having strong directionality, the rotation variant Sobel edge operator, which has an influence on prominent tool marks, are applied on the image. The Sobel edge operator is applied on the image so that all the horizontal edges will get predominant and sharpened in the image. Considering the different edge operators, the gradient has a stronger response in the areas of significant grey level transition. The response of the gradient to noise and fine detail is lower than the Laplacian.

In Figure 6.7(d), it can be seen that wherever there is a high peak in the original image, the transition from high level to low level is high in the sobel-filtered image. When the slope is less, the transition almost remains the same which indicates that only high level transition are highlighted. When a Sobel filter is applied on the image, the edges will be more dominant than the Laplacian image.

Hence by applying a Sobel operation, the high transition is highlighted and by applying the Laplacian, even the smaller variations are highlighted. Hence, to enhance the image, both the operators are applied on the image and added to get a sharpened image. Figure 6.7(e) shows the image, which is obtained by adding the Sobel image and Laplacian image. It can be seen from the figure that the transition of grey level are identified in the higher peak as well in the valley portion of the image. An averaging operator is applied on the image to reduce the effect of noise present in the image. The
significant increase in sharpness of the details in the image over the original is evident in most part of the images. This type of improvement will not have been possible by using Laplacian operator or Sobel operator alone.

The $G_a$ values obtained from the same positions in the image after applying the edge operations is shown in Table 6.1 for mild steel milling specimen and Table 6.2 for the grinding specimens. Figures 6.8 and 6.9 show the variation of $G_a$ value with surface roughness. It can be seen from the graph that the $G_a$ values are higher when the edge-enhancing operations are done on the image, which indicates that the grey level variations are highlighted after processing of the image.

The correlation coefficient obtained between the $G_a$ value and the stylus roughness for different images is shown in Table 6.3. From Table 6.3, it can be seen that the correlation coefficient of $G_a$ value with roughness increases for the milling and grinding specimens when the edge operators are applied on the image. However, when the images are enhanced with the combination of the Sobel and the Laplacian operators, the correlation coefficient is higher. This implies that the combination of the edge operations can give better result.
Figure 6.7 Variation of the grey level along a line at the same position for the enhanced images
### Table 6.1 \( G_a \) values obtained from the different images – milling

<table>
<thead>
<tr>
<th>S.No</th>
<th>Stylus roughness ( \mu m ) - ( R_a )</th>
<th>The ( G_a ) value obtained from the images after enhancement</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Original</td>
</tr>
<tr>
<td>1</td>
<td>0.58</td>
<td>8.41</td>
</tr>
<tr>
<td>2</td>
<td>3.20</td>
<td>14.42</td>
</tr>
<tr>
<td>3</td>
<td>2.18</td>
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<td>4</td>
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<td>21.68</td>
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<tr>
<td>5</td>
<td>2.76</td>
<td>14.08</td>
</tr>
<tr>
<td>6</td>
<td>2.52</td>
<td>16.22</td>
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<tr>
<td>7</td>
<td>3.02</td>
<td>16.37</td>
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<td>21.87</td>
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<td>9.21</td>
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<tr>
<td>10</td>
<td>6.78</td>
<td>23.78</td>
</tr>
<tr>
<td>11</td>
<td>4.04</td>
<td>19.11</td>
</tr>
<tr>
<td>12</td>
<td>4.40</td>
<td>17.86</td>
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</table>

### Table 6.2 \( G_a \) values obtained from the different images – grinding

<table>
<thead>
<tr>
<th>S.No</th>
<th>Surface roughness ( \mu m - R_a )</th>
<th>The ( G_a ) value obtained from the images after enhancement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Original</td>
</tr>
<tr>
<td>1</td>
<td>0.55</td>
<td>11.55</td>
</tr>
<tr>
<td>2</td>
<td>0.62</td>
<td>11.77</td>
</tr>
<tr>
<td>3</td>
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<td>10.95</td>
</tr>
<tr>
<td>4</td>
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<td>12.25</td>
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<td>5</td>
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</tr>
<tr>
<td>6</td>
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<td>12.98</td>
</tr>
<tr>
<td>7</td>
<td>1.02</td>
<td>12.17</td>
</tr>
<tr>
<td>8</td>
<td>1.22</td>
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<td>9</td>
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<td>15.4</td>
</tr>
<tr>
<td>10</td>
<td>1.08</td>
<td>12.62</td>
</tr>
</tbody>
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Table 6.3  Correlation coefficient of $G_a$ with stylus roughness

<table>
<thead>
<tr>
<th>Specimen</th>
<th>Original</th>
<th>Laplacian</th>
<th>Laplacian of Gaussian</th>
<th>Sobel</th>
<th>Laplacian and Sobel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Milling</td>
<td>0.850</td>
<td>0.900</td>
<td>0.912</td>
<td>0.903</td>
<td>0.924</td>
</tr>
<tr>
<td>Grinding</td>
<td>0.815</td>
<td>0.833</td>
<td>0.838</td>
<td>0.816</td>
<td>0.862</td>
</tr>
</tbody>
</table>

Figure 6.8  Variation of $G_a$ with roughness for original image and enhanced image - milling specimen

Figure 6.9  Variation of $G_a$ with roughness for original image and enhanced image - grinding specimen