University of Huddersfield Repository

Zhu, Hao, Blunt, Liam, Jiang, Xiang and Xiao, Shaojun

Recognition of Features from Micro Scale Patterned Surfaces

Original Citation


This version is available at http://eprints.hud.ac.uk/id/eprint/4032/

The University Repository is a digital collection of the research output of the University, available on Open Access. Copyright and Moral Rights for the items on this site are retained by the individual author and/or other copyright owners. Users may access full items free of charge; copies of full text items generally can be reproduced, displayed or performed and given to third parties in any format or medium for personal research or study, educational or not-for-profit purposes without prior permission or charge, provided:

- The authors, title and full bibliographic details is credited in any copy;
- A hyperlink and/or URL is included for the original metadata page; and
- The content is not changed in any way.

For more information, including our policy and submission procedure, please contact the Repository Team at: E.mailbox@hud.ac.uk.

http://eprints.hud.ac.uk/
Recognition of Features from Micro Scale Patterned Surfaces

H.Zhu, L.Blunt, X.Jiang*, S.Xiao

Centre for Precision Technologies (CPT)
University of Huddersfield
Queensgate, Huddersfield, UK HD1 3DH
*Corresponding Author: Tel.: + 44 (0) 1484 473634  E-mail: x.jiang@hud.ac.uk

Abstract

It is recognised that surface feature is one of the most important factors affecting the functionality and reliability of micro/nano scale patterned surfaces. The information in all surface geometrical patterns is contained in the attributes of the individual pattern features and the structural relationships between these features. To extract this information the individual pattern features need to be identified [1]. A stable syntactic extraction technique of significant surface features from what is termed a structured surface has been developed. Different feature extraction techniques applied for the different types of structured surfaces are illustrated [2-3]. Examples have been selected to demonstrate the feasibility and applicability of the surface pattern analysis techniques. Finally, experimental results will be given and discussed in this paper.

Keywords: Micro patterned surface, segmentation, edge detection

1. Introduction

As the rapid development in the microtechnology, especially for Micro Electro Mechanical Systems (MEMS) proceeds micro scale patterned surfaces now play an important role in many industrial fields. It is therefore vital that techniques are available which can accurately, reliably and cost-effectively characterise these micro scale patterned surfaces.

Broadly speaking, pattern recognition is a technology that concerns the description or classification of measurements. The three main approaches to pattern analysis are identified by Schalkoff as: Statistical, Syntactic and Neural Pattern Analysis [4]. The structure of a typical pattern recognition system consists a sensor (in this study, the Talysurf CCI system), a feature extraction mechanism (algorithm), and a classification or description algorithm (depending on the approach). The structure is shown in Figure 1.

![Fig. 1. Typical pattern recognition system structures](image)

2. Experimental investigations

In this work a white light interferometer (Taylor Hobson CCI System) has been used in a clean room environment to measure a range of structured surfaces. For instance, a 50×
objective lens allows this machine to measure a sample area of approximately $300 \times 300 \mu m$
( imaged onto a CCD array of $1024 \times 1024$ pixels) with a working distance of 3.4mm between
lens and measured surfaces, and a measurement time of one to two minutes. Lower
magnifications can be used to enable larger areas to be examined but this will increase the
minimum achievable lateral resolution. The major specifications of the Taylor Hobson CCI
System are summarised in table 1.

Table 1. Specifications of the Taylor Hobson CCI System

<table>
<thead>
<tr>
<th>Talysurf CCI 3000</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vertical resolution</td>
<td>0.01nm</td>
</tr>
<tr>
<td>Maximum lateral resolution</td>
<td>0.36µm</td>
</tr>
<tr>
<td>Vertical range</td>
<td>100µm</td>
</tr>
<tr>
<td>Maximum measurement area</td>
<td>$7.2 \times 7.2 mm^2$</td>
</tr>
<tr>
<td>Data points</td>
<td>1024x1024 pixel array</td>
</tr>
<tr>
<td>Root mean square repeatability</td>
<td>3pm</td>
</tr>
<tr>
<td>Typical measurement time</td>
<td>10–20 seconds</td>
</tr>
</tbody>
</table>

Typical measurement results are show below in Figure 2.

![Figure 2](image)

(a) micro chip pin surface (b) laser etched landing zone of hard disk surface

3. Analysis of experimental data

The classification of 3-D geometrical objects from visual data is an important pattern
recognition task. This task includes feature selection, dimensionality reduction (3-D
information is mapped onto a 2-D image), and the use of qualitative and structural descriptors.

Histogram equalization is a technique which consists of adjusting the grey scale of the
image so that the grey level histogram of the input image is mapped onto a uniform histogram.
Let the variable $r$ represents a random variable which indicates the grey level of an image.
We can assume that $r$ is continuous and lies within the closed interval $[0:1]$ with $r = 0$
representing black and $r = 1$ representing white. For any $r$ in the specified interval let us
consider a transformation of the form

$$s = T(r)$$ (1)

Let the original and transformed grey levels be characterized by their probability density
functions $p_r(r)$ and $p_s(s)$ respectively. Then from elementary probability theory, if $p_r(r)$
and $p_s(s)$ are known then the probability density function of the transformed grey level is
given by:
If the transformation is given by:

\[ s = T(r) = \int_0^r P_w(w)dw \]  

Then substituting \( \frac{dr}{ds} = \frac{1}{p_r(r)} \) in Eq. 2 we obtain \( p_s(s) = 1 \). Thus it is possible to obtain a uniformly distributed histogram of an image by the transformation described by Eq. 3.

An algorithm to implement histogram equalization for a grey level image is given below. For every pixel in the image then the grey level value is a variable \( i \), \( \text{hist}^i[i] = \text{hist}^i[i] + 1 \) when \( i = 0 \) to \( L - 1 \) for a \( L \) level image. From the histogram array, one can get a cumulative frequency of histogram \( \text{hist}_{c}[i] = \text{hist}_{c}[i-1] + \text{hist}[i] \). The generated equalized histogram is given as

\[ \text{eqhist}[i] = \frac{L \times \text{hist}_{c}[i] - N^2}{N^2} \]  

Where, \( L \) is the number of grey levels present in the image, \( N^2 \) is number of pixels in the \( N \times N \) image, \( [x] \) is the truncation of \( x \) to the nearest integer. Replacing the grey value \( i \) by \( \text{eqhist}[i] \) for each \( i \), then \( \text{eqhist} \) contains the new mapping of grey values.

Considering Figure 3 the histogram of the original image is non-uniform due to many surface undulations, the histogram of the equalized image has more or less a uniform density function.

![Fig. 3. (a) Original image of hard disk surface (b) histogram of the image (c) equalized histogram (d) enhanced image of hard disk surface](image)

A number of edge detectors have been developed by various researchers. Edge detection by gradient operations works fairly well with images that have sharp intensity transitions and low noise. The most important operators are the Robert operator, Sobel operator, Prewitt...
operator, Canny operator and Krisch operator. In this study, the Sobel operator is selected [3]. The Sobel operator is a $3 \times 3$ neighborhood based gradient operator. The convolution masks for the Sobel operator are defined by the two kernels shown in Figure 4. The two masks are separately applied on the input image to yield two gradient components $G_x$ and $G_y$ in the horizontal and vertical orientations respectively.

![Fig. 4 Sobel masks to compute (a) gradient $G_x$, (b) gradient $G_y$](image)

The result of an edge image of an etched Si structure generated by Sobel operator is shown in Figure 5.

![Fig. 5 Detection of an etched Si microstructure using Sobel edge detector](image)

For other types of feature extraction task, for example, a chip pin surface, active contours can be used, and this is the case in the present study. Active contours or snakes are a completely different approach to feature extraction compared to the Sobel operator. An active contour is a set of points that aims to enclose a target feature i.e. the feature to be extracted. An analogy would be using a balloon to find a sharp point. An initial contour is placed outside the target feature, and is then evolved so as to enclose it. Active contours are express as an energy minimization process. The target feature is a minimum of a suitably formulated energy function. This energy function includes more than just edge information [5].

To achieve this goal, an external energy is explicitly defined that can move the zero level curves toward the object boundaries. Let $I$ be an image, and $g$ be the edge indicator function defined by

$$g = \frac{1}{1 + \left| \nabla G_\sigma * I \right|^2}$$  \hspace{1cm} (5)

Where $G_\sigma$ is the Gaussian kernel with standard deviation $\sigma$. An external energy for a function $\Phi(x,y)$ is defined as below,

$$\varepsilon_{g,\lambda,\nu}(\Phi) = \lambda L_g(\Phi) + \nu A_g(\Phi)$$  \hspace{1cm} (6)

Where $\lambda > 0$ and $\nu$ are constants, and the terms $L_{g(\Phi)}$ and $A_{g(\Phi)}$ are defined by

$$L_g(\Phi) = \int_{\Omega} g \delta(\Phi) \left| \nabla \Phi \right| dxdy$$  \hspace{1cm} (7)

and
\[ A_g(\Phi) = \int_{\Omega} gH(-\Phi) \, dx \, dy \]  

(8)

Respectively, where \( \delta \) is a Dirac function, \( H \) is a Heaviside function.

Now, the following total energy function is defined

\[ \epsilon(\Phi) = \mu P(\Phi) + \epsilon_{g,\lambda,\rho}(\Phi) \]  

(9)

The external energy \( \epsilon_{g,\lambda,\rho} \) drives the zero level set toward the object boundaries, while the internal energy \( \mu P(\Phi) \) penalizes the deviation of \( \Phi \) from a signed distance function during its evolution. An example of feature extraction results are shown in Figure 6.

Fig. 6. Feature extraction of an etched Si microstructure and micro chip pin surface based on active contours

4. Conclusions

In this paper, a framework of pattern recognition is introduced. The basic principles involved in the preprocessing of the Histogram equalization and image enhancement have been presented. Edge detection algorithms based on Sobel operator and Active contours have also been introduced. The measured data and the experimental results based on different techniques are given to illustrate the techniques. Sobel edge detection operator has a good performance on low-level surface feature extraction. Active contour is a flexible technique with sufficient accuracy for surface feature extraction, and incorporate higher-level information.

5. Acknowledgements

The project is supported by the Major Program of the National Natural Science Foundation of China (No. 50535030).

References