Application to detect of scratches on a surface using nano topology

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Abstract: This main goal of this paper is to investigate how the conditions of nano topology is applied in image processing to detect the scratches and a surface using the nano topological spaces.

Keywords: Blockchain, smart contract, online entrance exam, education

1. Introduction

A method of surface scratch detection is proposed in order to realize the automatic detection of surface scratches of molded products. This method uses contourlet transform to decompose the image, extracts the mean and variance of the different sub-bands and different directions for the matrix as the eigen vectors and uses the distance between the calculation point and the scoring center to identify scratches, to construct a product scratch detection system based on contourlet transform.

Experimental results show that compared with traditional methods, the method has higher retrieval accuracy and retrieval speed.

In the molding process, scratches that differ in the length, direction and depth often exist in product surface. Defective products need to be discarded through scratch detection, which can be realized by real-time monitoring of molded products using machine vision technology. The product surface image collected by the camera is processed to decide whether the product is scratched and forwarded to the controller to be dealt with. The surface scratches of the product are caused by the collision friction of the mold during the manufacturing process. The main features of the collected images are as follows:

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The basic definitions for nano topology and filter (Laplace filtering) are recollected from the following papers [1,2,3,4,6,7,8,9,10,11]. Throughout this paper neighbourhoods, closure, interior, boundary, limit point, isolated point are represents the nano neighbourhoods, nano closure, nano interior, nano boundary, nano limit point, nano isolated point respectively.

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- Due to the difference in illumination and depth, the surface showed irregular grayscale changes.
- Due to frequent mechanical collision, fixed image acquisition device cannot guarantee zero geometric deviation between the images collected at different times and the high frequency signal at the edge of the image has an influence on the extraction.
- A scratch is usually a multi-directional irregular line of $3 \approx 10$ pixels width.

In view of the above problems, research has been done from different aspects. Standard detection [1], [15], [2] techniques deal with regions of interest based on different space-time averages and median filtering. These low-computational-cost methods work perfectly on still images, but are less effective on sequence images, are prone to blurring and are more severe due to the fixed position of vertical scratches. The Kokaram model mentioned in literature [4], [3] is one of the most common airspace models, which proposes cosine distribution for the brightness attenuation of the scratch, and uses the median filter and the Hough transform to perform the initial screening and then uses Gibbs sampling to get the edge distribution of the center brightness of the scratch to decide whether it is scratch or false alarm. This method tends to misscratches that are shorter than half the length of the image. In literature [5], a vertical scribe detection method based on wavelet analysis is proposed.

The algorithm first carries out two-layer wavelet decomposition of the image and then marks all possible scratches according to the relevant characteristics of the wavelet coefficients in the horizontal and vertical directions. But this method is applied to film scratches, which is different from mold surface scratches. Based on the above literature, this paper adopts the Contourlet transform in multi-scale analysis and proposes a product scratches detection algorithm using nonsubsampled Contourlet transform. The mean and variance of the transform coefficient matrix are extracted as scratch features by nonsubsampled Contourlet transform, to achieve automatic detection of the product surface scratches.

2. Basic relationship between pixels

Neighbors of a Pixel 1. $N_4(P)$: 4-neighbors of P.

- Any pixel $p(x,y)$ has two vertical and two horizontal neighbors, given by $(x+1,y),(x-1,y),(x,y+1),(x,y-1)$
- This set of pixels are called the 4-neighbors of P and is denoted by $N_4(P)$
- Each of them is at a unit distance from P.

2. ND(P)

- This set of pixels, called 4-neighbors and denoted by ND(P).
- ND(P): four diagonal neighbors of P have coordinates $(x+1,y+1),(x+1,y-1),(x-1,y+1),(x-1,y-1)$

3. $N_8(P)$: 8-neighbors of P.

- $N_4(P)$ and $ND(P)$ together are called 8-neighbors of P, denoted by $N_8(P)$.

$N8 = N4 \cup ND$

• Some of the points in the N_4, ND and N_8 may fall outside image when P lies on the border of image. Neighbourhood operations simply operate on a larger neighbourhood of pixels than point operations

F (x-1, y-1)	F (x-1, y)	F (x-1, y+1)
F (x, y-1)	F (x, y)	F (x, y+1)
F (x+1, y-1)	F (x+1, y)	F (x+1, y+1)

N_8 (p)

Fig:1

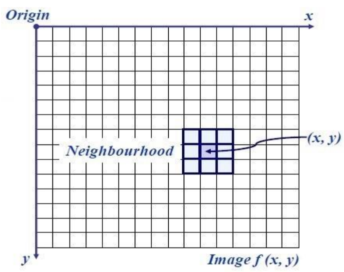


Fig:2

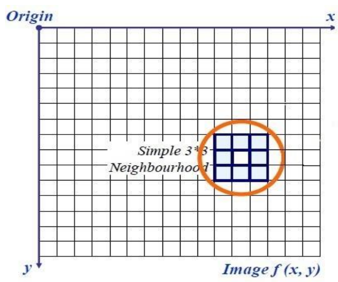


Fig:3

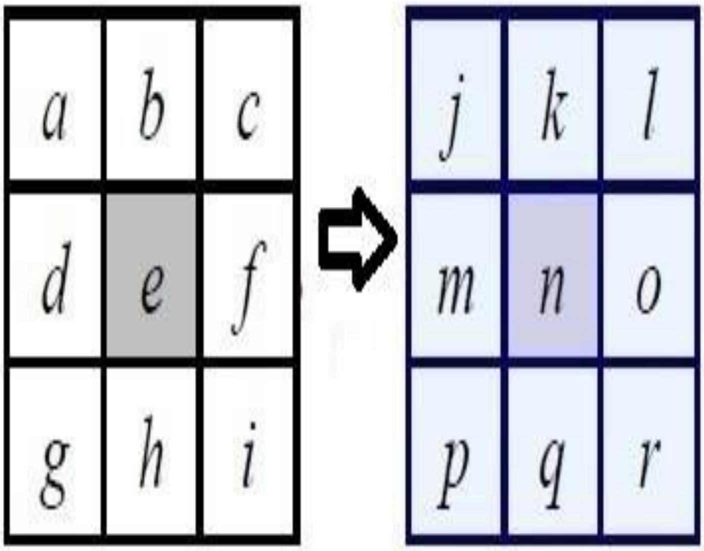


Fig:4

$e_{processed} = n \Rightarrow e+j \Rightarrow a+k \Rightarrow b+l \Rightarrow c+m \Rightarrow d+o \Rightarrow f+p \Rightarrow g+q \Rightarrow h+r \Rightarrow i$

The above is repeated for every pixel in the original image to generate the filtered image

Since U is a universal set, it can represent various space such as a 2 or 3dimensional rectangular lattice or triangular lattice space. neighborhood $U(x)$ can be considered as a set of points which has an adjacency relation with point x. Figure

5, shows various shapes of neighborhoods. The 5-neighborhood shown by Fig. 5(1), and 9 neighborhood are shown in 5(6). As these examples, it is often assumed that the space is a set of 2D rectangles, and that the neighborhood is symmetric, $x \in U(x)$.

Since the form of the space and of the neighborhoods in the nano topology has no restriction, it is possible to consider a neighborhood of a point n which does not include x itself as shown by Fig. 5(4).

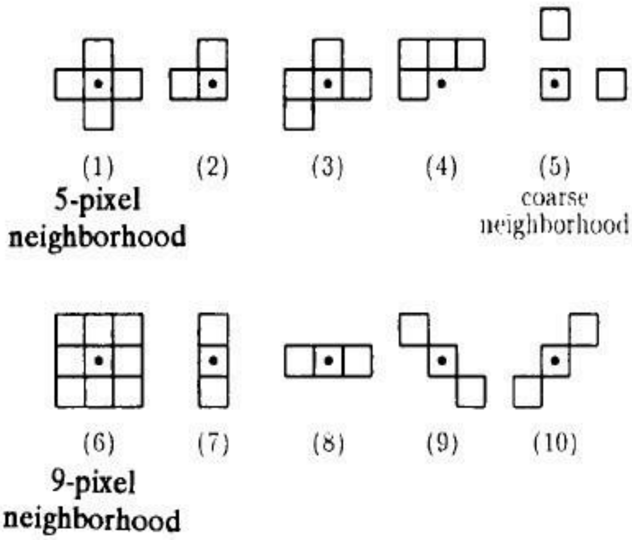


Fig:5

Definition 2.1. *A nano topological space* (U,K) *is called a nano filled space* $\forall x \in U : x \in U(x)$

Note: the adjacency relation is not limited to adjacent pixels. In some cases, it is more appropriate to consider a coarse neighborhood, such as that shown in Fig. 5(5) in which some pixels are outside the 9-neighborhood.

Definition 2.2. *A nano topological space* (U,K) *is said to be nano symmetric if* $\forall\, x,y \in U : y \in U(x) \Rightarrow x \in U(y)$ *In Fig. 5(1, 6, 7, 8, 9, 10) are symmetric nano neighborhoods, and (2, 3, 4, 5) are asymmetric nano neighborhoods.*

3. Relation between nano Topology and Image Processing

The boundary of an image is a typical element in an image processing. It consists of a set of points which have an adjacency relation with both the inside and outside of the image.

Definition 3.1. *The boundary set A^{∂} of subset A of* N *is defined by*
$A^{\partial} = \{x : \mathrm{N}(x) \cap A \; 6= \emptyset \textit{ and } \mathrm{N}(x) \cap A^{c} \; 6= \emptyset\}$

A boundary set depends on a nano topology N. The boundary set with respect to (w.r.t) the 5-neighborhood of an image shown in Fig. 6(b) is given as Fig. 6(b). This figure looks like usual boundary of the image. When the vertical 3-pixel neighborhood (Fig. 5(7)) is applied to an image (Fig. 6(a)), a horizontal contour (Fig. 7) is obtained. Because a boundary set A^{∂} varies depending on the nano topology N, the notation $A^{\partial hNi\backslash ti}$ is sometimes used.

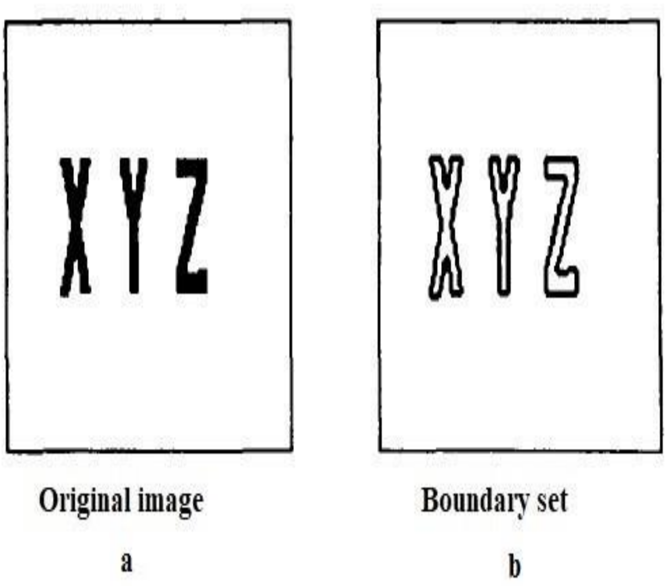


Fig:6

Definition 3.2. The nano closure set of A is represented by A^{Ncl}, and given by $A^{Ncl} = \{x : N(x) \cap A \; 6= \emptyset\}$

In the Figure 7, shows the closure for the 5-nano neighborhood shown in and this is an image expanded by the thickness of one pixel.

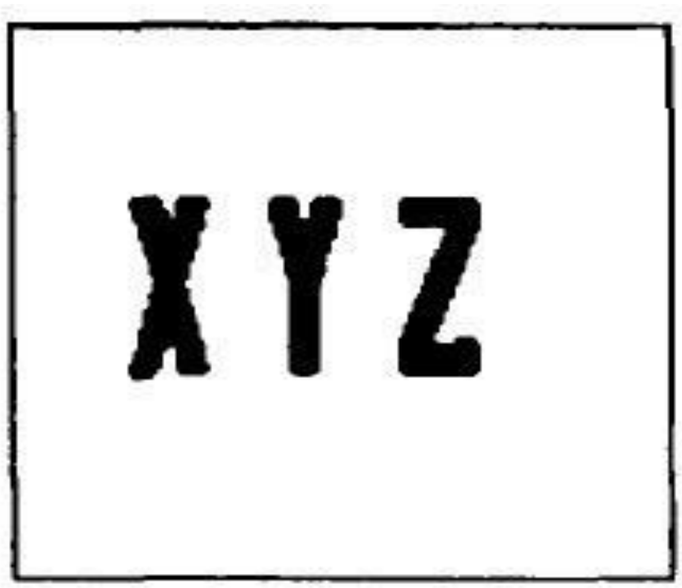


Fig:7

The process of removing all boundary points from a picture is called shrinking. This can be represented by the set of all points whose nano neighborhoods are contained in the picture. Such a set is called an interior set in the nano topology.

Definition 3.3. *The nano interior set of A is defined by*
$A^{Nint} = \{x : \mathrm{N}(x) \in A\}$

Example 3.4. $Nint(\{b\}) = \{b\}$, $Nint(\{a,b,c\}) = \{a,b,c\}$, $Nint(\{a,c\}) = \{a,c\}$

Figure 8 shows the nano interior set of the picture shown in Fig. 5 obtained by using the 5-nano neighborhood. This is thinner than the original image by the thickness of one pixel. The closure set and the interior set vary depending on the neighborhood as well as the boundary set. The former is represented by $A^{NclhNinti}$, and the latter by $A^{NinthNinti}$, indicating they are based on a neighborhood N.

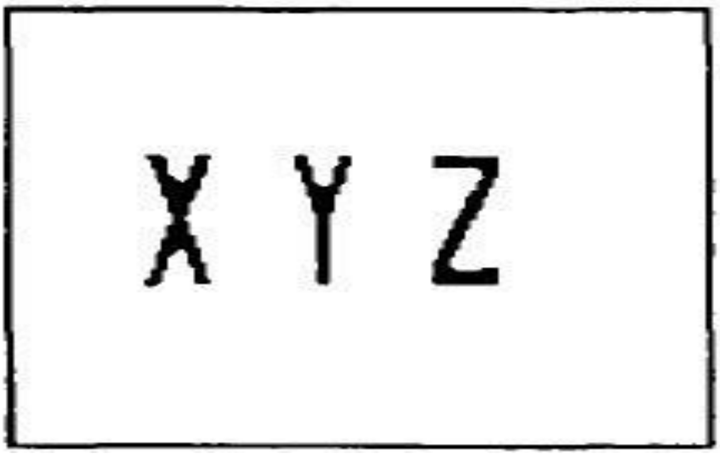


Fig:8

Remark 3.5. The closure set and the interior set have the following relationship:

1. $((Ac)Nint)c = ANcl$
2. $((Ac)Ncl)c = ANint$

If the neighborhood of a pixel of a picture A contain no other pixel of A; this pixel is considered to be isolated in A, defined as follows.

Definition 3.6. *The nano isolated point set of A, expressed by* A^{NS}*, is defined by* $A^{NS} = \{x : x \in A \text{ and } (N(x)\backslash\{x\}) \cap A = \emptyset\}$

Nano isolated points of a picture can be considered as noise, and this noise can be removed by eliminating the isolated points.

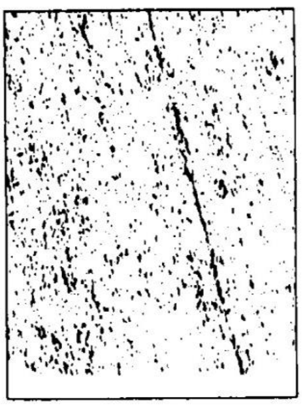
Definition 3.7. *The nano limit point set* A^l *of A is defined by*

$A^l = A\backslash A^s$

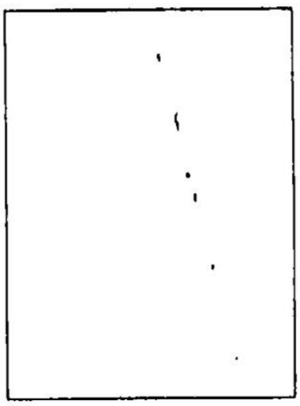
4. Detection of scratches on hard disk

To detect an image from an original image with noises, the noise must be eliminated. The elimination of isolated points (definition 3.5) can be applied for this purpose. To eliminate noise from an object having many isolatedpoints, such as a hard disk, the operation must be applied repeatedly. According to the following theorem 4.1, however, multiple application of isolated- point elimination has the same effect as a single operation. The noise of a hard disk cannot be perfectly eliminated by this method, since this kind of noise does not necessarily consist of isolated points alone.

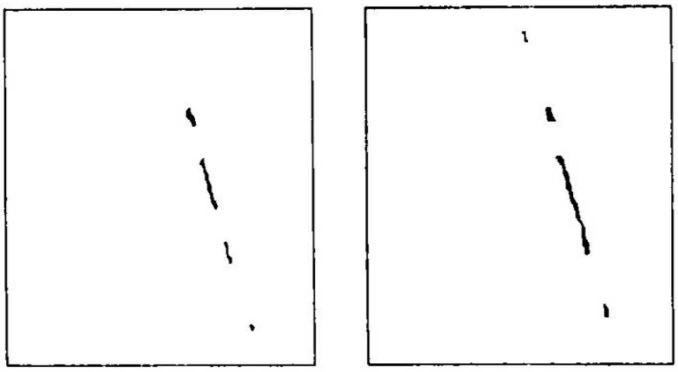
Theorem 4.1. If N is a nano topological space, then $A^n = (A^n)^n$ Noises can also be eliminated by using the characteristic of 'shrinking' which eliminates small blocks. However, shrinking eliminates part of the scratches as well as the noise, since the scratches consist of small isolated blocks. To overcome this difficulty, the directions of the scratches are taken into account.



Original Image



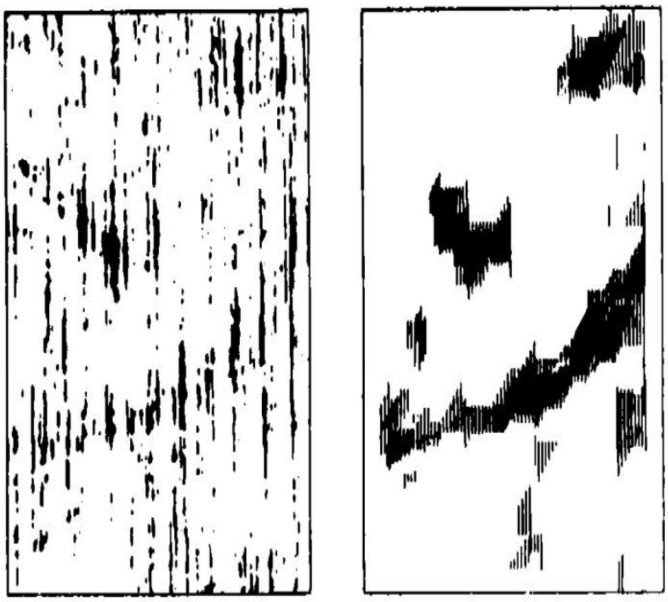
Results of processing with 3-pixel neighbouhoods



Processing with non-filled neighbourhoods

Processing with coarse neighbourhoods

Processing using 3-pixel neighborhoods The direction of scratches on a hard disk is almost constant and is related to the direction of the movement of the disk during its manufacturing. Therefore, such a direction can be used for the detection of scratches. For example, the scratches shown in Fig. 4 incline toward the lower right. Such a line is detected by repeated application of an interior operation to the image w.r.t. *U* in Fig. 6. Here, an interior operation w.r.t. N transforms an arbitrary subset A of *U* to its interior set A'(V. This processing is represented in nano topology as:

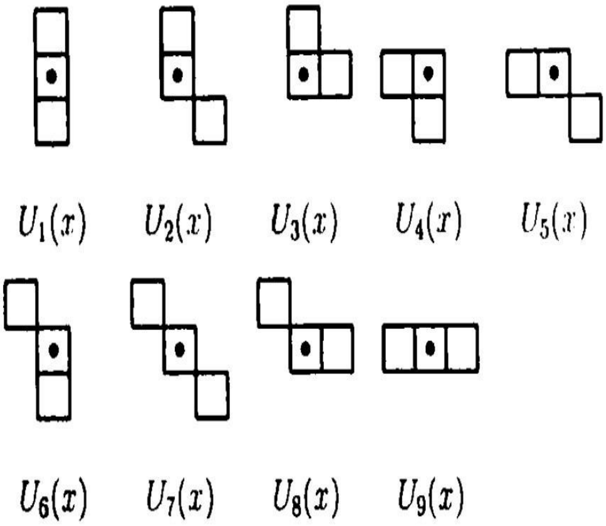


Original Images

Detected Images

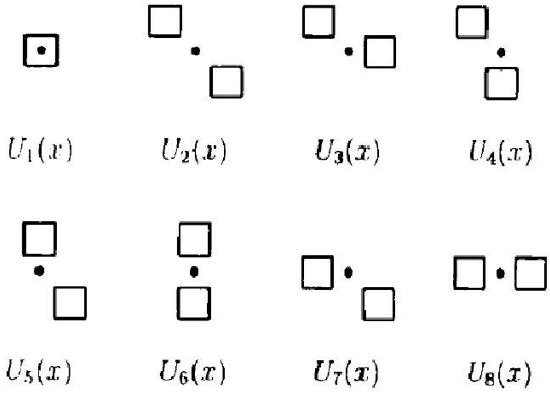
where $N(x) = \{N_1(x), N_2(x) ....N_9(x)$ and N_1 to $N_9(x)$.

Figure 6 is a collection of 3-pixel neighborhoods inclined toward the lower right. Images that do not match these patterns are eliminated during the repeated interior operations. The number of repetitions should be selected so that the image of a scratch is not reduced too much. For example, the original image shown in Fig. 4(1) was processed by applying 7 interior operations to obtain the image of the scratch shown in Fig. 4(2). But the number of scratches detected is greatly reduced. As this example shows, scratches as well as noise are reduced when an interior operation is repeated. It is important, therefore, to select the number of the operations appropriately. In very noisy cases, scratches may be detected by this processing.



Neighbourhoods for slanted scrtches with negative

Detection using un-filled neighborhoods It is difficult to detect scratches in a hard disk by using an interior set w.r.t. connected neighborhoods. This is due to the fact that scratches consist of many separated small blocks. If a gap between blocks forming a scratch is filled in, this problem will be solved. If an interior set is formed by using an un-filled neighborhood, an exterior point of the original set may be included in the interior set. This property can be used to connect separated blocks. N_2 to N_8 in Fig. 7 show a collection of un-filled neighborhoods, each sloping toward the lower right. Interior sets using these neighborhoods can be used to obtain the pixels which is between separated pixels on slanted scratches with negative slopes. $N_1(x) = \{x\}$, the original pixels remain in the interior set. Thus, making interior set by using N_1, to N_8 in Fig. 7 is a means of filling the gaps of 10 slanted scratches.



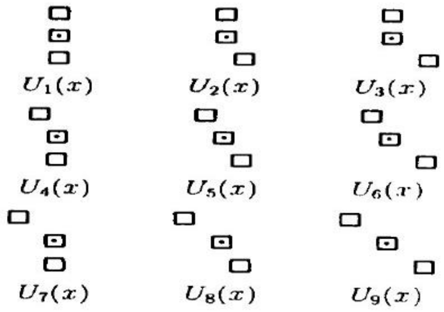
Base of neighborhoods for separated pixels along negative slope.

where $N(x) = \{N_1(x), N_2(x) .... N_8(x)$ and N_1 to $N_8(x)$.

Figure 4(3) shows the scratch detected by applying process 5.2 once, followed by applying process 5.1 seventeen times. Comparing this result with Fig. 4(2), the improvement is clearly shown. As this example shows, enhancement of the original image (processing 5.2) makes the detection of a scratch easy.

Process using coarse neighborhood If scratches have wider gaps than the previous example, the gaps cannot be filled by the previous method. For such a case, relationships between pixels in a wider region must be taken into account, including pixels at a distance. Therefore, a coarse neighborhood including a pixel outside of the 9-neighborhood should be used.

Figure 8 shows a collection of coarse neighborhoods whose pixel orientations are between the vertical and -45 degrees. A scratch having an angle in this range can be detected by making the interior set of the image based on $N(x) = \{N_1(x), N_2(x) ..., N_9(x)\}$ of Fig. 8.



Coarse neighborhoods for scratches ranging vertical direction

Figure 4(4) shows the processed result of Fig. 4(1). This was obtained by applying the closureoperation based on the 3-pixel neighborhood shown by $\mathcal{N}_3^3(x)$ in Fig. 1(9), and repeatedly (10 times) applying the interior operation w.r.t. coarse neighborhoods of Fig. 8. This processing produces a better result than procedures 5.1 and 5.2.

In a coarse neighborhood, the scratch detection angle can be chosen more precisely, since the freedom of the shape of a neighborhood is larger than that in the 9-neighborhood. Figure 9 shows a collection of shapes of pixels having angle between -45" and the horizontal. A scratch having an angle in this range can be detected by using Fig. 9. A set of neighborhoods whose shapes are left-to-right symmetric to Fig. 9 can be used to detect a scratch having an angle in such a range. It is possible to detect scratches of arbitrary orientation by applying coarse neighborhoods with various angles. Figures 10 to 13 show other results obtained by procedure 5.3.

Detection of scratches on a hairline-finished metal surface Connected components forming a scratch on a hairline-finished metal surface are more widely separated than those on a hard disk. It is necessary, therefore, to consider a wider neighborhood than that discussed above. For example, a family of coarse neighborhoods shown in Fig. 14 was applied to the Original image Detected scratches image shown in Fig. 5(1), since it contains scratches rising slightly toward the right. Figure 5(2) was obtained by applying the closure operation (Fig. 14) five times and the interior operation also five times. This shows that a scratch having quite widely separated components can be processed by using coarse neighborhoods.

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