Toward Automatic Defects Clustering in Industrial Production Process Combining Optical Detection and Unsupervised Artificial Neural Network Techniques

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Abstract. A major step for high-quality optical surfaces faults diagnosis concerns scratches and digs defects detection and characterization in products. This challenging operation is very important since it is directly linked with the produced optical component's quality. A new scratches and digs defects detection and characterization method exploiting Nomarski microscopy issued imaging has been developed. The items detected using this high-performance approach can correspond to real defects on the structure but some dusts and cleaning marks are detected too. Thus, a classification phase is necessary to complete optical devices diagnosis. In this paper, we describe a data extraction method, which supplies pertinent features from raw Nomarski images issued from industrial process. Then we apply this method to construct a database from real images. Finally we analyse the pertinence of features and the complexity of obtained database by clustering operation using an unsupervised Self Organizing Maps technique.

1 Introduction

We are involved in the fault diagnosis of optical devices in industrial environment. In fact, faults detection and issued information processing are among chief phases for succeeding in such diagnosis. This paper focuses mainly on these two aspects with a particular attention on scratches and digs defects, which are among the most frequent shortcomings in high-tech optical devices. These kinds of aesthetic flaws, shaped during different manufacturing steps, could provoke harmful effects on optical devices' functional specificities, as well as on their optical performances by generating undesirable scatter light, which could seriously degrade the expected optical features. Taking into account the above-mentioned points, a reliable diagnosis of these defects in high-quality optical devices becomes a crucial task to ensure products' nominal specification and to enhance the production quality. Moreover, the diagnosis of these defects is strongly motivated by manufacturing process correction requirements in

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order to guarantee mass production (repetitive) quality with the aim of maintaining acceptable production yield.

Unfortunately, detecting and measuring such defects is still a challenging dilemma in production conditions and the few available automatic control solutions remain ineffective. That's why, in most of cases, the diagnosis is performed on the basis of a human expert based visual inspection of the whole production. However, this usual solution suffers from several acute restrictions related to human operators' intrinsic limitations (reduced sensitivity for very small defects, detection exhaustiveness alteration due to attentiveness shrinkage, operators' tiredness and weariness due to repetitive nature of fault detection and fault diagnosis tasks).

To overcome these problems we propose an approach based on Nomarski microscopy issued imaging [1]. This method provides robust detection and reliable measurement of outward defects, making plausible a fully automatic inspection of optical products. However, the above-mentioned detection process should be completed by an automatic classification system in order to discriminate the "false" defects (correctable defects) from "abiding" (permanent) ones. In fact, because of industrial environment, a number of correctable defects (like dusts or cleaning marks) are usually present beside the potential "abiding" defects. That is why the association of a faults classification system to the aforementioned detection module is a foremost supply to ensure a reliable diagnosis. Since they have shown many attractive features in complex pattern recognition and classification tasks [2] [3], neural network based techniques will be used to solve this challenging task. Relevant data extraction is a key issue to ensure the accuracy of a classification scheme. In this paper, a method in two phases is proposed: the first one consists in extracting items from Nomarski image; the second one allows coding each isolated item. Consequently the suggested classification process is described in broad outline in the diagram of Figure 1.The present article deals also with the pertinence of proposed information coding method and with the structure of obtained data, using the Self-Organizing Maps.

Fig. 1. The block diagram of the proposed defect classification scheme.

This paper is organized as follows: in the next section, the Nomarski microscopy technique used to properly detect the defects and its advantages are presented. Then, in Section 3, we describe the proposed method to extract pertinent data from raw Nomarski images. The Section 4 deals with the data analysis methods. In Section 5, some investigations on real industrial data are carried out and the obtained results are discussed. Finally, the last section will conclude the presented work and will give a number of perspectives.

2 Defects Detection Method

Detecting defects as small as 1µm in an efficient and robust way is a challenging task. In order to overcome this difficulty, an approach based on Nomarski microscopy is proposed.

2.1 Nomarski Mcroscopy Tchnique.

The Nomarski microscopy, known also as “Differential Interference Contrast” microscopy (DIC), is a differential interference technique [4]. The principle of this technique is to laterally split the incident electromagnetic wave into two waves each influenced by a close but separate part of the specimen, and then to recompose these two waves to obtain an interference figure. Imaging a given surface with such a microscope leads to interference figure displaying the studied surface’s gradient related information [5]. Figure 3 a) gives an example of a Nomarski microscopy issued image.

Three main advantages distinguish DIC microscopy from other microscopy techniques. The first of them is related to the higher sensitivity of this technique comparing to the other classical microscopy techniques (Dark Field, Bright Field [6]). Figure 2 shows a comparative example: the two scratches on the right of the image can only be observed by DIC microscopy. In fact, DIC microscopy allows detecting defects attaining 1 nm depth.

Fig. 2. The same microscope field image obtained by a) Left: Bright Field microscopy; b) Middle: Dark Field microscopy; and c) Right: Nomarski microscopy.

Furthermore, the DIC microscopy is robust regarding lighting non-homogeneity while Bright Field and Dark Field are not. Finally, this technology provides information relative to depth (3-th dimension), which could be exploited to typify roughness or defect’s depth. This last advantage offers precious additional potentiality to characterize scratches and digs flaws in high-tech optical devices. Therefore, Nomarski microscopy seems to be a suitable technique to detect surface imperfections.

2.2 Items Detection.

A new method to exploit images issued from such technology has been developed [1]. It provides robust, reliable and accurate detection and dimensional characterization of items (Figure 3).We have demonstrated the pertinence of suggested approach by applying this concept to automatically control quality of a SAGEM product. Since this method uses an adaptive matching phase exploiting physical considerations, it allows the detection of all items deeper than roughness range. It ensures that all defects to detect actually are; however, as it has been mentioned before, it implies that some other items (among which, dust or cleaning marks) could also be detected as plausible defects. That is why the classification of detected items remains a chief necessity for an efficient automatic control system able to diagnose defects on optical devices.

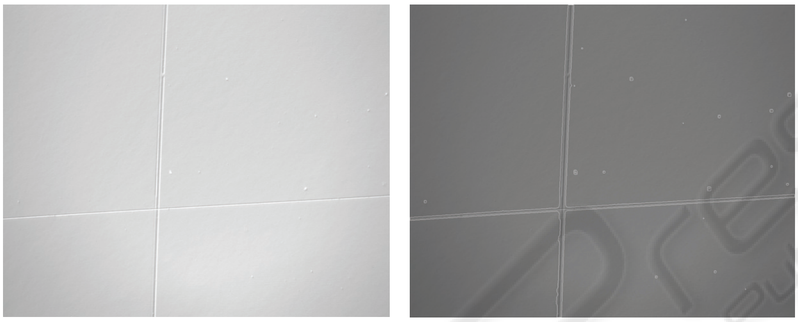

Fig. 3. a) Left: Image obtained from DIC microscopy; b) Right: The same image after item detection processing.

3 Relevant Data Extraction Method

In order to obtain exploitable data for a classification scheme, we first need to extract relevant information from raw Nomarski microscopy issued images. We propose to proceed in two steps: first a detected items images extraction phase and then an appropriated coding of the extracted images.

The image associated to a given detected item is constructed considering a stripe of ten pixels around its pixels. Thus the obtained image gives an isolated (from other items) representation of the defect (e.g. depicts the defect in its immediate environment). Figure 4 gives four examples of detected items images using the aforementioned technique. These images have been generated using the detection step described in Section 2, performed on raw images of an optical device in industrial environment. It shows different characteristic items which could be found on such device.

The information contained in such images is highly redundant. Furthermore, the generated images don’t have necessarily the same dimension (typically this dimension can turn out to be hundred times as high). That’s why these raw data (images) cannot be directly processed, and have to be appropriately encoded. This is done using a set of transformations described bellow.

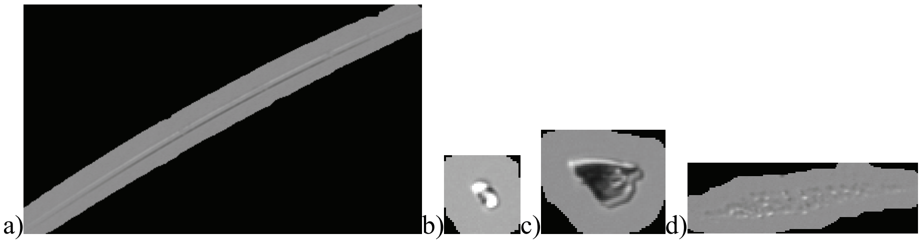

Fig. 4. Images of different characteristic items: a) scratch; b) dig; c) dust; d) cleaning marks.

An appropriate transformation is applied on the image in order to extract pertinent non-redundant information. Such transformation must naturally be invariant to geometric transformations (translation, rotation and scaling) and robust regarding different perturbations (noise, luminance variation and background variation). Fourier-Mellin transform is used as it provides invariant descriptors, which are considered to have good coding capacity in classification tasks (see [7]). The Fourier-Mellin transform of a function $f(r;\theta)$, in polar coordinates, is given by relation (1), with q∈ Z, s = σ + ip ∈ C (see[8]):

$$M_f(q;s) = \int_{r=0}^{\infty} \int_{\theta=0}^{2\pi} r^{s-1} \exp(-iq\theta) f(r;\theta) dr d\theta \tag{1}$$

In [9], is proposed a set of features invariant on geometric transformation:

$$I_f(q;s) = M_f(q;s)\left[M_f(0;\sigma)\right]^{\frac{-s}{\sigma}} \left[M_f(1;\sigma)\right]^{-q} \left|M_f(1;\sigma)\right|^{q} \tag{2}$$

In order to calculate efficiently Fourier-Mellin transform using discrete Cartesian coordinates, we perform the convolution of the image with an appropriate filters bench proposed in [10]:

$$M_f(q;\sigma + ip) \approx \sum_{k} \sum_{l}_{1 \le (k^2+l^2) \le r_{\max}{}^2} h_{p,q}(k,l) f(k_0 - k, l_0 - l) \tag{3}$$

where $f(i;j)$ is the grey-level of pixel whose Cartesian coordinates are $(i;j)$, $(k_0;l_0)$ are the Cartesian coordinates of the image's centre of gravity, $r_{\max}$ is the maximal radius of the image, and where :

$$h_{p,q}(k,l) = \frac{\exp\left(i\left[\frac{p}{2}\ln(k^2+l^2) - q \cdot \arctan(\frac{l}{k})\right]\right)}{(k^2+l^2)^{1-\frac{\sigma}{2}}} \tag{4}$$

Finally, the processed features have to be normalized. In this purpose, we use the centring-reducing transformation, modifying each feature F_i as follows:

$$F_i = \frac{F_i - M}{\sigma} \tag{5}$$

where M is the mean value of the feature F_i over the database and σ its standard deviation.

In order to evaluate the number of degrees of freedom of features, the Grassberger-Procaccia algorithm [11] is used. 42^d samples, where d is the true intrinsic dimension of the features, are necessary to properly evaluate this dimension [12].To overcome this limitation, we process an approached value of the dimension (underestimated).

4 Data Analysis Method

In the aim of studying the structure of space described by database and evaluating the pertinence of adopted data coding scheme, we perform a clustering operation using an unsupervised neural network technique, the Self-Organizing Map (SOM) [13]. This algorithm projects a multidimensional space into a low-dimensional representation. Typically a SOM consists of a two dimensional grid of neurons. A vector of features is associated with each neuron. During the training phase, these vectors are tuned to represent training data. Similar data are projected to the same or nearby neurons in the SOM, while different ones are mapped to neurons located further from each other, resulting in clustered data. Thus SOM is an efficient tool for quantizing the data space and projecting this space onto a low-dimensional space, while conserving its topology. SOM is often used in industrial engineering [14], [15] to characterize high-dimensional data or to carry out classification tasks.

Since the considered space has a dimension (number of features) greater than 2, we cannot show directly the neurons in the weights space. To properly project neurons grid onto a 2-dimensional representation, we use the curvilinear representation introduced in [16]. It consists in representing the neurons by their curvilinear coordinates on the surface described by the neurons grid in the weights space.

The evaluation of the quality of non-linear projection of the data space onto the neurons grid space is performed by studying, for each pair of neurons, the distance dx between this two neurons in the data space versus the distance dy between this two neurons in the grid space [17]. For each couple of neurons $(i;j)$ we draw a point $(dy(i,j);dx(i,j))$ where $dx(i,j) = \left\|\vec{x}_i - \vec{x}_j\right\|$ and $dy(i,j) = \left\|\vec{y}_i - \vec{y}_j\right\|$. $\vec{x}_k$ (resp. $\vec{y}_k$) is the vector of features corresponding to the k-th neuron in the data space (resp. in the grid space). If the topology of the data space is not well respected, dx is not related to dy and we obtain a diffuse cloud of points. On the contrary, if the neurons organization is correct, the drawn points are almost arranged along a straight line.

5 Implementation and Validation on Industrial Data

We carried out an experiment on real data which allows us to study:

- the pertinence of the chosen raw data coding method,
- the complexity of the data space,
- the ability of SOM to map and clusterize this space.

5.1 Experimental Set-up

5000 items images were extracted from raw Nomarski images acquired during two scans on two different optical devices (it represents 1180 microscopic field images and an approximate surface of 28 cm²). Nomarski microscopy issued images were supplied by Olympus BX52 microscope combined with a Corvus stage, which allows scanning of optical piece. 50x magnification was used that leads to microscopic 1,77mm x 1,33 mm fields and 1,28µmx1,28µm sized pixels. The two studied devices were not specially cleaned, what accounts for the presence of some dusts and cleaning marks. Images were coded using the Fourier-Mellin transform with $\sigma = 0$ and $(q, p) \in \{(q, p)/(q = 0; 0 \le p \le P) \cup (1 \le q \le Q; -P \le p \le P)\}$ where $P = 1$ and $Q = 2$ (see Equation 2). Such transform provides a set of 13 features for each defect. Using the Grassberger-Procaccia algorithm we found out that the studied features have an intrinsic dimension about 7. Then we trained a Self Organized Map with the defects database. SOM's neurons are arranged along a 15 x 7 rectangular grid and the distance between two neurons is the classical Euclidean distance. The shape of the grid has been set experimentally by maximizing topology conservation (by the study of the dy-dx graphs).

5.2 Results and Discussion

Figure 6 shows the raw grid of neurons. The similarities between adjacent nodes are apparent and some clusters of similar data are identified. Moreover, in major cases, database items projected in the same neurons have the same appearance; an example is presented in the Figure 5. Such defects probably belong to the same class of defects. Thus, the performed clustering operation seems relevant. However, data projected onto neurons which are near “natural” class boundaries, are sometimes heterogeneous.

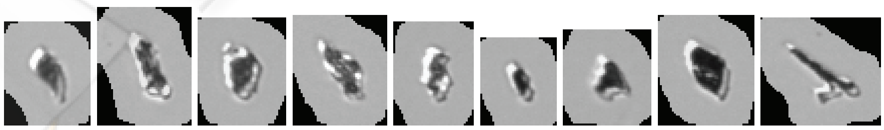

Fig. 5. Some items corresponding to the 28th neuron.

The curvilinear representation, which emphasizes the distance between the nodes of the grid (Figure 7) shows that neurons corresponding to scratches are clearly separate from the others.

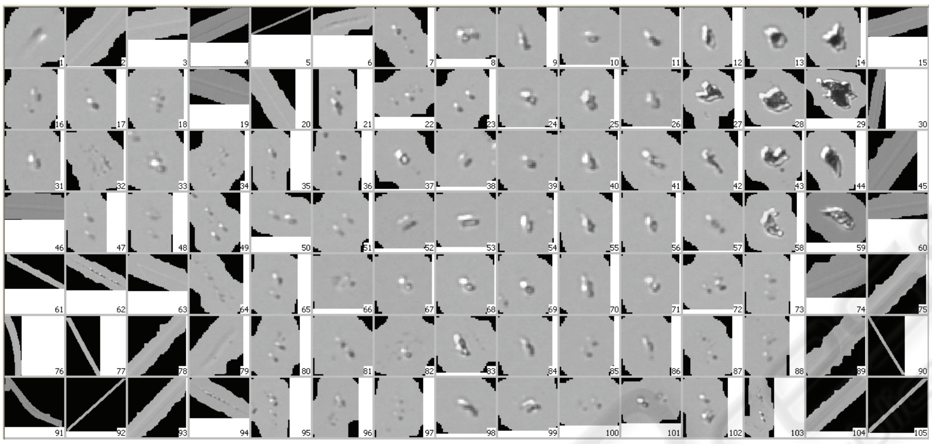

Fig. 6. Representation of the map (the depicted defect for each node is chosen randomly among the examples of the database which are projected onto the node under consideration; the size of images is normalized, so the real scale is not respected).

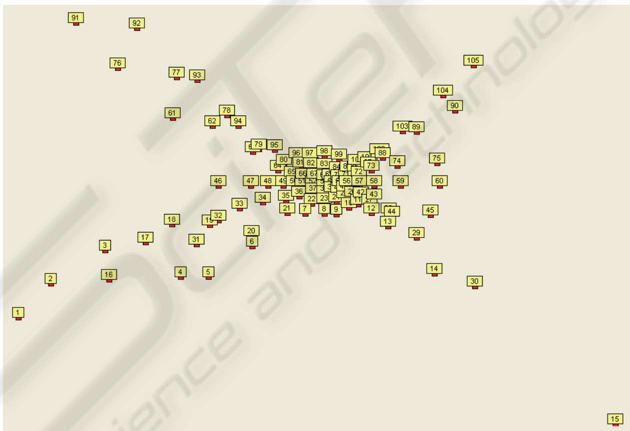

Fig. 7. Curvilinear representation of the SOM's neurons (the number associated with each neuron is the same as in the Figure 6). It highlights the relative distances between neurons in the weights space.

Finally, we check the accuracy of the projection using the dy-dx representation. As shown in Figure 8, the curve constituted by averages of dx for each dy is uniformly monotonic; it means that the topology of data space is kept, on the whole. However, we can see that the group of dots is relatively diffuse. This can be explained by the fact that the projection of a space of intrinsic dimension 7 onto a bidimensional space is necessarily imperfect!

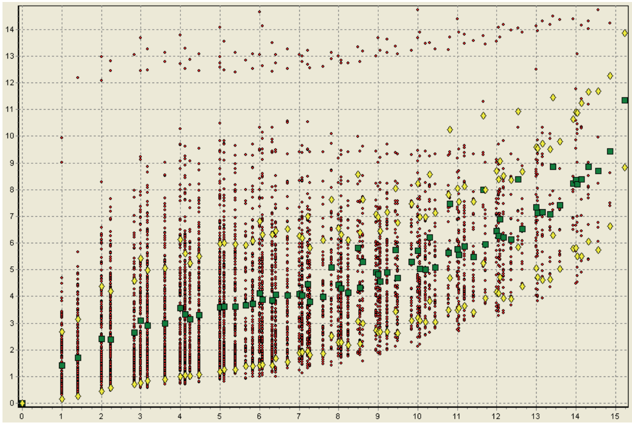

Fig. 8. dy-dx representation of SOM (mean □ and standard deviation ◊ of dx are also represented for each dy). It depicts the relative distances between neurons in the grid space (abscissa) versus in the weights space (ordinate).

First, since the described experiment shows the emergence of well-founded clustering and consistent clusters of data, the proposed data coding scheme is pertinent. However, using shape features (like binary Fourier-Mellin invariants) in conjunction with texture features (like wavelet coefficients) could also be attractive. Furthermore, if the structure of database is highly non-linear, the used centring-reducing normalization is certainly a suboptimal solution. On the other hand, since we work with a high-dimensional data space and even if we obtain a correct representation of data space with a 2 dimension SOM, using a greater dimension SOM can probably improve the results. There are also limitations using SOM: first the neuron grid's structure is set a priori and unfortunately such a structure, if not suited to the data distribution shape, leads to inappropriate projection. Moreover, SOM provides a discrete projection onto a low-dimensional space, but it could be desirable to continuously project data.

6 Conclusion and Perspectives

A reliable diagnosis of the aesthetic flaws in high-quality optical devices is a crucial task to ensure products' nominal specification and to enhance the production quality by studying the impact of the process on such defects. We propose an approach based on Nomarski microscopy, which provides robust detection and reliable measurement of outward defects. To ensure a reliable diagnosis, this process should be completed by an automatic classification system in order to discriminate the "false" defects (correctable defects) from "abiding" (permanent) ones. We first need to extract relevant information from raw Nomarski image, to obtain exploitable data for a classification scheme. This paper has presented a data extraction method and studied a real database using SOM. It can be compared with [18] (use of Fourrier-Mellin transform for data coding in an artificial neural network based pattern recognition system) or [19] (use of SOM for pattern recognition tasks). Since well-founded clusters and pretty homogeneous neuron associated data are exhibited, the proposed method is pertinent. On the other hand, using SOM is in itself attractive, because it allows exploiting non-labelled samples (without expert intervention). However, data projected onto neurons which are near "natural" class boundaries, are sometimes heterogeneous. If this problem is overcome, classification could be directly completed by expert neuron labelling [20]. SOM can also constitute an efficient pre-processing phase for a finer classification.

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