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Detection of Irregularities in Regular Dot Patterns

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Abstract

In this study, a periodic image element structure, referred to as regular dot pattern is defined. Two methods are introduced to detect irregularities in regular dot patterns. In the experimental part the proposed methods are applied to detect missing elements, dots, from digitized Heliotest samples which are considered to form a regular dot pattern. Heliotest assessment is used in the paper and printing industry to measure printability of different paper grades.

1 Introduction

In many quality assurance tests it is desirable to to locate defects in order to determine quality of a product. Many manmade objects are also repetitive in nature: e.g., fabrics have stripes that repeat throughout the whole fabric, halftone printed images consist of small dots that form letters or images, etc. In this study, we first search repetitive patterns from images and by utilizing reqularity we detect irregularities from patterns. The irregularities may represent defects in an observed product and should be reported in order to determine the final quality of a product.

An example application can be found from quality control of halftone printing: detection of missing dots in rotogravure prints. The test is usually performed manually off-line by laboratory experts and is called Heliotest paper printability test in paper and printing industry. There have been several propositions for missing dot detection, e.g., by Langinmaa [6] and Heeschen and Smith [5], but they have failed to satisfy the requirements of paper and printing industry.

In this study the regular dot patterns are defined and then based on the definition two methods are proposed for accurate irregularity detection. In the experimental part the proposed methods are applied to missing dot detection from rotogravure test print strips. The goal of this research is to implement a machine vision based system that will locate missing dots from Heliotest images.

2 Pattern regularity

Regularity is a property which means that some mnemonic instances follow predefined rules. In the spatial domain regularity typically means that a pattern consists of a periodic or quasi-periodic structure of smaller pattern units or atoms, and thus, it is worthwhile to explore pattern regularity in terms of periodical functions and especially via their Fourier transforms. The following is mainly based on definitions in solid state physics and is related to Bravais lattice formulations [1].

Bravais lattice is an infinite array of discrete points with an arrangement and orientation that appears exactly the same, from whichever of the points the array is viewed. A two-dimensional Bravis lattice consists of points with position vectors $\mathbf{R}$ of the form

$$\mathbf{R} = n_1\vec{a}_1 + n_2\vec{a}_2 \tag{1}$$

where $\vec{a}_1$ and $\vec{a}_2$ are any two vectors not both on the same line and n_1 and n_2 range through all integer values. The vectors $\vec{a}_i$ are called prime vectors and are said to generate or span the lattice. In Figure 1 is shown a portion of two-dimensional Bravais lattice.

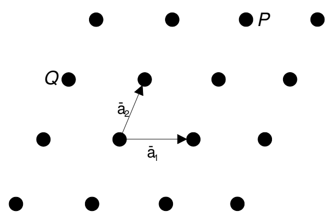

Figure 1: A two-dimensional Bravais lattice. All points are linear combinations of two primitive vectors (e.g. $P = \vec{a}_1 + 2\vec{a}_2$ and $Q = -\vec{a}_1 + \vec{a}_2$).

The definition of Bravais lattice refers to points, but it can also refer to a set of vectors which represent another structure. A point as an atom can also be replaced with any, preferably locally concentrated, structure. A region which includes exactly one lattice point is called a primitive unit cell and $\vec{a}_i$ now define spatial relationship of unit cells. Unit cells can also be defined as non-primitive but in both cases they must fill the space without any overlapping.

2.1 Fourier transform of 2-d periodic functions

Let us consider a function $f(\vec{r})$ (where $\vec{r} = (x, y)$) in which the spatial domain is a periodic extension of a unit cell. Periodicity can be formally described. Let M be a 2×2 matrix which is invertible and such that

$$f(M\vec{m} + \vec{r}) = f(\vec{r}) \tag{2}$$

where $\vec{m}$ is any 2-dimensional integer vector. Now, every point $\vec{r}$ in the space can be written uniquely as

$$\vec{r} = M(\vec{n} + \vec{u}) \tag{3}$$

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where $\vec{n}$ is a 2-dimensional integer vector and $\vec{u}$ is a vector where each coordinate satisfies $0 \leq u_i < 1$. The unit cell $\mathcal{U}(M)$ is a region in space corresponding to all points $M\vec{u}$. It can be shown that the volume of unit cell is $V = |\det M|$.

The set of all points $\mathcal{L}(M)$ of the form $M\vec{n}$ is called the lattice induced by M. Any point in the space corresponds to a point in the unit cell translated by a lattice vector. Note that a sum of two lattice vectors is a lattice vector and the periodicity of function f implies that its value is invariant under translations by multiples of the lattice vector. A matrix $\hat{M}$ can be obtained by inverting and transposing M

$$\hat{M} = M^{-T} \quad . \tag{4}$$

For $\hat{M}$ new lattice and unit cell can be associated, called the reciprocal lattice $\mathcal{L}\left(\hat{M}\right)$ and the reciprocal unit cell $\mathcal{U}\left(\hat{M}\right)$, respectively. If we consider wave number space, each vector $\vec{k}$ is written uniquely as

$$\vec{k} = \hat{M}\left(\vec{\kappa} + \vec{\xi}\right) \tag{5}$$

where $\vec{\kappa}$ is a 2-dimensional integer vector and $\vec{\xi}$ contains all ordinates $0 \leq \xi_i < 1$. The reciprocal lattice vectors span the lattice points $\hat{M}\vec{\kappa}$.

The fundamental result is that the Fourier transform of a periodic function with a unit cell specified by M has a discrete spectrum, peaks located at the reciprocal lattice points specified by $\hat{M}$ [1]. That is, the wavenumber vectors are constrained to lie at the reciprocal lattice points. The explicit transform and inverse transform formulas are

$$\hat{f}_M\left(\vec{k}\right) = \frac{1}{|\det M|}\int_{\vec{r}\in\mathcal{U}(M)} f(\vec{r})\, e^{-j\left(\vec{k}\cdot\vec{r}\right)} dV(\vec{r}) \qquad , \vec{k} \in \mathcal{L}\left(\hat{M}\right) \tag{6}$$

and

$$f(\vec{r}) = \sum_{\vec{k}\in\mathcal{L}\left(\hat{M}\right)} \hat{f}_M\left(\vec{k}\right) e^{j\vec{k}\cdot\vec{r}} \quad . \tag{7}$$

The discrete spectrum can be interpreted as a continuous spectrum consisting of Dirac impulse functions located at the reciprocal lattice points

$$\hat{f}\left(\vec{k}\right) = \sum_{\vec{\kappa}\in\mathcal{Z}^D} \hat{f}_M\left(\hat{M}\vec{\kappa}\right)\delta\left(\vec{k} - \hat{M}\vec{\kappa}\right) \quad . \tag{8}$$

2.2 Fourier transform of 2-d quasi-periodic functions

Unfortunately in the real world the structures are usually only approximately periodic (quasi-periodic). In an ideal case where a pattern image whose unit cell and lattice structures are specified by M, is unbounded in all directions. Then it is the superposition of waves whose wavenumber vectors are necessarily precisely lattice vectors in the reciprocal lattice specified by $\hat{M} = M^{-T}$.

However, a real image has finite extent and has imperfections (irregularities). The ideally periodic function must be constrained to satisfy practical boundary conditions. This can be illustrated by considering a situation, where the pattern is comprised by a finite number of translates of unit cell. Let V denote the finite region occupied by the pattern, and consider the window function $w_\nu(\vec{r})$ defined as

$$w_\nu(\vec{r}) = \begin{cases} 1\,, & \vec{r} \in \mathcal{V} \\ 0\,, & \text{otherwise} \end{cases} \tag{9}$$

If $f(\vec{r})$ is the ideal, truly periodic function (periodicity specified by M) and $f_\nu(\vec{r})$ is the truncated function

$$f_\mathcal{V}(\vec{r}) = w_\mathcal{V}(\vec{r})\, f(\vec{r}) = \begin{cases} f(\vec{r})\,, & \vec{r} \in \mathcal{V} \\ 0\,, & \text{otherwise} \end{cases} \tag{10}$$

then $f_\mathcal{V}(\vec{r})$ has a continuous spectrum given by

$$\hat{f}_\nu(\vec{k}) = \sum_{\vec{\kappa}\in\mathbb{Z}^2} \hat{f}_M(\hat{M}\vec{\kappa})\hat{w}_\nu(\vec{k} - \hat{M}\vec{\kappa}) \tag{11}$$

where $\hat{w}_\nu$ is the Fourier transform of w_ν. It can be shown that $\hat{w}_\nu$ contains a continous spectrum which has infinite extent, but which fades out proportionately fast with $1/\left|\vec{k}\right|$.

The most important result is that quasi-periodic functions have quasi-discrete spectra, with the spectral energy concentrated at points in the reciprocal lattice. Thus in terms of function periodicity, pattern irregularity can be defined as an aperiodic function $\epsilon(x, y)$, with spatial energy $|\epsilon| \ll |f_\nu|$.

Finally, the initial 2-d pattern image can be represented as

$$f_\nu(\vec{r}) = w_\nu(\vec{r})f(\vec{r}) + \epsilon(\vec{r}) \tag{12}$$

and the problem is to separate the regular part $w_\nu(\vec{r})f(\vec{r})$ and the irregular part $\epsilon(\vec{r})$ as accurately as possible.

3 Extracting regular pattern information

As it was described in the previous section the construction of model of ideal regular part of an image is crucial for the irregularity detection. Without first detecting the regular pattern underlying in an image, it is impossible to detect any irregularity in it. The more accurate model of regular image can be established, the more accurate detection and classification of irregularities can be done. Detail level needed for the regular part formation is particularly high for example in Heliotest images [9], and thus, typical texture segmentation methods (e.g., [4]) or defect detection methods (e.g., [2]) do not provide a sufficient accuracy. One attractive approach to estimate an ideal regular pattern is to form an analytical model and to estimate model parameters based on the input image [2], but this requires correct and very accurate analytical model which cannot be achieved due to discrete image resolution and expensive computations.

3.1 Exploiting Fourier domain

Let us consider real images which represent regular dot patterns, such as the images produced by the Heliotest assessment. An example image and its Fourier spectra are shown in Figure 2. From the figure, it is possible to see the distinctive frequency peaks which in turn are located at the reciprocal lattice points.

By filtering the reciprocal lattice frequencies it is possible to estimate the faultless periodic component, i.e., the ideal regular pattern of input image. By filtering all other frequencies than reciprocal lattice frequencies, the irregular part of original image can be estimated. The regular and irregular parts that are estimated are now called as regular

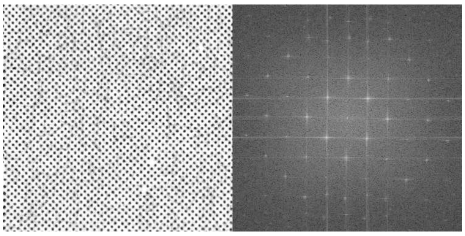

Figure 2: Example of regular dot pattern image (Heliotest) and its Fourier spectra magnitude.

and irregular parts of image. The separation process can be formulated as

$$\begin{aligned}\xi(x,y) &= \mathfrak{F}^{-1}\{\Xi(u,v)\} = \\ &\mathfrak{F}^{-1}\{\mathfrak{M}(u,v)\Xi(u,v) + (I(u,v) - \mathfrak{M}(u,v))\Xi(u,v)\} = \\ &\mathfrak{F}^{-1}\{\mathfrak{M}(u,v)\Xi(u,v)\} + \mathfrak{F}^{-1}\{(I(u,v) - \mathfrak{M}(u,v))\Xi(u,v)\}\end{aligned} \tag{13}$$

where $\xi(x,y)$ is an image, $\mathfrak{F}$ and $\mathfrak{F}^{-1}$ are the forward and inverse discrete Fourier transforms, $\mathfrak{M}(u,v)$ is a mask filter (real valued function of the same definition domain as $\Xi(u,v)$), and $I(x,y)$ is a unit function. The decomposition in Eq. (13) is possible according to identity of the addition operation in the spatial and frequency domains. The mask $\mathfrak{M}(u,v)$ is used to filter frequencies at peak locations in the frequency domain.

4 Irregularity detection algorithms

The following algorithms detect missing dots from images of a 2-d periodic dot patterns.

4.1 Method based on global gray-level processing

This method (Method 1) is based on the fact that the periodic regular structure provides intensity peaks in the Fourier domain as was previously demonstrated. If the mask $\mathfrak{M}$ can be automatically generated by utilizing locations of the peaks in the frequency domain, then the regular and irregular parts of an image can be extracted as shown in Eq. (13). From the irregular image it is possible to find irregularities by thresholding and then by processing the binary areas. The original image can be preprocessed in order to eliminate illumination changes and acquisition noise.

Next, it is assumed that the dots forming the regular pattern are represented by high gray-level intensity values and the background by low intensity values. Furthermore, the values are assumed to be normalized between 0 and 1. Irregular component extraction is presented in Algorithm 1.

Algorithm 1 *Irregular image extraction*

1. *Compute magnitude of the Fourier transform $|\Xi|$ of an input image ξ.*
2. *Form the reciprocal lattice vectors using locations of magnitude peaks.*
3. *Create the mask $\mathfrak{M}$ by setting Gaussian band-pass filters to reciprocal lattice points.*
4. *Extract the irregular component from ξ using the mask $\mathfrak{M}$ and the inverse Fourier transform.*

Most of the steps are clear enough, but the second step requires some more explaining. The purpose of Step 2 is to locate all the high frequency peaks in the Fourier domain. The reciprocal lattice is defined by the primitive vectors, which can be estimated within a sub-pixel accuracy using the peak locations, but estimation may be sensitive to the initial guess. The estimation ambiguity occurs due to harmonic components and can only be prevented using a sufficiently accurate initial guess. Another ad hoc solution would be to locate all frequency peaks, but since the frequency plane is discrete, the harmonic set estimation based on lower frequencies is not accurate and they need to be adjusted to actual local maxima. This adjustment is performed by looking for a local maximum in a certain neighborhood. For example rectangular neighborhood can be used.

The irregular image needs to be processed in order to distinquish the significant irregularities from the noise that is also present in real images. Algorithm 2 can be used for that purpose.

Algorithm 2 *Detecting irregularities from irregular image*

1. *Threshold the irregular image ξ_I using the threshold limit τ.*
2. *Remove foreground areas of a size less than S.*
3. *Compute centers of each foreground areas.*
4. *Return centers as irregularity coordinates.*

There are various methods for binary processing tasks, e.g., areas less than size S can be removed by using the binary opening procedure [3]. Due to the image normalization in the previous stages, the parameters τ and S can be fixed and the value selection remains an application specific task.

4.2 Method based on local gray-level processing

This approach (Method 2) is divided into two parts. First the spatial lattice points are estimated and then the spatial points are locally classified.

Spatial lattice estimation correspond to the estimation of irregularities in the regular part, and thus, Algorithms 1 and 2 can be used to locate centroids of the unit cells. The only difference is that the regular image part is used instead of the irregular one. When all the centroids of the regular image part are located, the original image is processed and analyzed at each unit cell location.

Local classification at the locations of the unit cells is then performed in order to determine whether it is regular or irregular, missing or not missing. First some kind of feature extraction is needed, e.g, vector of all gray-level values. After feature extraction the unit cells can be classified using a classifier, e.g., for vectors of gray-level values a principal component subspace classifier can be used [8]. It should be noted that a separate training set is needed in this approach, but on the other hand the local processing also provides detailed information about an error type of a missing dot.

5 Experiments

In the experiments the methods and algorithms were applied to real data.

5.1 Heliotest data

Paper printability is a property which describes how a certain type of paper behaves in a printing process. In general, the printability property depends on interactions between paper and printing ink, and variables of printing process itself. Good printability generally means that the paper is not sensitive to the variations in the variables and provides a good printing quality. In practice, an estimation of the print

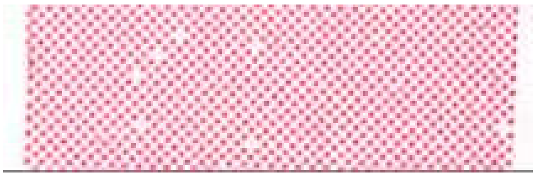

Figure 3: Part of a typical Heliotest strip. The dimensions of a whole test strip are 110mm by 85mm.

quality can be achieved by several different quality assessments [7].

In rotogravure printing process, the greatest problem involves reproduction of light and medium tones. In the reproduction of tones, the two recognized defects are missing dots and waving. In the missing dot defects, the ink is not transferred to the paper which is considered to be due to a bad quality of paper. Paper surface does not allow the ink to soak into the paper. Ink adhesion can be tested by using a special Heliotest machine which generates a rotogravure print samples from which the missing dots are then calculated by visual inspection. An example of Heliotest strip can be seen in Figure 3.

For the experiments, a set of reproduced Heliotest strips were scanned using 1200 dpi resolution. The training set consisted of 75 images and the test set of 70 images. The training set was needed to train two set of classes: a dot and a missing dot. In addition, because the parameters of the rotogravure printing cylinder change along the strip, i.e., ink cups get smaller, and respectively the dots become smaller and lighter, it was practical to process strips in separate windows. Each processing window had their own parameter values in irregularity detection. For the selection of parameters, the training set was used.

5.2 Results

Ground truth of missing dots was created by visually inspecting the strips and the comparison between the two proposed methods was done with respect to the ground truth.

Paper and printing industry measuser a distance to the 20th missing dot from the beginning of strip. The same measure was used in this study. Fig. 4 shows errors for the both methods as compared to manually found distances to the 20th missing dot. Method 2 was more accurate, but slower. As it can be seen from Figures 4(b) and 4(c), errors for both methods were less than 1 cm. The whole length of the test strip was 11 cm. The accuracies of both methods were adequate for industry purposes.

6 Conclusions

Two methods were proposed to detect irregularities in regular dot patterns. Both methods assume that an image can be divided into regular and irregular parts, where the regular part is sufficiently strong to be detected in the reciprocal space. The first method directly utilizes the irregular parts and processes it globally to detect the most visible irregularities. The second method utilizes the regular part to find the centroids of all unit cells and then locally classifies whether a cell is distorted or not.

Based on the proposed methods an automatic apparatus can be built to be used in the Heliotest assessment. In the future industry requires a more specific information of different kind of irregularities in dot shapes. For that purpose the proposed method 2 can be further developed.

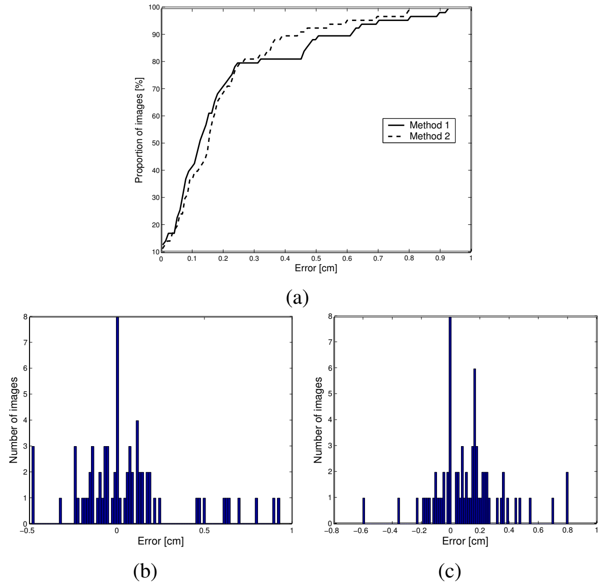

Figure 4: Accuracy of distances to the 20th missing dot as compared to the ground truth: (a) Percentage of images where specific accuracy was achieved; Error histograms for (b) Method 1 and (c) Method 2.

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