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Robust image processing technique for Knoop hardness measurement

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Abstract-Rapid increase of computational performance of personal computers has enabled employment of automatic hardness measurement in the last decade. It reduces the human factor in measurement and speeds up the measurement process. On the other hand, the automatic measurement often fails, when the specimen surface is not well prepared. Robust image processing algorithm is crucial for the automatic hardness measurement. The article introduces a combination of an advanced image processing technique called Active Shape Modeling (ASM) and a sophisticated model estimation technique called Particle Filtering (PF). It enables measurement of rough polished specimens and minimizes the effect of specimen surface properties.

I. Introduction

More sophisticated products require better knowledge of construction materials and their properties, one of which is also hardness. At the current global market with semi-finished products and final products, it is necessary to have suitable tools for testing material properties. Measuring hardness is important for testing quality of the processed materials and the final industrial products. In recent years due to the increased amount of low quality materials imported to the European market there has been a growing need to test hardness to verify the quality. These imported semi-finished products are interesting for a number of manufacturers for their low price; they must, however, pay attention to the input control of their properties. Hence it is necessary to use such testing technologies which enable fast and reliable discovery of low quality material and help to prevent its use in the production process. Automatic hardness measurement can speed up the measurement process and provide repeatable results in contrast to manual measurement that is time consuming and always affected by human factor.

Several different approaches to automatic hardness measurement were presented in the past. The articles mainly focus on the Vickers hardness measurement but most of the issues discussed are applicable for Knoop hardness measurement as well. Straightforward technique of indentation vertex calculation is presented in [1]. It uses the least square method for the average diagonal length calculation. Key issue of the threshold determination is discussed there as well. Region growing technique is presented in [2]. More sophisticated method that utilizes thick line Hough transform is discussed in [3]. In [4], the hardness measurement process is divided in three steps: image preprocessing, indentation recognition and indentation measurement. Different techniques for each stage are briefly introduced. Another advanced approach that utilizes wavelet functions is discussed in [5, 6].
The paper is organized as follows. Section II introduces principle of hardness testing. The stress is laid on the Knoop hardness test. General principles of ASM and PF and their application in the hardness measurement algorithm are explained in section III. The results are summarized in section IV. Section V concludes the paper.

II. Principle of hardness testing

Hardness is one of the important mechanical properties of the construction materials and therefore is very often measured in technical practice. The main advantage of these hardness tests is their easiness, repeatability and also the fact that in many cases the measurement can be performed directly on the product or on samples produced and designed for other types of mechanical tests.
Hardness can be defined as the resistance of material (surface of the material in the measured spot) against local deformation caused by a pressing material (so-called indenter) of a specific geometrical shape, at a defined load. The degree of hardness is determined by the size of the permanent plastic deformation.
Hardness tests can be divided according to different criteria: In terms of principle we recognize a scratch test, indentation test, impact test and rebound test. In terms of the speed of effect of the loading force we recognize

static and dynamic tests for hardness. Further we recognize tests of macro and microhardness. The name "microhardness" is used for hardness determined by very small loads causing only very small indentations. Very often the borderline between macro and microhardness is stated as 19.8 N. Microhardness cannot be determined by usual hardness tester because it requires much higher precision during load application as well as when measuring the indentation.
The most frequent methods of measuring hardness are static methods of Brinell (ČSN EN ISO 6506), Rockwell (ČSN EN ISO 6508), Vickers (ČSN EN ISO 6507) and Knoop (ČSN EN ISO 4545).

A. Microhardness according to Knoop

Knoop hardness test

The method of Knoop hardness test for metal materials is stipulated by the international standard ČSN ISO 4545, and applies the test load up to 9.807 N.

Principle of the test

The principle of the Knoop test consists in pressing a diamond indenter with prescribed dimensions and angles of the opposite sides against the surface of a test material. Then the length of the long diagonal of the indentation, which remains after the test load is removed, is measured.

The value of hardness by Knoop is expressed as the ratio of the load applied to the area of the indentation. The impression area has the shape of pyramid with a diamond-shaped base and top angles equaling angles of the indenter:

Where HK is hardness by Knoop
HK = constant* test load/impression area

$$HK = 0.102 \cdot \frac{F}{d^2 \cdot c} = 0.102 \cdot \frac{F}{0.07028 \cdot d^2} = 1.451 \cdot \frac{F}{d^2}$$

Where
d length of the long diagonal in mm
F test load in N

Constant $$\frac{1}{g_n} = \frac{1}{9.80665} = 0.102$$

Constant of the indenter $$c = \frac{\tan \beta / 2}{2 \tan \alpha / 2} = 0.07028$$

Hardness by Knoop is marked by symbol HK, which are followed by numbers which stand for the size of the test load and the time of effect of the test load in seconds, if different from the prescribed time (10-15 s):
Example no.1: 640 HV 0.1 = hardness by Knoop 640 determined at test load of 0.9807 N
for the time of 10 to 15 s
Example no..2: 640 HV 0.1/20 = hardness by Knoop 640 determined at test load of 0.9807 N
for the time of 20 s

The advantage of Knoop indenter is that the deformation is relatively greatest at the short diagonal and the greatest suspension is, therefore, at load removal. In the direction of the long diagonal the suspension is insignificant. Another advantage is that the indentations can be formed in such a way that it is possible to measure hardness with a high precision at narrow materials, e.g. wires. If the long diagonal is placed parallel to the surface of materials, it is possible to measure the changes of hardness at cemented and nitride surfaces more sensitively than in the case of Vickers indenter. Given the small depth of the penetration of the indenter, this method can be used for materials with a thin surface layer.

III. Image Processing

While specimens are specular polished, there is a wide range of algorithms that can be used for the automatic measurement. However, specimens often have polishing scratches, are etched or are rough polished in the practical applications. The following images illustrate such cases.

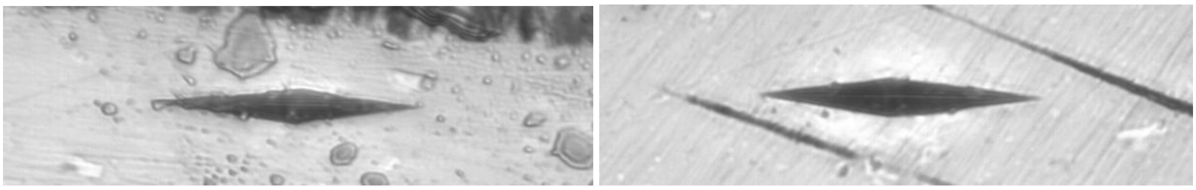

Figure 1. Examples of KNOOP indentation

Due to rust or inclusion particles, indentation can be locally deformed.

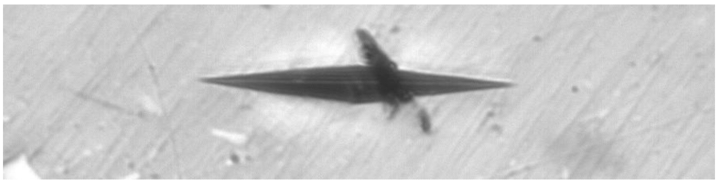

Figure 2. Example of inclusion particle

The aim is to minimize the effects of the specimen surface properties on the automatic measurement algorithm. Despite of the "pixel oriented" techniques [1, 2, 4], the method discussed in the following chapter searches for the best fit of the whole indentation while respecting the shape of the indenter.

In this chapter we first introduce methods of image and signal processing which are used in the presented hardness measurement algorithm. In section III.C we describe the algorithm in detail concerning Knoop hardness measurement specifics.

A. Active Shape Model

ASM is a statistical shape description method introduced by Tim Cootes [9] to detect an object in an image under various appearances. It has been successfully applied in face recognition, face identification or in medicine to describe the shape of bones or organs. In the KNOOP hardness test the modeled shape is an elongated diamond as a result of the indention. An indenter leaves a different mark depending on the quality of the tested material. The differences in the appearance of the indention are statistically dependent.

In ASM the shape is represented as a set of landmarks. The landmarks are usually chosen by hand for more complex shapes or alternatively they can be synthesized. They should describe the shape well and they should be easily detectable. Landmarks usually lie on the edges of the shape. Their connectivity is recorded by ordering. Next, the set of connected landmarks is turned into a vector. Usually a set [x(1..N),y(1..N)] becomes a vector $[x(1),x(2),...,x(N),y(1),...y(N)]^T$. Each shape generates a vector in a $\boldsymbol{R}^{2N}$ space. When we obtain more shapes they form a distribution in this space. The idea is to find a statistical description of the distribution. Principal component analysis (PCA) is used to achieve this [10]. It is an efficient method to reduce the dimensionality of statistically dependent data (equation 2).

$$x = \bar{x} + Pb \qquad (2)$$

where x is a vector form $\boldsymbol{R}^{2N}$ representing a shape, $\bar{x}$ is the mean of all training shapes, P is formed column wise by eigenvectors of the covariance matrix of training shapes and b is a vector in the reduced dimension. By changing the vector b in limited intervals we obtain new plausible shapes which resemble the ones used in training. The advantage of this is that we can find an optimal solution in a lower dimension space, saving computation time and rejecting improbable solutions.

B. Particle Filtering

PF is a model estimation technique based on simulation. It uses a set of particles to describe a distribution of model parameters. In general, the particles are vectors belonging to the model parameters' space. Weights are associated with particles representing their importance. Generally, there are more approaches on how to estimate the model parameters using PF [11]. In our case we use a version of Sampling Importance Resampling. This means that in each step of the algorithm a set of possible particles is drawn from an estimated distribution. Importance of these particles is measured and propagated. From the importance sampling step a new distribution of particles is estimated and so on. The algorithm ends when required conditions are met.

C. Description of the hardness measurement algorithm

First, we synthesized samples of indention shapes to train ASM. The shape was modeled as four vertexes of an elongated diamond. The relative position of the vertexes is defined by the shape of the indenter. In reality the shape of the indention is rarely a perfect diamond shape. This is caused by non-ideal conditions of the hardness test. The variations in the appearance under our scope include the position, scale and rotation. ASM is used to model the rotation and the scale. The position is handled by PF in later stages of the algorithm. A set of possible landmarks is synthesized using a scale and rotation transforms (equation 3).

$$X_i = \begin{bmatrix} s_i \cdot \cos(\alpha_i) & -\sin(\alpha_i) \\ \sin(\alpha_i) & s_i \cdot \cos(\alpha_i) \end{bmatrix} \cdot V^T, i \in \langle 1..N \rangle \qquad (3)$$

where s_i is the ith scale parameter, α_i is the ith angle and V is a matrix containing vertexes of an aligned indention shape. In our experiments $s = <0.5;2>$, $\alpha = <-\pi/10; \pi/10>$ and V = [0 0.0703;0.5 0;0 -0.0703;-0.5 0]. Then X_i is a matrix containing the vertexes of a transformed indention shape. Next, we create vectors x_i^T = [X(1,1), X(2,1),..,X(N,1),X(1,2),..,X(N,2)] and apply PCA. Since we trained the model with synthesized data we obtain two shape parameters representing the rotation and the scale. In general, more complex indention shapes can be used to handle more variations of the shape at the cost of computation time.

The second step is to prepare an observation image. The input image has to be preprocessed in order to amplify important features of the indention. In most cases the shape is well defined by its edges. On the other hand, the edge is almost never a straight line. Therefore we use statistical methods like ASM and PF to cope with this problem. To detect the edges we use a bank of filters to estimate the gradient field in the image. The amplitude of the gradient field is regarded as the observation image. This makes the edges broader and they are aligned in a direction, thus they are well suited for line approximation.

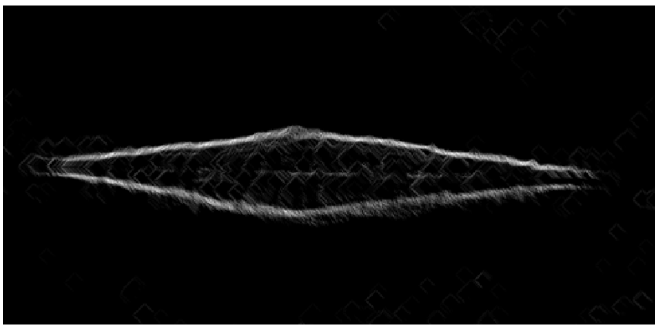

Figure 3. Edge detection using a bank of filters

The third step is to estimate the position, rotation and scale of a model shape using PF. At first, a set of particles is generated. The particles are samples from the model parameter space. At the beginning we pick the particles equidistantly from an experimentally chosen interval. Next, we measure importance of these particles. It is the intensity of edge points in the observation image along the edges of the model shape. This way we want to respect the shape of the indention. The weights are computed as normalized results of the importance measurement. The best scoring particle is remembered as the parameter estimation in this step. Particles are resampled according to the distribution of the weights. The better score a particle achieves the better chance it has to be resampled. We add additional noise to the resampled particles. This assures that one particle is not resampled several times at the same position. Importance of the resampled particles is measured in the image and the process repeats until the estimation converges.

IV. Results

The results we achieved are promising. The detection is robust and fails only on very damaged specimens. Usually it occurs in cases where the indention does not fulfill the predefined norm. Our results are shown on the selected examples of KNOOP hardness test.

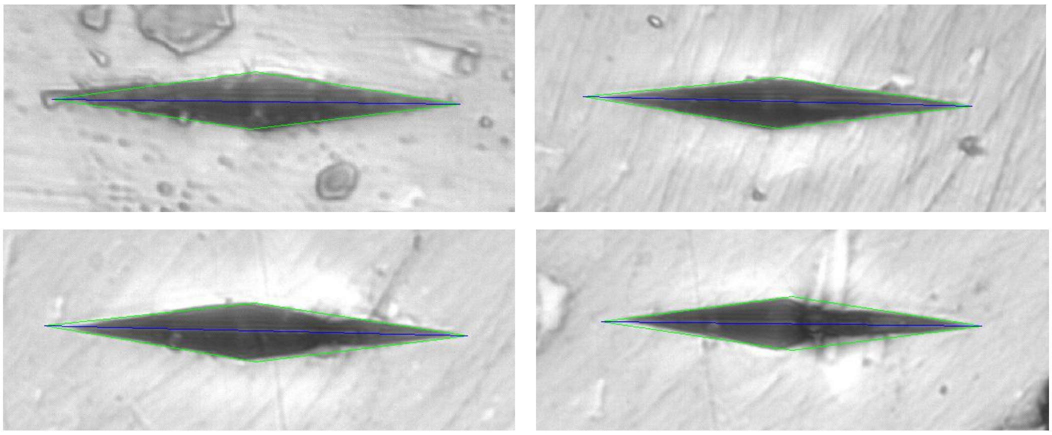

Figure 4. Examples of algorithm detection

The results show that our goal is not to detect the indention shape perfectly, but rather estimate the state of an ideal indention. This is an important property of our method. Knoop hardness test is based on the deterministic relation between the indentation size in the image and the hardness of the tested specimen. Therefore, the aim is to estimate the whole shape of indentation in the image instead of detecting the exact profile of each edge (possibly affected by the specimen surface properties). It can be seen on the left bottom specimen in Figure 4.

For better illustration of our algorithm we show intermediate results on images below.

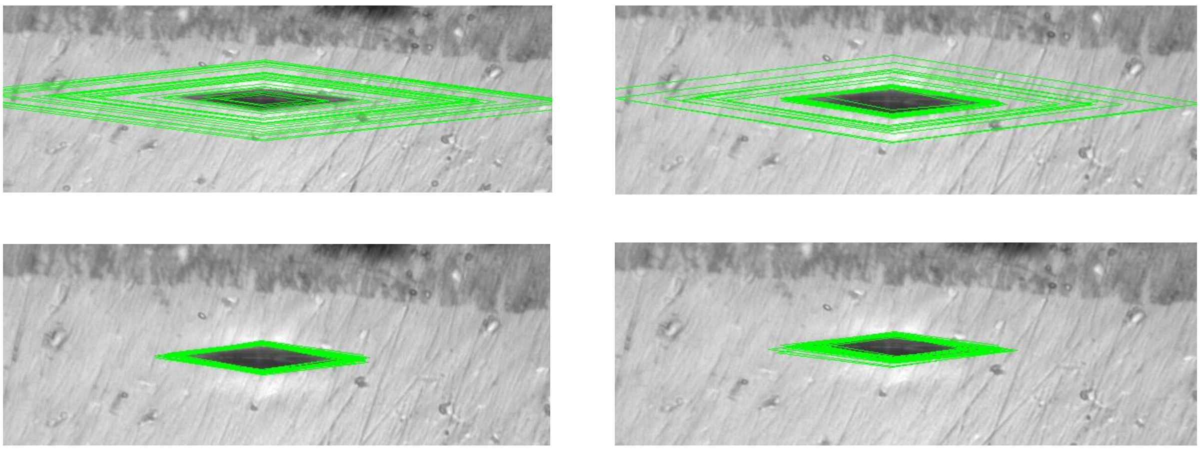

Figure 5. Intermediate results of particle filtering. The generated particles are rendered in green. From top-left to bottom-right the iteration steps 1, 2, 3 and 8 are shown.

The first step is initialization step. It covers all possibilities of indention shapes (from the smallest to the biggest). In the next step only the most probable particles are resampled and in the third step the particles representing non-existing indention shapes disappear.

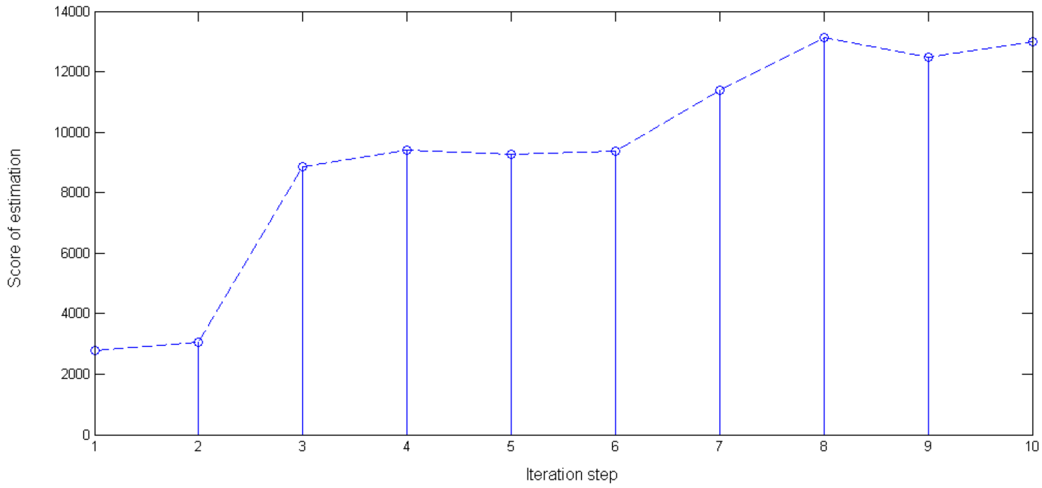

Figure 5. The evolution of score function. Higher score means better fit.

V. Conclusion

The novel image processing technique for Knoop hardness measurement was presented. The results are encouraging and confirmed that the presented technique can handle rough polished specimens as well as rust or inclusion particles. The technique was implemented for Knoop hardness measurement but thanks to the application of the Active Shape Model it can be used for Vickers or Brinell hardness testing as well. This will be the focus of the future developments.

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