

KNOOP HARDNESS MEASUREMENT USING COMPUTER VISION

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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.*

Key words: *microhardness, knoop, active shape modeling*

1. 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 (Sugimoto et al., 1997; Mendes et al., 2003). The articles mainly focus on the Vickers hardness measurement but most of the issues discussed are applicable for Knoop hardness measurement as well.

2. EXPERIMENT

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 (Stanek et al., 2005).

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).

3. RESULTS AND DISCUSSION

ASM is a statistical shape description method introduced by Tim Cootes (Cootes, 2000) to detect an object in an image under various appearances. It has been successfully applied in face recognition, lip tracking (Krňoul et al., 2007) 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 indentation. An indenter leaves a different mark depending on the quality of the tested material. The differences in the appearance of the indentation are statistically dependent.

$$x = \bar{x} + Pb \quad (1)$$

where x is a vector form 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. 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 (Šimandl et al., 2007). 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. 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 $[x(1),x(2),\dots,x(N),y(1),\dots,y(N)]^T$. Each shape generates a vector in a 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. It is an efficient method to reduce the dimensionality of statistically dependent data (equation 1). First, we synthesized samples of indentation 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 indentation is rarely a perfect diamond shape. This is caused by non-ideal conditions of the hardness test (Mendes et al., 2003). 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 2).

$$X_i = \begin{bmatrix} s_i \cdot \cos(\alpha_i) & -\sin(\alpha_i) \\ \sin(\alpha_i) & s_i \cdot \cos(\alpha_i) \end{bmatrix} \cdot V^T, i \in \langle 1..N \rangle \quad (2)$$

where s_i is the i^{th} scale parameter, α_i is the i^{th} angle and V is a matrix containing vertexes of an elongated indentation shape.

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 indentation. 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.



Fig. 1. Edge detection using a bank of filters

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

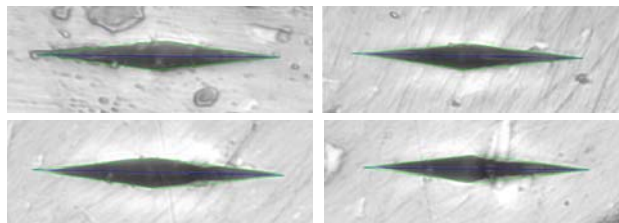


Fig. 2. Examples of algorithm detection

The results show that our goal is not to detect the indentation shape perfectly, but rather estimate the state of an ideal indentation. 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 in Figure 2.

4. 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.

5. ACKNOWLEDGEMENTS

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