The Impact of Unfocused Vickers Indentation Images on the Segmentation Performance

Michael Gadermayr, Andreas Maier, and Andreas Uhl

Department of Computer Sciences, University of Salzburg, Austria
{mgadermayr,andi,uhl}@cosy.sbg.ac.at

Abstract. Whereas common Vickers indentation segmentation algorithms are precise with high quality images, low quality images often cannot be segmented appropriately. We investigate an approach, where unfocused images are segmented. On the one hand, the segmentation accuracy of low quality images can be improved. On the other hand we aim in reducing the overall runtime of the hardness testing method. We introduce one approach based on single unfocused images and one gradual enhancement approach based on image series.

1 Introduction

In Vickers hardness testing, a pyramidal indenter causes a square indentation in a specimen. A major issue is to measure the diagonal lengths of the indentation. Therefore the square object must be segmented from the background to identify the vertices. Especially images of rough surfaces are likely to be highly noisy or have low contrast. The indentation images which should be segmented, approximately fit the following description: The object has a square geometry and is darker than the background. The diagonals are approximately aligned horizontally and vertically. Figure 1 shows example images and the manually determined vertice positions. Whereas the first image is quite perfect, the others suffer from noise and low contrast, respectively. There are several proposals for automated

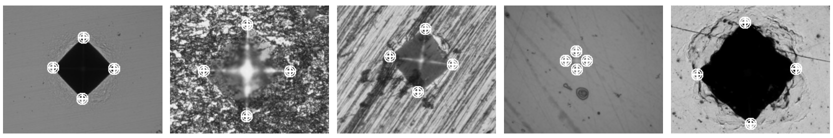


Fig. 1: Vickers indentation images - evaluated vertice positions

image segmentation of Vickers indentations. The methods proposed in [1, 2] rely on template matching. Others are based on edge detection and Hough transform [3], wavelet analysis [4, 5], thresholding [6–8] and axis projection [9].

In order to acquire focused images, the Vickers hardness testing facilities rely on autofocus systems. The autofocus system takes pictures, computes the focus metric and moves the camera for one step until the peak of the focus metric (i.e. the focused image) is reached. We investigate if it is possible to compute approximative segmentation results from unfocused images. This could be advantageous, because an unfocused image is earlier available than the focused image as the autofocus takes a significant amount of time. Moreover, a failure of the autofocus might determine the wrong image to be in focus. Furthermore, we introduce a gradual enhancement approach, which is able to utilize free cpu cycles (caused when moving the camera) to incrementally improve the segmentation results.

This paper is structured in to following way: In Sect. 2, optical effects which occur with focused and unfocused images are explained. In Sect. 3, two different strategies are introduced which are based on unfocused images. In Sect. 4, the results are explained and compared with traditional approaches. Section 5 concludes this paper.

2 Focusing in Vickers Hardness Testing

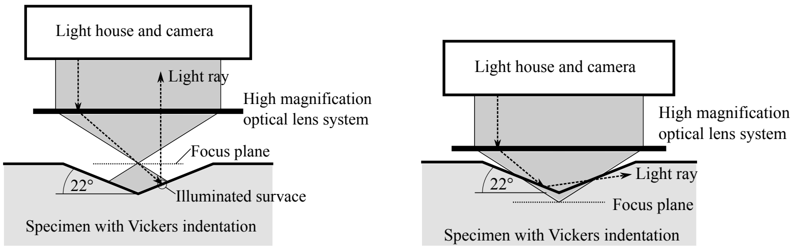
A modern Vickers hardness testing equipment like the emcoTEST DuraScan hardness tester, used in the experiments, includes an inspection unit which is more or less a camera mounted on a microscope. Hardness indentations are analysed and measured with the inspection unit. The size of the indentations is in the millimetre or sub-millimetre range, so the magnification of the microscope is usually between 10x and 100x, and due to the non-transparency of the specimen, the illumination of the specimen takes place through the optics of the microscope.

In an indentation image a high contrast between the indentation and the surface of the specimen is desired. A high contrast facilitates the perception of the indentation when it is measured manually but also simplifies the segmentation when the image is processed automatically. Usually the indentation appears darker than the surrounding because of the groove that is caused by the pyramidal Vickers indenter.

In certain conditions (due to optical effects in high magnification optics) parts of the indentation do appear brighter than the surrounding or the contrast between the indentation and the surrounding is very small or vanishes completely. Such scenarios are challenging for automatic hardness measurement because algorithms often fail to detect the indentation and thus even do not provide approximate numbers for its position and size.

Figure 2a shows a schema of how an indentation image is taken. In a regular configuration the focus of the optical unit is aligned such that the edges and vertices of the indentation are best focused. This corresponds to a focus level that is roughly at the level of the specimen surface. Because the illumination passes through the optics it has the same focus plane. It can be seen from the figure that especially for high magnification optics (with 60x or 100x magnification) the illumination is considerably spread again when it reaches the bottom of the indentation. Due to the spread it includes a substantial amount of light rays that hit the walls of the indentation pyramid in such an angle that they are reflected back into the lens system. These rays act as an illumination for the indentation and are responsible for the reduced or missing contrast with respect to the surrounding.

If the focus of the optical system is shifted down and below the bottom of the indentation, the images are blurred considerably (see Fig. 4) but gain at the same time a substantially increased contrast for the whole or major parts



(a) Focused state

(b) De-focused state, focus plane below indentation

Fig. 2: Schema of the optical unit of Vickers hardness testing equipment with different alignments of the focus plane.

of the indentation. Figure 2b shows such a scenario where the focus plane of the optics and thus the illumination is moved below the deepest point of the indentation. The angle at which the light hits the walls of the indentation is now different and most of the reflected light rays miss the lens system and thus do not illuminate the indentation. The indentation appears darker in many respects and has exceptionally dark areas along the diagonal. The effect increases as the focus plane is lowered but at a certain point the blur becomes so high that the indentation starts to disintegrate in the image and is no longer identifiable.

On such de-focused images the exact measurement of the indentation is no longer possible due to the considerable amount of blur in the image but the increased contrast between indentation and surrounding make de-focused images of this kind a promising candidate for an approximative indentation localisation and size estimation. The result of this first step is then a good starting point for the exact indentation measurement in the focused images.

3 Approaches Based on Unfocused Images

We especially investigate a former 2-stage active contours approach [10] with reference to different kinds of unfocused images: In the first stage, the parameters (position, size and rotation) of a square template are iteratively computed by a gradient descent method. The gradient descent minimizes an energy criterion based on probabilities. The method is not able to exactly segment the indentation, as the indentations slightly vary from a perfect square but a robust localization can be achieved. In the second stage, a region based level set method is initialized with the results of the first stage, to refine the results. To make a more general statement, moreover the 3-stage segmentation method [11] based on approximative template matching [1] is investigated with reference to unfocused indentation images. In Sect. 3.1 a segmentation approach based on single unfocused images and in Sect. 3.2 a gradual enhancement approach based on the approach 2-stage active contours approach is introduced.

3.1 Segmentation of Single Unfocused Images

Our first step is, to find out if it is possible to compute approximative segmentation results from unfocused images. This might be beneficial, as the autofocus algorithm consumes a lot of time, which could be used by an approximative segmentation algorithm based on unfocused images.

We investigate the effect of wrongly focused images on the segmentation algorithms. We have sorted the images according to their focus level (fl). If the focus level is below zero, regions are in focus which are farther away (Fig. 3, dotted line) from the camera than the background (i.e. the indentation might be in focus). If the focus level is above zero, regions are in focus which are nearer to the camera (Fig. 3, dashed line). In our case, no regions are nearer than the background (i.e. nothing is in focus). The step size between two consecutive focus levels is declared in Sect. 4. Differently focused images of the same indentation are shown in Fig. 4.

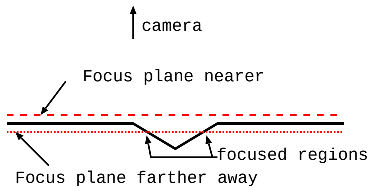


Fig. 3: Cut of Vickers indentation

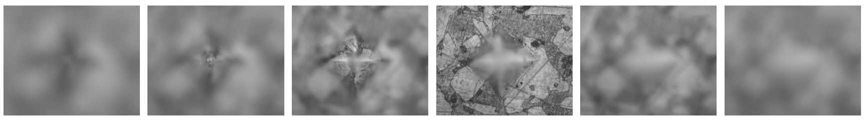


Fig. 4: Different focus settings, reaching from $fl << 0$ (left) to $fl >> 0$ (right)

3.2 Gradual Enhancement Approach

In Sect. 3.1, we considered to segment images of different focus levels. But to identify the focus level, first we have to know the best focus configuration, as the focus levels are defined relatively (focused image: $fl := 0$). Consequently, an approximative segmentation of e.g. the image with $fl = 5$ cannot start before the focused image is known. As we aim in utilizing the free cpu cycles (caused by the autofocus system) for an approximate localization of the indentation, now we consider the following 3 steps based on the gradient descent approach [10]:

1. The focus starting setting is chosen that the focus plane is farther away than any part of the specimen ($fl << 0$).
2. Start the proposed first stage gradient descent segmentation algorithm on the unfocused image which is taken with the mentioned focus setting. Approximative results are achieved.
3. Until the end-criterion is reached:
   - Increase the focus level by one step and get the image.
   - Initialize the gradient descent algorithm with the current approximative results and the new image.
   - Run the algorithm with only 5 iterations to enhance the approximative results.
   - New approximative results are achieved.

The first image to segment is highly unfocused. Consequently, an exact segmentation surely cannot be achieved. However, the blurred image can be segmented robustly. Whereas the first image is segmented as proposed in [10], the enhanced images are not. These images are initialized according to the current approximative results and only 5 iterations of the gradient descent approach are applied. The proposed policy allows to start the segmentation even before the final focused image is available.

Appropriate Endcriterion The intention is, that the results could be enhanced until the focused image is reached. Actually, this is not true. The best results are achieved, when stopping with the image of a focus level below zero. In practice, this is not possible, as the focus levels are defined relatively to the focused image. However, when saving the result history, these results can be recovered.

Speeding up the initial segmentation Whereas the enhancement steps (3) are fast, the initial step (2) takes quite a long time. As the initial contour starts at the boundary of the image (initial radius is about 50 pixels as the images are downscaled by factor 10), has to shrink until it collapses and shrinks one pixel per iteration, about 50 iterations are necessary. Wheras a further reduction of the image size affects the segmentation accuracy, increasing the step size of the contour does not, as far as robustness is concerned. Instead of modifying the evolving shape parameters by one per iteration, we propose to increase the step size (i.e. in one iteration, each parameter is adjusted by the positive or negative step size or stays the same). Increasing the step size to 4, we achieved less accurate results after the initial segmentation step, but after the enhancement steps, the results were exactly the same (the results are shown in Sect. 4.2).

4 Experiments

A database is used with 25 indentations and 40 images (with different focus settings) per indentation. The quality of the images is quite low.

The exact step size between two consecutive focus level images cannot be generally specified, as it depends on the optical zoom of the camera, as shown in Table 1. For example, if an image is 10x magnified, a step size of 10,000

Table 1: Focus step size dependent on the zoom factor

zoom factor	step size
10 x	10,000 nm
20 x	5,000 nm
40 x	1,000 nm

nm is chosen (i.e. while the camera moves, every 10,000 nm a picture is taken). The higher the zoom factor, the smaller the step size must be (because of the different depth of field). For example $fl = 5$ means that the focused plane is five steps nearer to the camera than with the best focus level ($fl = 0$).

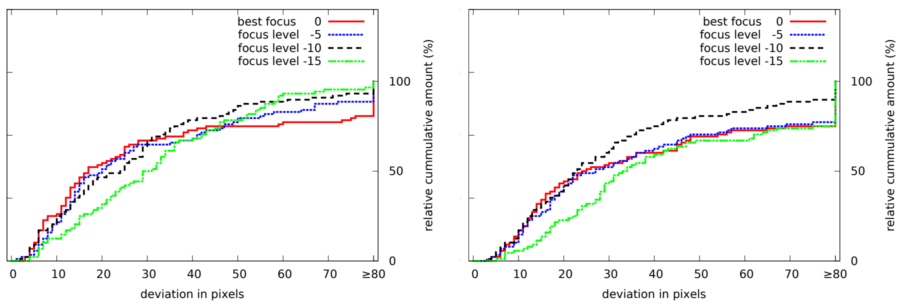
Our aim is to detect the four vertices of the approximately square Vickers indentations. In the following analysises, the distances between detected vertices and the ground truth are measured. The ground thruth is determined by taking the mean of the manual measures of four independent experts. In these figures, for each deviation bin (Euclidean distance in pixels) on the x-axis, the number of vertices detected within the deviation is shown on the y-axis.

4.1 Single Unfocused Images

Approximative Stage First of all, we investigate the effect of unfocused images on the approximative indentation segmentation approach introduced in [10]. Figure 5a shows results of the approximative method. The focus plane is farther away from the camera compared with the best-focus strategy (red line).

The robustness (i.e. few outliers) of the segmentation did not only stay unchanged as expected, but can actually be increased if the unfocused images are used. However, the segmentation accuracy (e.g. the ratio of vertices with a deviation of maximal 20 pixels) slightly decreases. As the curves are crossing, we cannot identify a best configuration just by looking at the results.

In Fig. 5b, a similar effect on the indentation localization stage [1] is shown. Especially focus level -10 seems to be a good choice.



(a) Focal point farther away Shape Prior approach

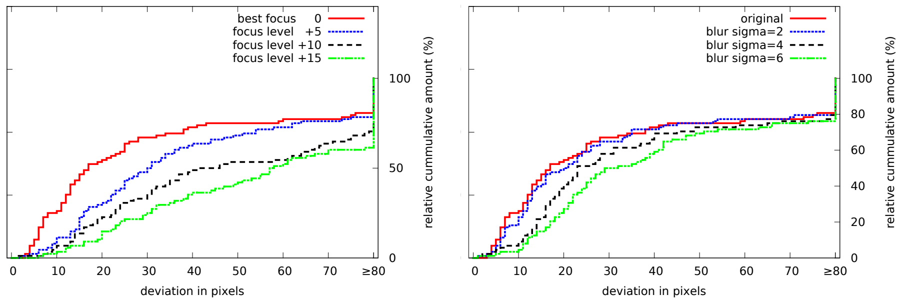
(b) Focal point farther away [1]

Fig. 5: Single unfocused images: Advantageous settings (2 approaches)

The results in Fig. 6a are achieved with the approximative approach and images where the distance to the focus plane is lower than the distance to any part of the specimen. The segmentation performance with these images definitely decreases. Consequently, we specialize on focus levels shown in Fig. 5a.

As unfocused images look similar to blurred images, we also investigate the impact of differently blurred images on the segmentation performance. Especially we would like to know if a similar enhancement of robustness can be achieved as with appropriate unfocused images. Figure 6b shows the results with different Gaussian filters ($\sigma = 2, 4, 6$). Actually, unlike with unfocused images, the number of outliers cannot be decreased significantly. The probability of a precise segmentation suffers as with the unfocused images.

Precise Stage Next, we initialized a precise level set segmentation method [10] with the results, gathered from the approximative method with different



(a) Focal point nearer [10] (b) Blurring

Fig. 6: Single unfocused images: Disadvantageous settings

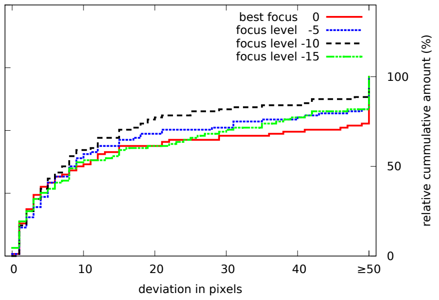
focus levels to get a knowledge of the impact on the overall performance of the multi-resolution algorithm. However, the level set algorithm still operates on the focused images. The question is, how accurate the first stage results have to be in order to achieve precise overall results of the second stage.

Figure 7a shows that the differences of the initializations definitely influences the overall segmentation output of the dual-resolution algorithm. The dual-resolution algorithm does not generate the best results if the best focused images are provided to the first stage algorithm. When regarding the gradient descent algorithm (Figure 5a) we cannot identify a winning focus-configuration, as the curves are crossing. Now, the focus level $fl = -10$ (first stage) is superior to the others for nearly each maximal deviation. Especially the number of outliers declines considerably. So we come to the conclusion that the segmentation of unfocused images with our proposed first stage gradient descent algorithm is even superior to the segmentation of perfectly focused images, as far as an appropriate focus level is chosen. The precomputed results with the $fl = -10$ gradient descent strategy are just slightly less accurate (if small deviations are regarded) than the best focus strategy, but the number of outliers is minor, which is beneficial. Although the $fl = -15$ strategy has even less outliers, the overall performance decreases, as the accuracy suffers too much.

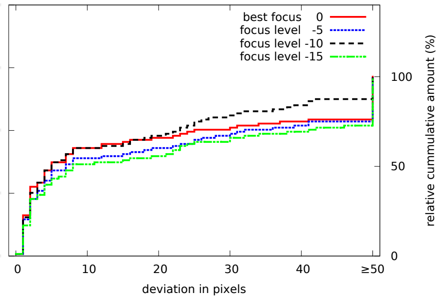
A similar behavior can be observed with the 3-stage Vickers segmentation algorithm proposed in [11]. The method is based on the approximative template matching [1] and adds 2 enhancement stages. Only in the first stage the unfocused images are segmented. In Fig. 7b, the impact on this enhancement method is shown (based on the different approximative results in Fig. 5b).

As with the level set method, the best overall results can be achieved when the approximative segmentation method is based on the images with the focus level -10.

So far we have investigated the impact of unfocused images on the first approximative stages. As the segmentation performance even increases, next we investigate the impact on the proposed stage 2 (level set) algorithm. We initialize the level set method with the results achieved with the focus level $fl = -10$, as it turned out to be the best choice for our database.



(a) Level set: different initializations



(b) Alternative method: different init. [11]

Fig. 7: Single unfocused images: Effect on precise stages (2 approaches)

The level set segmentation method is evaluated with different focus levels. In Fig. 8 you can see that the segmentation accuracy definitely suffers, if the images for the second stage algorithm are not focused.

To put it in a nutshell, the overall segmentation performance decreases if the images for the second stage algorithm are not focused. However, the performance even increases, if the approximative first stage algorithm segments appropriate unfocused images (e.g. $fl = -10$).

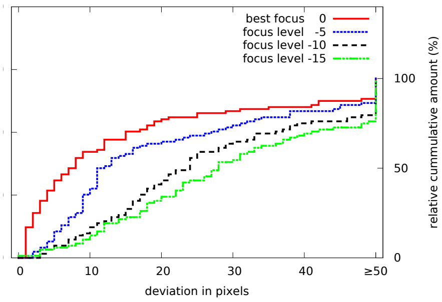
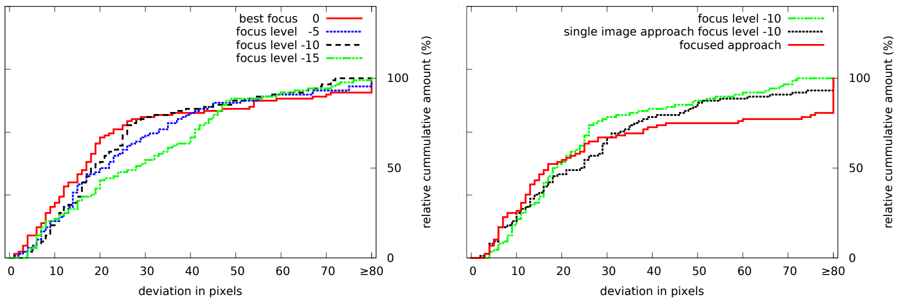


Fig. 8: Single unfocused images: Precise stage also with unfocused images

4.2 Gradual Enhancement Approach

First, we would like to know, if it is advantageous to process until the focused image is reached or if the segmentation should stop earlier, as the results do not necessarily improve until the best focused image is reached. We started with the image of the focus level -20 and iteratively increased the focus level.

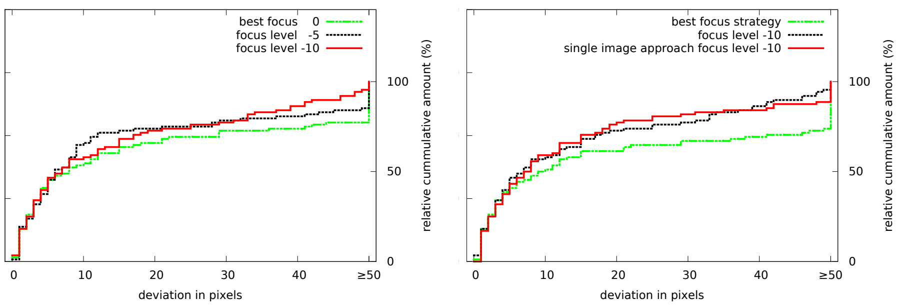
The results with different focus levels as stopping conditions are shown in Fig. 9a. Although the behavior is similar to the behavior with one single unfocused image (best stopping level: $fl = -10$), the effect is smaller. The outliers ratio generally is lower than with the single image approach (shown in Fig. 5a). In Fig. 9b, the gradual enhancement approach with the best stopping focus level ($fl = -10$) is compared with the best results achieved with one single (unfocused) image and with the results with the focused image. The gradual enhancement approach definitely is more competitive as far as the approximative stage is concerned than the best focus approach and even more robust (less outliers) than the single unfocused image approach (more vertices with a deviation of ≤ 80 pixels).



(a) Different stopping levels: first stage (b) Best stopping level vs. focused approach

Fig. 9: Gradual enhancement approach

The results seem to be more similar compared with the single image approach. However, the impact of the different initialization results, on the level set algorithm is considerable, as shown in Fig. 10a. Especially the number of outliers can considerably be decreased when stopping earlier ($fl = -10$). Consequently, we define the stop level -10 to be the best choice. In Fig. 10b the achieved results of best configurations (gradual enhancement and single unfocused image) are compared with the focused image approach. The performance of the methods using unfocused images definitely are higher than the performance of the simple approach dealing with the focused image. The gradual enhancement approach is even slightly more robust (very few outliers) than the single unfocused image approach. In Fig. 11, an indentation is shown which can be segmented with the introduced gradual enhancement approach based on unfocused images, but not with the traditional approach [10].



(a) Effect of init.: level set algorithm (b) Effect of init.: level set algorithm

Fig. 10: Gradual enhancement approach: Effect on the precise stage

4.3 Execution Runtimes

We observed the execution runtimes on an Intel Core 2 Duo processor T5500 (1.66 GHz). The approaches are implemented in Java. The traditional approximative gradient descent approach [10] takes about 2.2 s per image. The gradual enhancement approach takes 1.0 s for the initial segmentation and 0.14 s for each enhancement step.

5 Conclusion

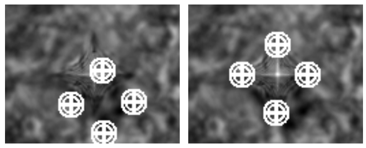


Fig. 11: Segmentation example: Traditional approach (left) and proposed approach (right)

The overall segmentation accuracy can be increased with the single unfocused image approach and with the gradual enhancement approach. The accuracy of the approaches is very similar, but significantly better than the traditional approach based on the focused images. With the gradual enhancement approach, the execution runtime potentially can be decreased as the segmentation might start before the focused image is available.

Acknowledgment

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