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A Robust Method for AOI System Design

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***Abstract* — Automated optical inspection systems suffer a lot problems seriously from their working environment such as illumination control and vibrating workplatform. In this paper, we proposed a tailored design method which combines a keypoint based alignment and an illumination adjusted comparison algorithm for the automated optical inspection systems. Together with an error tolerance control method for inherited noises and computational errors, our method can significantly reduce the impact of the physical light source requirement in manufacturing lines and gain high accuracy in the quality control of production. Validation experiment results showed that our method can reach very high accuracy in a simple and crude testing environment.**

Keyword: AOI system, image alignment, illumination normalization.

I. Introduction

Rather than examining manufactured products manually, Automated Optic Inspection (AOI) [23] systems take images through digital cameras as the input, and then find flaws, if any, of them in production lines using image processing methods.

To save cost and gain more efficiency and accuracy with the daily improved high-tech, automated inspection system is playing more and more important role in massive product manufacturing. To install and operate more automated assembly lines means the more AOI systems are needed in mass production plants. In the future, automated inspection systems will be essential to all automated manufacturing lines. That is, instead of "nice to have" an AOI system now, it will soon be "must have" one.

In the early stage, AOI systems were mainly designed to serve the PCB quality inspection [18,19,28], but nowadays, they have been applied to many other categories of massive product production lines as accurate, faithful, and tireless quality controllers.

In order to distinguish defects from good products, AOI systems take images of so-called golden samples as a standard of qualification procedure. With pre-processed information obtained from images of golden samples, AOI systems examine images of manufactured products, referred to as Devices Under Test (DUTs), compare to the images of golden samples to look for mismatches, and then make a decision on whether to accept the products or not. In the following, we will call images of a DUT as *target images* and *reference images* for images of a golden sample.

In this paper, we used cells of plastic carrier strip (tape) for electronic components as our illustrative examples. Figure 1 demonstrates original unprocessed images of the example cells.

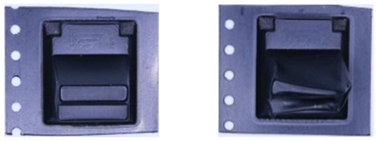

Figure 1. Images of samples of plastic carrier cells.The left is an example of reference (golden sample) image and the one on the right is a (bad) target image.

Physically, AOI systems consist of image input (digital cameras), lighting, synchronizing, embedded computer, and control subsystems as well as an "invisible" software system. Our method introduced in this paper concentrated only on the software system. In the following, when we say AOI system, we refer the term to the software portion of the system, that is, an image processing subsystem.

II. Background

The core procedure of our method is the image comparison method as well as an acceptance decision making procedure. Although the image matching and comparison problems have been well studied for decades [1,3, 8,10], they are mainly designed for different purposes which are not fully fittable to the requirements of AOI systems.

Most matching methods [5,15] concentrate on looking for a pattern or template, in a given image. On the other hand, AOI systems need to examine the whole images of DUTs and golden samples to look for all differences between them. On top of similarity of template matching methods, AOI systems also concern superfluous parts in target images. In other words, traditional pattern matching methods focus on one-way matching, whilst AOI systems consider matching in both ways.

In this paper, we proposed a method which applies a set of algorithms for AOI system design and development. Our method is based on very simple concept of exploring differences of each corresponding pair of pixels from the two images, and with a rather complicate noise control to gain high accuracy of acceptance decision.

Although the concept of our method is simple, to achieve an effective and high accurate method is not an easy job. High accuracy is a fundamental and mandatory requirement of AOI systems, while most image matching methods do not take this into account seriously.

All negative influential factors like light source as well as vibration/shock from the working environment must be controlled to the lowest level before deploying the inspection systems on line. The method introduced in this paper can release the influence of light sources and position shifting to the systems as much as possible.

Naïve comparison using the differences between corresponding pixels in reference and target images is both too simple to gain expressiveness and too rough to be accurate for AOI systems. Reference angle, illumination, thermal, impulse and quantization noises can easily make the images different in terms of intensity values of pixels. Without aligning images and applying a tolerance to the differences, almost all comparisons of digital images may fail to work properly.

Besides position alignment, we also applied methods to align the brightness and contrast distribution by modifying intensity values to reduce the light source impact. By means of software modification of intensity values of images, our method can lower down the physical lighting source requirement, and hence the cost.

III. Related Methods

The method proposed here is rooted on many previous works. Roughly, we categorize them into the following two groups of methods and algorithms.

A. Image Alignment

The first step towards image comparison is to align the reference and target images. There are several approaches such as feature- and intensity-based methods [2,7] widely used in image registration/alignment solutions. Intensity-based approach uses sub-images and correlation metrics as the tools to find geometric information for the alignment. It would suffer from both time consuming and illumination difference problems.

Alternatively, in feature-based methods, kinds of keypoints [11-14,16] for image matching and alignment have been proposed and discussed. Among them, the extrema keypoints introduced in SIFT [17] has been hugely referenced and applied in thousands of image processing works. Extrema keypoints of SIFT are invariant under rotation, scale and illumination which all are essential to AOI systems. Figure 2 shows the extrema of reference and target images found by SIFT.

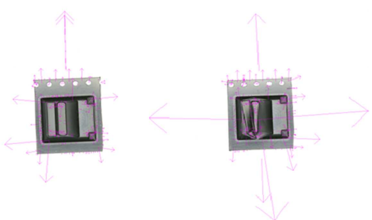

Figure 2. Keypoints located by SIFT

Keypoint based alignment methods involve matching of keypoints between the reference and target images. Unfortunately this job is very inefficient in general cases. However, under the assumption that our reference and target images are very similar in most cases, the search size could be reduced to a very small number without hurting the accuracy and hence can save a lot processing time.

B. Image Comparison

After the reference and target images are aligned, another job of our method is the comparison of the aligned images. A straightforward naïve approach is to directly subtract the intensities of two corresponding pixels in both images. This would be fine if the illumination and noise conditions of target and reference images are the same. However it is usually not the case. When taking the images, the physical conditions are impossible to be the same and consequently the intensity values of corresponding pixels in images are always different.

Several image pixel intensity transforms have been proposed to make illumination distributions of two images as close as possible [4,9,21,29]. The intensity transform or mapping adopted in our method is the Histogram Matching (HM) [4,20,24-27] method. In our method, we employ HM to map the gray levels of the target image to the pre-calculated golden sample image. The reason for choosing HM is its simplicity and efficiency. HM can bring the intensities as well as the level of noise of the corresponding pixels close enough.

Once the brightness and contrast distributions were normalized by HM, the intensity values of the corresponding pixels would be closer. And hence the difference values of naïve subtraction method for the image comparison would also be reduced to a small amount. This gives us more confidence that the comparison indeed reflects DUT and golden sample are indistinguishable. Lastly, the remaining part of our method is the acceptance decision method, and it will be discussed in the next section.

IV. Our Method

Our method consists of the following four steps of image processing methods:

Step 1, image alignment

Step 2, image comparison

Step 3, noise and tolerance control

Step 4, defect decision

Details of them are introduced in the following subsections.

A. Step1, Image Alignment

The first step towards the comparison of images is to align two images. Before comparing the reference and target images, alignment must be applied to them. Deforming images may result in unpredictable and uncontrollable faults and should not be allowed in AOI systems. Thus tools or methods applied in our method should never distort the images. Fortunately, main tools, the translation and rotation rigid transformations, adopted in our method for aligning images do follow this restriction. Note not all widely used transformations can be safely employed in AOI systems without any further considerations.

For example, scaling, a commonly used affine transformation, is not a rigid transformation and thus should be applied in a more careful manner in AOI systems. Normally it can only be used when either the size of DUT is not an item examined by the AOI system or the geometric observation information, e.g., the distance and angle from camera to the DUT, is fully understood.

Using the extrema introduced in the SIFT as the features (keypoints), an efficient algorithm for matching them between the source and target images is developed by modifying the well-known keypoint matching algorithm RANSAC[6]. Though RANSAC could significantly reduce the notorious impracticable time consuming shortcoming of simple naïve matching algorithms, it is still too heavy to be applicable in real-time AOI systems. Nevertheless, real-time is an inherited property of AOI systems.

With off-line pre-computed and pre-selected keypoints in reference images and restricted area in target image, we can lower down the computation time sharply. Again, the effectiveness of this optimized approach depends heavily on the assumption of highly similar reference and target images. The SIFT matched keypoints between reference (right) and target (left) images of our demonstrative examples are shown in Figure 3.

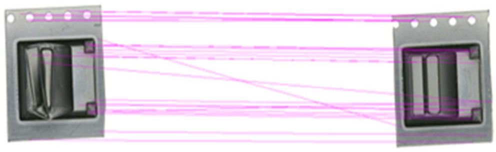

Figure 3. Matched key points between reference and target images

Based on the matched keypoints, we can compute the reference point (X, Y) and rotation angles θ which are essential parameters in the alignment procedure as follows. We choose the average position (X, Y) of positions (X_i, Y_i) of keypoints as the reference points of the translation transformation in both reference and target images. Further, for each keypoint, we compute its gradient angle θ_i, shown by the pink arrow in Figure 2, and then take the average angle θ of θ_i as the normalization angles for reference and target images alignment.

$$(X^{img}, Y^{img}) = \left(\frac{\sum X_i^{img}}{n}, \frac{\sum Y_i^{img}}{n}\right)$$

$$\theta_i^{img} = \tan^{-1}\frac{\mathcal{J}_{img}(X_i, Y_i+1) - \mathcal{J}_{img}(X_i, Y_i-1)}{\mathcal{J}_{img}(X_i+1, Y_i) - \mathcal{J}_{img}(X_i-1, Y_i)}$$

where $img \in \{target, reference\}$ indicates the image from which the keypoints and its gradient angle obtained. The global rotation angle of the target image can be computed as the difference of average gradient angles of corresponding keypoints as following

$$\theta = \frac{\sum(\theta_i^{ref} - \theta_i^{targ})}{n}$$

Similarly, the displacement (X, Y) for the translation is computed as the difference between average positions (X^{ref}, Y^{ref}) and (X^{targ}, Y^{targ}).

Then the aligned image $\mathcal{J}_{align}$ could be computed as

$$\mathcal{J}_{align} = T_{(X,Y),\theta}(\mathcal{J}_{target})$$

B. Step 2, Image Comparison

Besides the position alignment, another factor could severely causes us great trouble in AOI system design is the stability of luminance problem. With carefully designed light source, we can control the intensity values between the golden samples and DUTs, but variation could never be completely eliminated due to a lot of inherited reasons, for example, thermal noise. To reduce the difference of luminance between images, we do not concentrate on efforts on physical light source control, instead, a software based method, histogram matching, is applied to make illuminations of corresponding pixels of both reference and target images as close as possible.

Histogram matching (specification) is a method which applies histogram equalization algorithm to a pair of images to make their gray-level distribution as close as possible. Let $h_A(i)$ and $h_B(i)$ be gray-level histograms of images A and B, respectively, and $L-1$ be the largest intensity value. Define the equalization mappings as

$$C_{\mathcal{J}}(k) = \sum_{i=0}^{k} \frac{h_{\mathcal{J}}(i)}{n_{\mathcal{J}}}$$

$$p_{\mathcal{J}}(k) = \left\lfloor \frac{C_{\mathcal{J}}(k) - C_{\mathcal{J},min}}{n_{\mathcal{J}} - C_{\mathcal{J},min}}(L-1) \right\rfloor$$

where $C_{\mathcal{J},min} = \min_{0\le i<L} C_{\mathcal{J}}(i)$, and $n_{\mathcal{J}}$ is the size of image $\mathcal{J}$, $\mathcal{J} \in \{A, B\}$.

Histogram matching uses the inverse mapping p_B^{-1} of p_B to convert gray level k in image A to the level $l = p_B^{-1}(p_A(k))$ according to the histogram distribution of image B. The output of histogram matching algorithm in the method is the intensity mapping table

$$M(k) = p_{ref}^{-1}\left(p_{targ}(k)\right)$$

where $0 \le M(k) < L, k = 0,1,\ldots,L-1$, which maps gray intensity level in the aligned target image to levels of the histogram of reference image.

Note the level values are integers only, thus the mapping $M(k)$ cannot map exact values from one histogram to another by HM. Alternatively, the mapping takes approximations with smallest differences, and therefore small computation errors will be brought in by the matching.

In our case, though the two images, reference and target images, to be matched are different, the contents of them are highly similar in most cases and hence we could treat them as the same images with different histograms. The HM adjusted image $\mathcal{I}_{norm}$ is obtained by mapping each intensity value k of the aligned target image to a new value $M(k)$

$$\mathcal{I}_{norm}(X,Y) = M\big(\mathcal{I}_{alined}(X,Y)\big)$$

for each pixel at (X,Y). We also use equation

$$\mathcal{I}_{norm} = M\big(\mathcal{I}_{align}\big)$$

to express the relation between aligned image $\mathcal{I}_{align}$ and illumination normalized image $\mathcal{I}_{norm}$. Now the naïve differential image could be applied straightforwardly as

$$\mathcal{I}_{diff}(X,Y) = \mathcal{I}_{ref}(X,Y) - \mathcal{I}_{HM}(X,Y)$$

Again, we use the simplified terms and equation to state the relation of the difference image $\mathcal{I}_{diff}$ between original reference image $\mathcal{I}_{ref}$ and processed target image $\mathcal{I}_{norm}$

$$\mathcal{I}_{diff} = \mathcal{I}_{ref} - \mathcal{I}_{norm}$$

Figure 4. is an example of the difference image of reference and aligned, histogram normalized, and thresholded target image. Differences are shown by composition of blue and red fields in RGB color representation of pixels. Pixels with colors other than black have intensity difference larger than the threshold. Further, pixels in blue are the pixels which have significant higher intensities in reference image than target image, and vice versa for red pixels. The purple pixels represent that pixels with the intensity values in both images are significant. The representation is a convenient way for our visual examination of image difference.

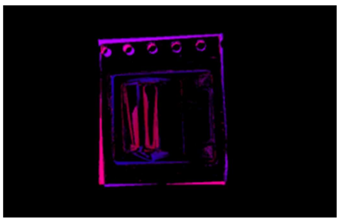

Figure 4. The difference image $\mathcal{I}_{diff}$

C. *Step 3, Noise and Tolerance Control*

Noises and computation errors are two instances of types of unintended, inherited and unavoidable factors which make no two digital images be identical. Noises have been immensely addressed in literature we will not repeat them here. Because of discrete nature of digital images, the rotation transformation for alignment as well as HM level mapping for illumination normalization both are examples of sources of computation errors generated in the earlier steps of our method.

For those undesirable but negligible errors brought either by noise or by the computation, we adopt thresholding and mathematic morphology [22] methods to remove or suppress them. Use empirically collected information and mapping error estimated from HM, we can set a threshold for the difference of each corresponding pair of pixels to remove lightly different pixels in $\mathcal{I}_{diff}$.

However, thresholding is useful only to the pixels in the "right" position. It cannot make any contribution to control errors caused by position shifting introduced by rounding errors, for example, of translation and rotation operations.

The closing operation, eroding first and then dilating, in mathematic morphology can be used to eliminate small area of "intruders". When we apply a closing operation with small size, or radius for round shape, structural element (SE), we can eliminate marginal errors/differences generated due to rounding errors in shifting of positions in alignment step. The size of SE applied in closing operation depends on the system precision requirement which relates to the image resolution and the pixel size.

If an isolated difference area is small or the difference area of pixels is slightly larger than the corresponding area in reference image, then they are very likely introduced by computation errors. Morphological closing operation can eliminate or reduce the impact caused by those kinds of error as desired. Figure 5 below is the results of applying closing operation on image in Figure 4.

Figure 5. After closing operation the different area has been significantly reduced

Now all the processing jobs are done, we have reached a final version of difference image $\mathcal{I}_{final}$ of the input target image as shown in Figure 6.

$$\mathcal{I}_{final} = Closing\ (\mathcal{I}_{diff})$$

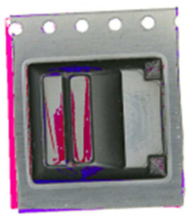

Figure 6. Images with non-gray colors as the differences between reference and target images

The remaining step is the procedure to make decision whether the DUT is acceptable or not.

D. Step 4, Accept/Reject Decision Procedure

When the image $\mathcal{I}_{final}$ is reached, we are ready to make a decision on whether to accept a DUT or not. It is well-known that there is no general algorithm to provide a universal decision procedure for all kinds of DUTs. Different kinds of products need different ways to make the acceptance decision. It could be as simple as just counting the size of mismatched regions and then compare to a bound as the decision procedure in some cases. But in other cases, a set of rather complicate rules are needed to make a final decision. In general, we have to ask the system users to provide a decision making procedure to accomplish the whole job.

What we can do here is to provide a set of tools to help system users/developers to develop a decision making procedure for themselves. Currently we designed a set of GUI tools for users to designate degree of importance of regions. In many cases we observed that differences in all regions are not equally important to system users. We might care more about the central region of an image, but less for the minor defects in the margins. Hopefully with the tool, systems designers can specify the weighted tolerance designated regions easily as shown in Figure 7.

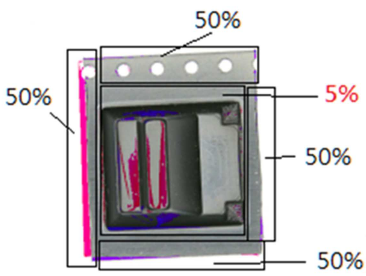

Figure 7. Set tolerance weights in different regions

The weighted differences of regions are then compared to an empirically preset error bound to make a final acceptance decision. Clearly, this tool set is just a preliminary design. Efforts are still needed to make it more practical and helpful, and thus applicable to more and more production lines.

For 3D object inspection, we need to take images from different angles to get information of different surfaces of the DUTs as illustrated in Figure 8 to gain higher accuracy. However, in doing this, we will face a lot more problems than 2D image processing. That is beyond the scope of the method discussed in this paper.

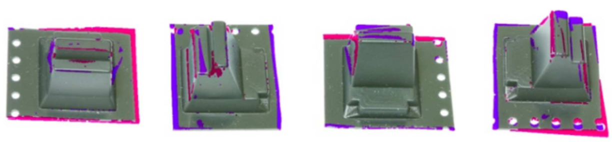

Figure 8. Multi-view are required for examining 3D objects

V. EXPERIMENTS

To validate our method, we have done experiments to examine 500 correct (good) and 500 defect (bad) sample cells of plastic carrier strip (tape) for electronic components. The experiments were conducted at our lab with simple and rough equipment, rather than at a real assembly line in a factory. We used a digital camera fixed in a tripod as the image grabbing tool without any special light sources. Samples were placed by hands on a desk. Bad samples were made by manually deforming qualified samples. The results are shown in following table 1.

	sample size	Accepted (good)	Rejected (defects)	Match failure	Success rate
Good samples	250	247	3	0	98.80%
Bad samples	250	4	237	9	94.80%
totals	500	251	240	9	98.60%

Table 1. Experiment result

In Table 1, we found that 3 correct sample were determined to be defected item (type I error) out of 250 “good” samples. The success rate is about 98.8% in accepting “good” samples. On the other hand, we have 94.8% success rate in finding defects. Further, there are 9 cases failed to generate enough matches of keypoints in the first step, of the method. Post examination showed that the match failures were all from the very large image differences. Hence, it is reasonable to classify match failure outcomes of the “bad samples” cases to the Rejected category. In doing so, samples the type II error rate, rate of wrong acceptance, is similar to type I error rate around1.4% .

Clearly, the results heavily depend on the tolerance settings and tolerance levels are decided by the AOI systems users.

VI. CONCLUSION

The method proposed in this paper has been successfully shown that our AOI system can compare two images with high tolerance in unmatched ranges of illumination and positions. The unmatched ranges are usually causing AOIS systems too sensitive and vulnerable to be practical. Our method concentrates on providing a software solution to lower down the physical equipment requirements to overcome the problems caused by operating environment. In this way, the cost of systems can be reduced and the installation can be highly adjustable and adaptable. In order to make AOI systems be more applicable to more manufacturing lines, there are still many problems, e.g., 3D DUT and real-time performance issues waiting for us to overcome.

REFERENCES

[1] Belongie, S., Malik, J., and Puzicha, J., “Shape Matching and Object Recognition Using Shape Contexts,” *IEEE Trans.*

Pattern Analysis and Machine Intelligence, vol. 2, no. 4, pp. 509-522, Apr. 2002.

[2] Brown, Lisa Gottesfeld, A survey of image registration techniques (abstract), *ACM Computing Surveys (CSUR) archive*, volume 24, issue 4, December 1992), pages 325 – 376

[3] Brunelli, ,R., Template Matching Techniques in Computer Vision: Theory and Practice, Wiley, ISBN 978-0-470-51706-2, 2009

[4] K. R. Castleman, *Digital Image Processing*, Prentice. Hall, 1998.

[5] Choi, M.S., Choi, Kim, W.Y., "A novel two stage template matching method for rotation and illumination invariance", *Pattern Recognition*, Volume 35, Issue 1, January 2002, Pages 119–129

[6] Fischler, Martin A., and Bolles, Robert C., "Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography". *Comm. of the ACM* **24** (6): 381–395. June 1981.

[7] Fitzpatrick, J.M., Hill, D.L.G., and Maurer, C.R. Jr., Image registration, *Handbook of medical imaging 2*, pp. 447-513.

[8] Freeman, W. and Adelson, E., "The Design and Use of Steerable Filters," IEEE Trans. *Pattern Analysis and Machine Intelligence*, vol. 13, no. 9, pp. 891-906, Sept.

[9] Gonzalez, R. C. and Woods, R. E., *Digital Image Processing*, Third Edition, 2008.

[10] Hauagge, D. C., and Snavely, N., "Image Matching using Local Symmetry Features", *Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 206-213.

[11] Haralick, R.M., "Image Analysis Using Mathematical Morphology," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. PAMI-9 (4) pp. 532–550, 1987.

[12] Harris, C. and Stephens, M.. A combined corner and edge detector. *In Alvey Vision Conference*, pp. 147–151, 1988.

[13] Johnson, A., and Herbet, M., "Object Recognition by Matching Oriented Points," *Proc. Conf. Computer Vision and Pattern Recognition*, pp. 684-689, 1997.

[14] Koenderink, J. and van Doorn, A., "Representation of Local Geometry in the Visual System," *Biological Cybernetics*, vol. 55, pp. 367-375, 1987.

[15] Lu, Cen, " Template match using local feature with view invariance ", *Proc. SPIE 8919, MIPPR 2013*: *Pattern Recognition and Computer Vision*, 89190C

[16] Lazebnik ,S., Schmid ,C., and Ponce, J., "Sparse Texture Representation Using Affine-Invariant Neighborhoods," *Proc. Conf. Computer Vision and Pattern Recognition*, pp. 319-324, 2003.1991.

[17] Lowe, David G., (2004), Distinctive image features from scale-invariant Key points.

[18] Moganti, M., Ercal,F., Dagli, C. H. and Tsunekawa, S., Automatic PCB inspection algorithms: A snrvey, *Compater Vision anil Image Understoniling*, vol.63, no.2, 1996.

[19] Tae-Hyoung Park, Hwa-Jung Kim, and Nam Kim, Path Planning of Automated Optical Inspection Machines for PCB Assembly Systemsm, I*nternational Journal of Control, Automation, and Systems*, vol. 4, no. 1, pp. 96-104, February 2006

[20] Rolland, J.P., Vo, V., and Abbey, D.K., "Fast Algorithm for Histogram Matching: Application to texture synthesis," *Journal of Electronic Imaging 9(1)*, pp. 39-45, 2000.

[21] Schaffalitzky, F., and Zisserman , A., "Multi-View Matching for Unordered Image Sets," *Proc. Seventh European Conf. Computer Vision*, pp. 414-431, 2002.

[22] Serra, Jean, "Introduction to mathematical morphology," *Computer Vision, Graphics, and Image Processing*, Vol 35(3),, September 1986, pp. 283-305.

[23] Wikipedia, Automated optical inspection , [Online] Available: http://en.wikipedia.org/wiki/Automated_optical_inspection

[24] Weeks, A. R., "Fundamentals of Electronic Image Processing," SPIE Optical Engineering, Bellingham, WA. (1996)

[25] Wegener, M., "Destriping multiple sensor imagery by improved histogram maching," Intl. J. Remote Sens. 11(5), pp. 859-875, 1990.

[26] Wikipedia, Histogram Equalization, [Online] Available: http://en.wikipedia.org/wiki/Histogram_equalization.

[27] Wikipedia, Histogram Matching, [Online] Available: http://en.wikipedia.org/wiki/Histogram_matching.

[28] Wu, W.-Y., Wang, M.-J. aud Liu, C.-M., Automated inspection of printed circuit boards through machine vision, Computers in Industry, vol.28, no.2, pp. 103-111, 1996.

[29] Zabih, R., and Woodfill, J., "Non-Parametric Local Transforms for Computing Visual Correspondance," *Proc. Third European Conf. Computer Vision*, pp. 151-158, 1994.