On RCE Like Neural Networks Based Image Processing and it's ZISC-036 Based Fully Parallel Implementation Solving Real World and Real Complexity Problems.
(Part-Two : industrial applications)

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Abstract: This paper deals withneural based image processing and solutions developed for noise reduction, image enhancement and visual probe mark inspection in VLSI production using the ZISC-036 neuro-processor, an IBM hardware processor which implements Restricted Coulomb Energy (RCE) and the K-Nearest Neighbor (KNN) neural models. The main characteristics of such systems are real-time control and high reliability in detection and classification tasks. Experimental results, validating the exposed concepts, have been reported showing quantitative and qualitative improvement as well as our solutions efficiency.

Key-Words: Restricted Coulomb Energy, Radial Basis Functions, ZISC-036, Hardware Implementation, Parallel, Image Processing, Parameters, Applications.

1 Introduction

An important point of the use of artificial neural networks (ANN lies in their adaptability : learning can be performed on-line to improve the response of the system. As it has been mentioned in Part-One of this paper, even though the usefulness of ANN has already been confirmed, very few papers deal with real applications of this kind of technology. The Part-One of this paper has studied the neural parameters influences on ZISC-036[2][3][4][5] (Zero Instruction Set Computer) based image processing The present part of the paper deals with application of ZISC-036 based neural image processing technique for image enhancement and visual probe mark inspection in VLSI production. The first set of applications have been developed in order to restore old movies (noise reduction, focus correction, etc.), to improve digital television, or to handle images which require adaptive processing (medical images, spatial images, special effects, etc.). The second application has been developed to improve production quality test process. This neural based automatic technique has been implemented at the IBM Essonnes plant. Real-time control and high reliability in fault detection and classification have been obtained.

The Part-Two of the paper has been dedicated to the industrial applications description, diacussion and validation. Noise reduction and image enhancement are reported in section 2. Visual probe mark inspection in VLSI production, using the ZISC-036 neuro-processor, are then described and discussed in section 3. Experimental results and a comparison of the presented method with classical ones have been reported in that sections. Finally, the conclusion highlights the obtained results.

2 Noise Reduction and Image Enhancement

Noise reduction of an image's represents an item of great interest for image analysis and understanding. Several solutions exist to accomplish this, such as median filter, lowpass and highpass filter, etc., [9]. The main drawback of the aforementioned methods lies in their restrictive efficiency. Each kind of filter is efficient for only a precise kind of noise (gaussian noise, impulse noise, etc.), or for a precise kind of image. Artificial Neural Networks present the important property of adaptability, because the same network can be trained to remove some precise noise or a mixture of several kinds of noise presented in [1].

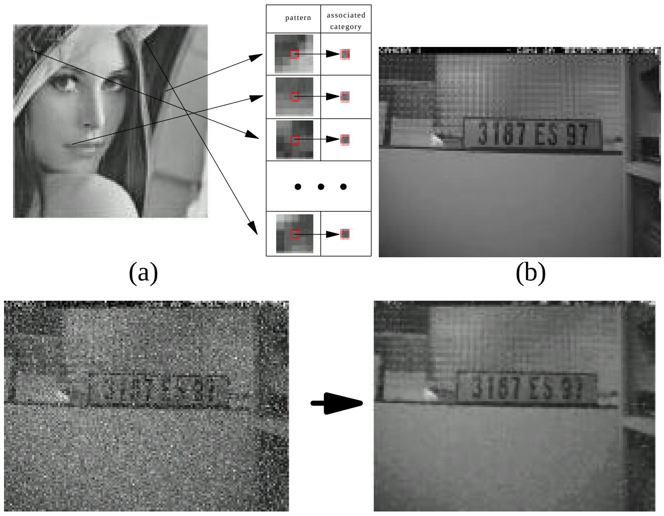
2.1 ZISC-036 Based Technique

The following examples show how ZISC-036 can be used for noise reduction and image enhancement. After a learning phase on a non corrupted image (image 1-a), this system can be used to clean different kinds of images. The presented principle is based on the fact that the number of existing shapes that can be seen with the human eye is limited. ZISC-036 is used to learn as many shapes as possible that could exist in an image, and then to replace inconsistent points by the middle value of the closest memorized example. The learning phase consists of memorizing small blocks of an image (as an example 5x5) and associating to each the value of the middle pixel as a category. These blocks must be chosen in such a way that they represent the maximum number of possible configurations in an image. To determine them, the proposed solution consists of computing the distances between all the blocks and keeping only the most different.

The learning algorithm used here incorporates a threshold and a learning criteria (Lean_Crit (V)). The learning criteria is the criteria given by relation (1) where V_l^k represents the l-th component of the input vector V^k, P_l^j represents the l-th component of the j-th memorized prototype, C^k represents the category value associated to the input vector V^k, C^j is the category value associated to the memorized prototype P^j and, α and β are real coefficients adjusted empirically.

$$Learn\_Crit\left(V^k\right) = a \sum_l \left|V_l^k - P_l^j\right| + b\left|C^k - C^j\right| \qquad (1)$$

A random example from the learning base is chosen and the learning criteria for that example is calculated. If the value of the learning criteria is greater than the threshold, then a neuron is engaged, and an index (the number of neurons used) is increased. However if the learning criteria is less than the threshold, no neuron is engaged. After each iteration, the aforementioned threshold is decreased. Once the index reaches the desired level the learning phase is terminated. As it has been mentioned in Part-One of the paper, the choice of the coefficients α and β is linked to the application and not previously defined. Numerous simulations were performed to adjust the optimal values. In order to smooth the resulting image, it is necessary to use a combination of the closest neighbors.



(c) (d)

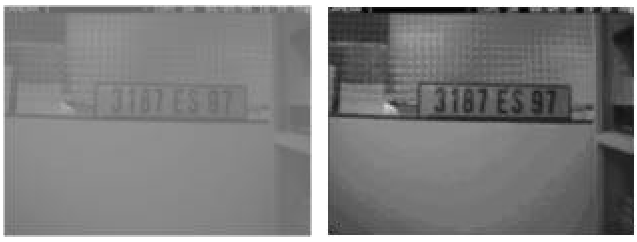
Fig.1 : Results relative to noise reduction. Image used for learning phase and category association strategy (a), unlearned image used for generalization phase (b), the noisy version the unlearned image and the result (d).

After having learned about one thousand noisy sub images from the image 1-a, a noise reduction process using the neural network (ZISC-036) have been performed on a noisy version of an unlearned image (image 1-b). The noisy version of the unlearned reference image is presented in figure 1-c. The result of noise elimination is given by image 1-d. The best results are generally obtained when the learning phase is done on one or several images taking into account several characteristics (mean gray level, gradient, etc.) close to those on which the recognition will performed.

The image enhancement principles are the same as those described above. The main difference lies in the pixel value associated to each memorized example. For example, consider the two image presented in figure 2. Image 2-a was obtained from image 2-b by reducing the coding dynamic and fuzzying the pixel value (each pixel is the mean of itself and its 8 neighbors). For each memorized example (a block of 5x5) from image 2-a, the middle pixel of the corresponding block from the image 2-b is used as the "corrected pixel value" and is memorized as the associated category. After having learned about one thousand five hundred examples from figure 2, the ZISC-036 based system is able to enhance the image presented in figure 3-a to obtain the result presented by figure 3-b.

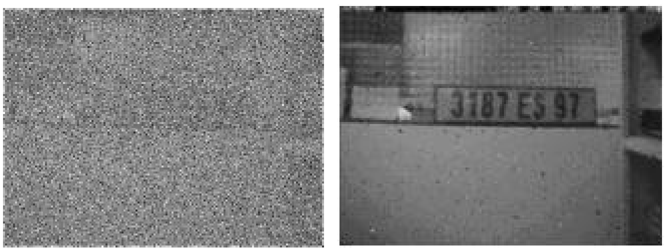
(a) (b)

Fig.2 : Example of learning the degraded image (a) obtained from the reference image (b).



(a) (b)

Fig.3 : Example of image enhancement on using previous learning. Degraded unlearned image (a) and obtained enhancement using the ZISC-036.



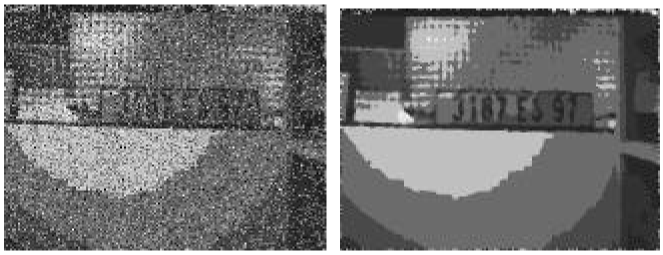
(a) (b)

Fig.4 : Example of image enhancement of a noisy unlearned image (a) and the ZISC-036 results (b).

The response time obtained with our evaluation system (not optimized) using a PCI card is less than 0.6s. By optimizing this algorithm and the associated hardware, it seems possible to divide the response time by a factor 10. In order to show the efficiency and robustness of the presented system, we have added random impulse noise to the already corrupted image 4-a. The resulting image enhancement is seen in figure 4-b.

2.2 A Comparative Study

In order to evaluate more effectively the presented results, this sub-section compares the results obtained using the above presented ZISC-036 based approaches with those obtained using the classical models of a histogram equalization followed by a median filter.



(a) (b)

Fig.5 : Example of image enhancement using histogram equalization (a) and followed by a median filter (b).

To quantify the comparison mentioned before, we considered the case of the image enhancement of figure 4. Firstly, a histogram equalization, consisting of adjusting the histogram of the original image’s gray levels for the desired coding (in this case for eight bits), has been performed equalizing the image’s gray level over the given range (result of such equalization is shown in figure 5-a). Then, using the image obtained from the equalization, a conventional median filtering, consisting of placing in numerical order all of the pixel values of the current viewing box and replacing the block’s central pixel with the median value[8], has been realized over the image using a five by five block (figure 5-b). The median filter is used to sharpen the edges and decrease the blurring. Graphs of the figure 6 represent a cross section of two images with the pixel index on the *x* axis and the corresponding gray level on the *y* axis. The figure 6-a compares the gray level of the original image with that of the noisy image. Figure 6-c and 6-d show the results after the global equalization followed by the median filter respectively. Finally, the figure 6-b shows the results obtained with the ZISC-036.

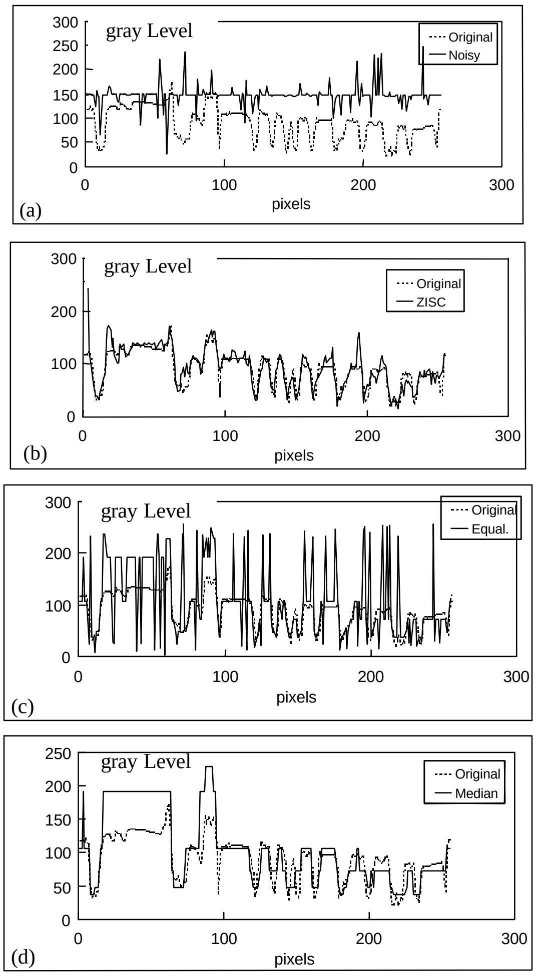


Fig.6 : Cross section of the original and noisy images (a), ZISC-036 evaluation (b), histogram equalization (c) and Median filter after the histogram equalization (d).

3 Visual Probe Mark Inspection

Many prober constructors had already developed Probe Mark Inspection (PMI) software based on conventional pattern recognition algorithms with little success. The difficulty lies in the real time execution with production speed constraints and in the method efficiency. Even sophisticated hardware using DSPs and ASICs specialized in image processing have not performed sufficiently well to convince industrials to switch from human visual defects recognition to electronically automatic PMI. By now, prober constructors have finally abandoned automatic PMI in favor of another approach to the probe damage problem : checking the map of the probe and increasing precision in the mechanical movements which are quite expensive.

Our PMI application, presented in [10], consists of a software and a PC equipped with this neural board, a video acquisition board connected to a camera and a GPIB control board connected to a wafer prober system. Its goal is image analysis and prober control. Figure 7 represents the bloc diagram of the application. The figure 8 shows an example of faulty and correct vias.

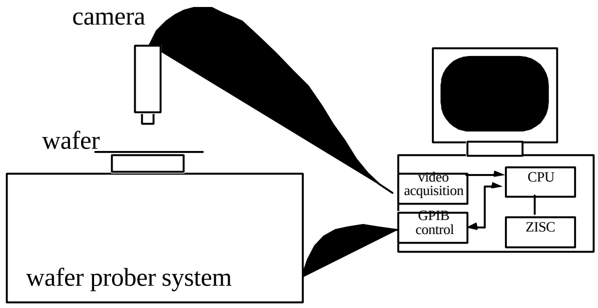


Fig.7 : Structure of the presented application.

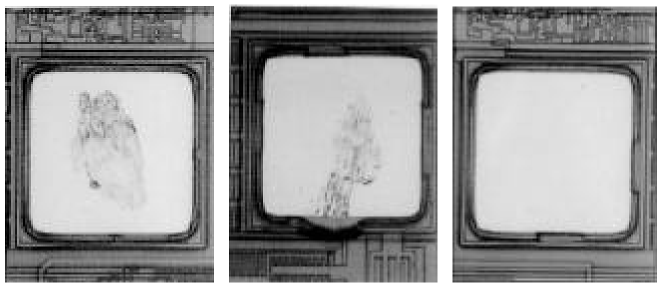


Fig.8 : Example of probe impact: good (a), faulty (b) and absent (c).

The process of analyzing a probe mark can be described with the following steps:

- the PC commands the prober to move the chuck so that the via to inspect is precisely located under the camera.
- an image of the via is taken through the video acquisition board.
- the application, using the ZISC-036, then:
  - finds the via on the image.
  - check the integrity of the border (for damage) of via.
  - locates the impact in the via and estimates its surface for statistics.

The application then moves on to the next via. At the end of the process, the system shows a wafer map which presents the results and statistics on the probe quality and its alignment with the wafer. All the defects are memorized in a log file. In summary, the detection and classification tasks of our PMI application are done in two steps:

- localize the via on the acquired image.
- classify the probe impact (good, bad or none) and estimate the size of this mark.

3.1 Centering the vias

The method which was retained for centering the vias is based on profiles analysis. Each extracted profile of the image (using a square shape, figure 9) are compared to a reference database in which each memorized profile is associated with its offset from the perfectly aligned profile.

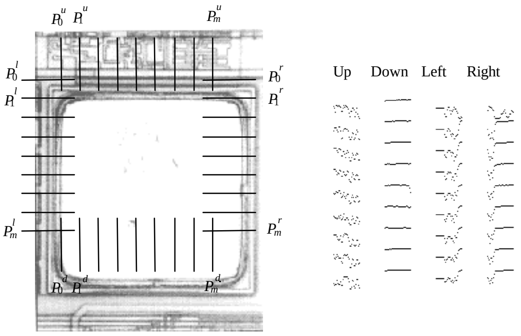


Fig.9 : Profiles extraction.

The used ISA card memorize all the examples and to do all the comparison in parallel. The used offset is a pseudo-linear extrapolation of the two offset given by the two nearest neighbor. This offset, for a profile, is also done using relation (2), where d_1 is the distance between the first nearest neighbor and the extracted profile, m_1 is the associated offset and d_2 and m_2 are the distance and the offset associated to the second nearest neighbor. In this kind of application, RCE's algorithm presents some drawbacks mainly due to the "hole" leaved during the space mapping out which explained why KNN has been chosen for this task.

$$d = \frac{d_1 \cdot m_2 + d_2 \cdot m_1}{d_1 + d_2} \qquad (2)$$

$$\overline{\Delta_x} = \frac{\sum_{i=1}^{m} d_i^l - \sum_{j=1}^{m} d_j^r}{2m} \quad \text{and} \quad \overline{\Delta_y} = \frac{\sum_{i=1}^{m} d_i^u - \sum_{j=1}^{m} d_j^d}{2m}$$

(3)

The mean of all responses gives a global offset (relation (3)) for x and y axes. This step is repeated until $\overline{\Delta_x}$ and $\overline{\Delta_y}$ are null or until the square formed by the profiles oscillate. The problem of oscillation means that this square's size is not adapted. In this case, its size is adjusted (reduced or extended), using the range of oscillation, until $\overline{\Delta_x}$ and $\overline{\Delta_y}$ converge to zero. This phase of centering needs about 30 neurons and takes about 10ms. A precise location needs, in general, 3 iterations.

3.2 Via Probe Mark Classification

Each extracted profile of the image is compared to a data base which contains good and bad profiles. The reference database is done by the user at the begin of the process or/and on-line when the system hesitates on a classification. The idea of hesitation is based on the distances which separates an extracted profile to a good one and to a bad one from the database. A via is declared bad if at less one of the extracted profile is nearest to a bad example of the data base than to a good one (without hesitation). At least a dozen of neurons are required in this phase to achieve 90 to 95% success. The classification of the border takes about 7ms.

Profile	Category	Profile	Category
	Faulty		OK
	Faulty		OK
	Faulty		OK

Fig.10 : Example of profiles to category association.

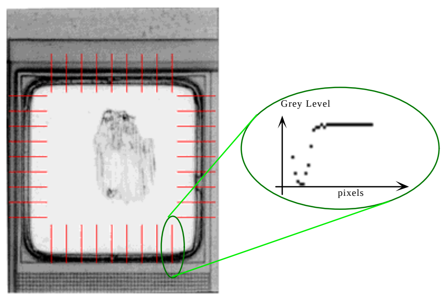


Fig.11 : Profiles extraction after via centering process.

Another important point is the size and localization estimation of the mark left by the probe during the test. These two parameters are used to estimate the wear and the adjustment of the probe. This estimation is done by using some profiles too. But those ones are different, they are the horizontal and vertical projections. Those profiles are compared with reference ones, memorized in the ZISC-036. All of the memorized profiles are associated with a position and a length. The use of the responses of the horizontal profile and of the vertical profile allows to estimates the size of the mark of the probe. Good results are obtained on the impact locating and surface estimating with 100 neurons. 10ms are required for this task.

5 Conclusion

In this article, we have presented a robust, adaptive, and fast neural based image processing concept. We have focused our purpose on neural based solutions developed for noise reduction, image enhancement and visual probe mark inspection in VLSI production using the ZISC-036 neuro-processor which implements the Restricted Coulomb Energy algorithm (RCE) and the K-Nearest Neighbor algorithm (KNN). We have analyzed computational, precision and learning parameters and criterions related to the RCE-KNN neural model and it's ZISC-036 based implementation. Obtained experimental results and a quantitative comparative study show that neural networks are well adapted to image enhancement, and presents the advantage of robustness.

The ZISC-036 based solution for visual probe mark inspection in VLSI production has been validated on Essonnes plant. Experiments on different kinds of chips and on various probe defects has proven the efficiency of our neural approach to this kind of perception problem. Our prototype outperformed the best solutions offered by competitors by 30% (the best response time per via we measured on other wafer probers was of 600 ms and our application analyzed one via every 400 ms, 300 of which were taken for the mechanical movements) Measures showed that the defects recognition neural module execution time was negligible compared to the time used for mechanical movements as well as for the image acquisition (a ratio of 12 to 1 on any via). This application is presently being inserted on a high throughput production line.

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