An Evolvable Hardware Chip for Illumination Enhancement in Computer Vision for Surface Roughness Estimation

***M. Rajaram Narayanan* †*, S.Gowri* ††*, A.Velayutham*†††*, S. Ravi* ††††**

† *Research Scholar, Dept of Manufacturing Engg., Anna University, Chennai-25, India.*
††*Professor & Head, Dept. of Manufacturing Engg., Anna University, Chennai-25, India.*
†††*Scientist D,CVRDE, Avadi, Chennai - 54, India.*
†††† *Professor Electronics Department, College Affiliated to Anna University.*

Abstract: Machine vision has evolved to become a mainstream automation tool, enabling computers to replace human vision in high speed and precision manufacturing techniques. Images usually acquired through modern cameras may be contaminated by a variety of noise sources and decreasing intensity and in most cases the type of noise and state of lighting are also not known a priori. In this paper, the design of image operator for illumination enhancement and noise filtering using evolutionary approach is presented. The advantage of the proposed structure is that it is evolved from primitives. The evolvable hardware (EHW) configuration uses reconfigurable Xilinx Virtex2 FPGA xc4000 architecture. The developed image operator is tested for its performance by applying it on images of surfaces of machined components grabbed using vision systems with linearly decreasing intensity. The evolutionary enhanced image is then processed and a relationship between the feature of the surface image and the actual surface roughness is obtained using polynomial networks. Comparing with the stylus method, the constructed computer vision system is useful method for measuring the surface roughness with faster, lower environment noise and lower price in computer integrated manufacturing process (CIM).

Key words:
Machine Vision, Evolvable hardware, Image Enhancement, Surface Roughness.

1. Introduction

Machine vision systems have become one of the most important parts of any CIM environment that extracts information using vision sensors and make intelligent decisions. In this context, image operators (like image filters or edge detectors) used mainly in the preprocessing phase, are an important part of the image recognition systems. There is a need for automatic design of such operators since the recognition systems should adapt to changing environments automatically. This requires computing architectures that are less complicated, highly flexible and more cost effective as compared to the traditional ones, which calculates the coefficients for a general-purpose model.

The objectives of this work are (i) to develop a EHW based image operator, which can improve the quality of the images of surfaces by coping with changes due to process variations and adverse conditions in a CIM environment such as contrast reversal and intensity gradients, angular uncertainties, blur caused by changes in depth field, scale changes, partial obliteration or missing features (ii) to apply polynomial network for evaluating the surface roughness of milled components (iii) to compare the surface finish obtained using each network with that using stylus approach.

The proposed system consists of a parallel genetic algorithm based reconfigurable system to evolve image operators and perform adaptive image processing. The image processing architecture is dedicated for implementing high performance image illumination enhancement on a Xilinx Virtex2 FPGA xcv4000, which is easily available as a low-cost commercial off-the-shelf hardware device. This allows complex and fast computation to be performed by dedicated hardware instead of software in digital computer, since hardware units can operate in parallel.

2. Measurement of the Surface Image of Workpiece

A schematic diagram of the machine vision system for inspecting surface roughness in milling operations is shown in fig. 1. It consists of the light source and a CCD camera of 512 x 640 resolution to capture the image of the surface, the captured image is given to the EHW system for subsequent analysis and image processing.

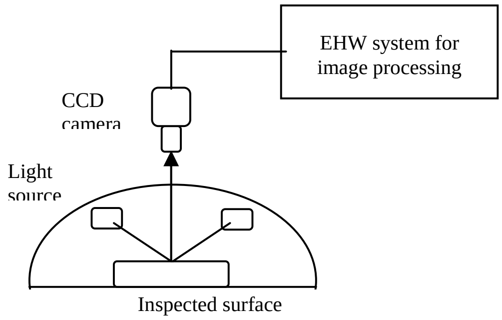

Fig .1. Machine vision system

To estimate surface roughness under different cutting conditions ,a number of cutting tests were carried out using a Milling machine with carbide tool and working on mild steel bars. Experimental data with regard to different cutting parameters (feed, speed and depth of cut) were performed. Machined surface roughness was estimated by a profile meter (Surfcorder SE1200) within a sampling length of 8mm and measurement speed of 0.5mm/s.

The surface roughness parameter used in this study is the average surface roughness (R_a). It is defined as the arithmetic average of the absolute value of the heights of roughness irregularities from the mean value measured and is given by

$$R_a = \sum_{i=1}^{n} \frac{|y_i|}{n}$$

Where y_i is the height of roughness irregularities from the mean value and 'n' is the number of sampling data. In this work, the arithmetic average of the gray level is used to estimate the surface roughness of the work-piece. The arithmetic average of the gray level can be expressed as

$A_G = (\sum(|g_1 - g_m| + |g_2 - g_m| + \ldots.. + |g_n - g_m|)/n$ where g_1, ---, g_n are the gray level values of a surface image along one line and g_m is the mean of the gray values and is determined as

$g_m = (\sum(g_1 + g_2 + \ldots.. + g_n))/n$.

3. Prediction of Surface Roughness using the Polynomial Network

The polynomial networks proposed by Ivakhnenko [7] are a method of data handling (GMDH) techniques [8]. In a polynomial network, complex systems are decomposed into simpler subsystems and grouped into several layers by using polynomial functional nodes. Inputs of the network are subdivided into groups, and then transmitted into individual functional nodes. These nodes evaluate the limited number of inputs by a polynomial function and generate an output to serve as an input to subsequent nodes of the next layer. The general methodology of dealing with a limited number of inputs at a time, then summarizing the input information, and then passing the summarized information to a higher reasoning level is directly related to human behavior. Therefore, polynomial networks can be recognized as a special class of biologically inspired networks with machine intelligence and can be used effectively as a predictor for estimating the outputs of complex systems.

The polynomial network for predicting surface roughness can be constructed based on the experimental data used for training tests. The input variables for the network are cutting speed v, feed rate f, depth of cut d, and the feature of surface image Ga. The output variable of the network is then the predicted surface roughness. The general polynomial function known as the Ivakhnenko polynomial in a polynomial functional node can be expressed as

$$y_0 = w_0 + \sum_{i=1}^{m} w_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m} w_{ij} x_i x_i + \sum_{i=1}^{m}\sum_{j=1}^{m}\sum_{k=1}^{m} w_{ijk} x_i x_j x_k + ..$$

Where x_i, x_j, x_k are the inputs, y_0 the outputs, and $w_0, w_i, w_{ij}, w_{ijk}$ are the coefficients of the polynomial functional node. In the present study, several specific types of polynomial functional nodes are used in the polynomial network for the modeling of cutting performance in milling operations.

4. Evolvable Hardware System

Evolvable hardware systems (EHW) are units built on software reconfigurable logic devices such as FPGA and whose architecture can be reconfigured using Genetic algorithm (GA) [1]. GA involves initiating a population, which is a set of members with each member described by a vector, called the chromosome. The fitness of each member is evaluated, and only a portion of the population is selected as the population for next generation. The structure of the reconfigurable device can be determined by downloading binary bit strings called the architecture bits [2]. The basic concept of evolvable hardware is shown in Fig. 2.

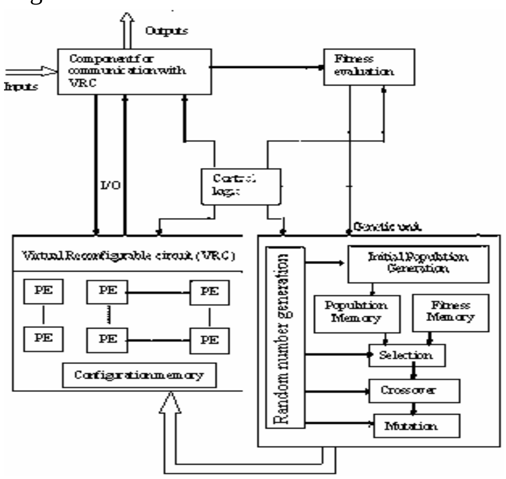

Fig. 2. Evolvable Hardware

5. Ga for Evolvable Computing

Genetic Algorithm [3] determines how the hardware structure should be reconfigured whenever a new hardware structure is needed for a better performance. GA was proposed to model adaptation of natural and artificial systems through evolution, and is one of the well known most powerful search procedures. The canonical GA has a population of chromosomes; each of them is obtained by encoding a point in the search space. Usually, they are represented by the strings of binary characters.

The sequence of operations performed by the GA is shown in Fig 3. At an initial state, chromosomes in the population are generated at random, and processed by many operations, such as evaluation, selection, crossover and mutation. The evaluation assigns the fitness values to the chromosomes, which indicates how well the chromosomes perform as solutions of the given problem. According to the fitness values, the selection determines which chromosomes can survive into the next generation. The crossover chooses some pairs of chromosomes, and exchanges their sub-strings at random. The mutation randomly picks some positions in the chromosome and flips their values.

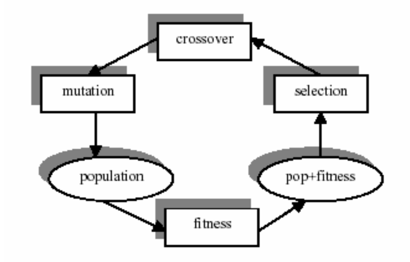

Fig. 3. Genetic Algorithm Flowchart

6. EHW System for Poor Illumination Compensation

The EHW system employed for poor illumination compensation consists of the Virtual reconfiguration chip (VRC), Genetic unit and components for communication with inputs and outputs.

6.1 DETAILS OF VRC

The main advantage of the VRC method is that the array, the routing circuits and the configuration memory can be designed exactly according to the requirements of a given application. Furthermore, style of reconfiguration and granularity of new virtual reconfigurable circuit can exactly reflect the needs of a given application. The VRC of the EHW unit is shown in figure 4. The reconfigurable circuit is modeled as an array of 'u' columns and 'v' rows programmable elements PE's (gates). Each PE can perform one of high-level functions such as addition, subtraction, multiplication, etc. The number of circuit inputs and outputs is fixed. The designer has to simply define the number of inputs and outputs along with a set of functions performed by PE's. In this work, a total of 25 PE's is used in the VRC.

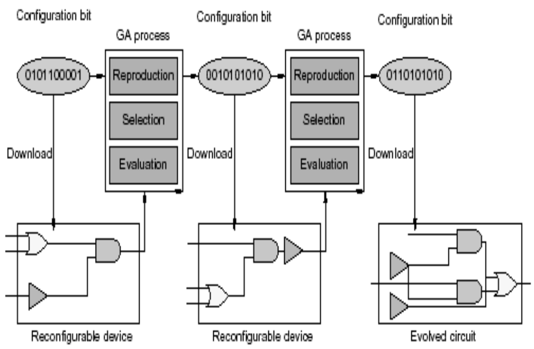

Fig. 4. EHW system with the VRC and Genetic unit

Figure 5 shows the hardware structure of the reconfigurable image filter banks represented as PE's. In this work, each PE except the first stage is assumed to receive inputs from any of the previous two stages.

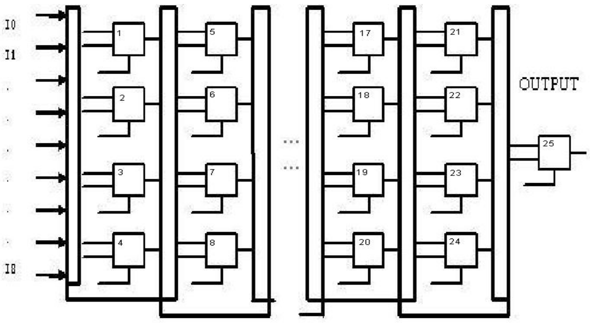

Fig. 5. Hardware structure of the PE's in VRC

6.2 Implementing the VRC Unit

The routing circuits are implemented using multiplexers. The configuration memory is composed of flip-flops. All bits of the configuration memory are connected to multiplexers that control routing and selection of functions in PEs. The number of PEs utilized in the VRC depends on a given application. The VRC unit is described in hardware descriptive language (HDL) and synthesized with various constraints for different target platforms. The architecture of single PE is shown in Fig. 6. Both sel_1 and sel_2 should not exceed the number of the multiplexer inputs. The sel3 input is the binary representation of the number of functions in the Table 1.1. The output of the PE is given by

$$\text{Output} = F\{\,\text{mux(sel1)}, \text{mux(sel2)}, \text{sel3}\,\}$$

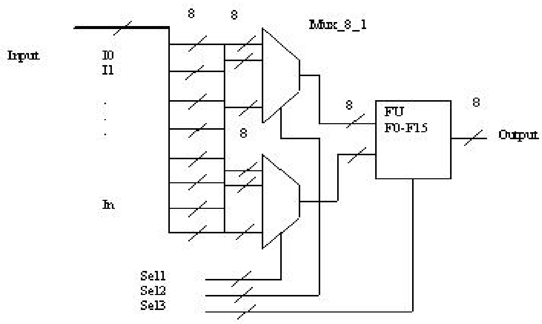

Fig. 6.Architecture of a single PE

Table.1

Code	Function	Code	Function
0000	X >> 1	1000	(X+Y+1) >> 1
0001	X >> 2	1001	X & 0x0F
0010	~ X	1010	X & 0xF0
0011	X & Y	1011	X | 0x0F
0100	X | Y	1100	X | 0x F0
0101	X ^ Y	1101	(X&0x0F) | (Y&0xF0)
0110	X + Y	1110	(X&0x0F) ^ (Y&0xF0)
0111	(X+Y) >> 1	1111	(X&0x0F)&(Y&0xF0)

7. Algorithm for Illumination Compensation

The algorithm for poor illumination compensation is given as follows:

1. Read the corrupted and reference images and store it in buffer.

2. Generate initial population of size 'n' with each of chromosome length L. Each chromosome contains details about the interconnection between PE's and also the function performed by the PE.

3. For each chromosome in the population

   Take 3x3 overlapping window and input nine pixel values to the VRC to replace the center pixel. Every pixel value of the filtered image is calculated using a corresponding pixel and its eight neighbors. This process is repeated for the whole image.

   - Calculate the Mean Difference Per Pixel (MDPP) and Fitness.
   - Retain the chromosome that has maximum fitness.

4. Select parent chromosomes according to roulette wheel selection procedure.
5. Apply crossover and mutation operations on the selected chromosomes to get the next generation strings.
6. Replace the old population.
7. Repeat from steps 3 for 'N' number of generations.

8. Hardware Implementation of EHW

The hardware implementation of the complete evolvable system is composed of basic modules such as input buffer, virtual reconfigurable circuit, pseudo-random number generator, population memory, selection unit, mutation unit, fitness evaluator and output buffer as shown in Fig. 7.

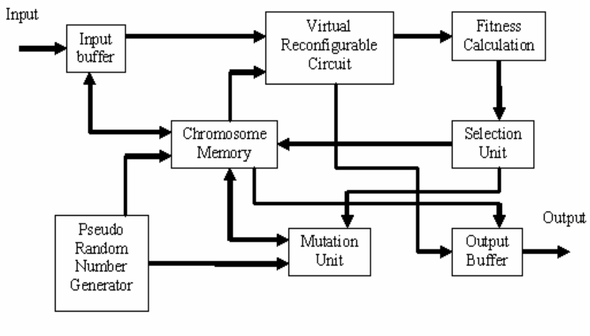

Fig. 7. Blocks of the EHW

Figure 8 Original raw image with noise

Figure 9 Image after processing with evolvable hardware system

8.1 FITNESS FUNCTION

Among the various approaches available to measure image visual quality the Peak Signal-to-Noise Ratio and the Mean Difference Per Pixel are the commonly used approaches. The MDPP fitness function is computationally easier for hardware implementation as compared to PSNR. For this reason, in this work, MDPP fitness function is taken for the fitness calculation. The fitness function using MDPP is given by

$$\mathrm{MDPP} = \frac{1}{\mathrm{NxN}} \sum_{i,j=1}^{N} |\mathrm{orig}(i,j) - \mathrm{filt}(i,j)| \quad (1.1)$$

$$\mathrm{Fitness} = 255 \text{ x } N \text{ x } N - \sum_{i,j=1}^{N} |\mathrm{orig}(i,j) - \mathrm{filt}(i,j)| \quad (1.2)$$

9. Results and Discussion

The surface images of the specimens grabbed using the CCD camera are given to the EHW chip and the configuration word is selected to eliminate the effects of improper illumination and noise. Preprocessing is performed to enhance the quality of images. Given an input image 'I' with a resolution $m \times n$, the chip extracts the edges and replaces the original low quality image with an output image 'O'. For experiments the number of initial population is set to 16 and each chromosome is evolved with crossover 0.9 and mutation 0.01. Figure 8 shows the images corrupted by noise and figure 9 shows the preprocessed image using the EHW system. The quality of the image is enhanced by 60.5% with the evolvable unit. The processed image has edges extracted and eliminates the effect of improper illumination and noise.

The surface roughness values obtained is listed in Table-2. The surface finish values predicted using the polynomial network and regression analysis is also given in Table 3 for comparison purposes. The error in using regression analysis without improving the quality of the images using EHW system was within 12%. The error in using polynomial network without improving the quality of the images using digital bank filters was within 6%. After using EHW system with the enhanced images ,the error was found to be within 7% for regression networks and within 2% for polynomial network.

Table – 2 surface roughness values for milled components before applying EHW system

S.N	Speed rpm	Feed (mm/rev)	Depth of cut (mm)	Ra (Stylus) (μm)	Rt (μm)	Rz (μm)	Ga
1	250	40	0.4	4.39	33.6	24.22	25.59
2	250	80	0.4	12.62	63.40	50.95	52.28
3	250	160	0.4	32.18	143.69	136.90	78.26
4	500	40	0.8	3.17	33.50	24.25	22.04
5	500	80	0.8	9.78	47.42	43.05	51.19
6	500	160	0.8	10.12	48.33	45.09	46.32
7	1000	40	1.6	1.60	11.52	10.22	18.54
8	1000	80	1.6	1.08	10.07	6.89	16.24
9	1000	160	1.6	0.45	4.13	2.99	6.33

Table – 3 Comparison of Surface finish values using various approaches for Milled Components

S.No	Ga	EHW Ga	Ra stylus (µm)	Ra (1) (µm)	Ra (2) (µm)	Ra (3) (µm)	Ra(4) (µm)
1	25.59	22.12	4.39	4.86	4.56	3.92	4.12
2	52.28	32.30	12.62	9.12	13.52	15.32	11.92
3	78.26	58.21	32.18	26.32	27.45	28.02	29.30
4	22.04	18.90	3.17	2.52	3.02	3.69	3.46
5	51.19	42.31	9.78	10.52	10.02	11.12	9.83
6	46.32	33.12	10.12	9.23	9.53	9.89	10.52
7	18.54	22.31	1.60	1.92	1.82	2.01	1.53
8	16.24	19.12	1.08	1.86	1.32	1.12	1.02
9	6.33	12.21	0.45	0.65	0.53	0.86	0.48

Ra (1) - Regression analysis Ra before applying EHW system
Ra (2) - Polynomial network Ra before applying EHW system
Ra (3) - Regression analysis Ra after applying EHW system
Ra (4) - Polynomial network Ra after applying EHW system

10. Conclusion

This paper has presented a genetic algorithm based EHW chip to perform preprocessing the images and compensate the effects of poor illumination and also to remove the noise. The correlation obtained using the regression and polynomial approach after improving the quality of the images of surfaces using EHW system was better than that without enhancing the images. The experimental results clearly indicate that the proposed technique can be used to evaluate the roughness of the machined surfaces.

References

1. Vandenberg et al: "Digital image processing techniques, fractal dimensionality and scale- space applied to surface roughness", Wear,159, (1992) 17-30.
2. P. Layzell. A New research Tool for Intrinsic Hardware Evolution. Proc. 2nd Int. Conf. On Evolvable Systems (ICES'98), 47-56, Springer-Verlag, 1998.
3. R. Poli: Genetic Programming for Image Analysis. Genetic Programming: Proceedings of the first Annual Conference (1996) 363-368.
4. C. Harris and B. Buxton: Evolving Edge Detectors. Research Note RN/96/3. University College London, Department of Computer Science (1996).
5. B. Ross, F. Feutan and D. Yashkir: Edge Detection of Petrigraphic Images using Genetic Programming Brock Computer Science Technical Reports, Brock University, Ontario, Canada CS-00-01 (2000).
6. Kiran et al: "Evaluation of surface roughness by vision system", International J. Mach. Tools Manufact. Vol. 38, Nos 5-6, (1998) pp. 685-690.
7. A. G. Ivakhnenko, polynomial theory of complex systems, IEEE Transactions on systems, Man and Cybernetics, 1 (4) (1971) 364 – 378.
8. G.E. Fulcher, D.E. Brown, A polynomial network for predicting temperature distributions, IEEE Trans. Neural Networks 5 (3) (1994) 372 – 379.

M. RAJARAM NARAYANAN, is a Research scholar in Manufacturing Engineering Department, college of Engineering, Anna University. His areas of interest are Evolvable Hardware, Computer Vision, Image Processing, Metrology, etc.

Dr. S.GOWRI is presently working as Professor & Head, Department of Manufacturing Engineering, Anna University, India. His research area includes Rapid prototyping, Advanced Manufacturing Technology, Precision Engineering, High speed machining., CAD/CAM/CIM etc..

Dr.A.VELAYUTHAM is working as Scientist 'D' in CVRDE, Ministry of Defence, India. His field of interest is CAD/CAM, Mechatronics, Advanced Manufacturing Technology, Composite materials, etc

Dr. S.RAVI, is presently working as Professor in the Dept. of Electronics and Communication Engineering in a college affiliated to Anna University, India. His fields of interest include Neural Networks, Evolvable hardware, Sensor Fusion etc.