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DESIGN IMPLEMENTATION AND HARDWARE STRUCTURE FOR IMAGE ENHANCEMENT AND SURFACE ROUGHNESS WITH FEATURE EXTRACTION USING DISCRETE WAVELET TRANSFORM

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ABSTRACT

In this study we provide the implementation design and hardware structure for the architecture proposed in the previous paper “Image Enhancement and Surface Roughness with Feature Extraction using DWT” IEEE DoI/10.1049/cp.2011.0464. The proposed architecture has been implemented in Microwind and Tanner for power analysis and characteristic study. The result shows very low power consumption than the existing method for a series of IEEE standard test images.

Keywords: Surface Roughness, Milling, Grinding, Noisy Filter, Edge Detector, Image Enhancement

1. INTRODUCTION

Comparing with real time application, the engineering application needs to provide good quality and performance of materials during production. The main quality of surface roughness can be measured by using two techniques, namely optical and stylus techniques. Radii of the diamond can be checked using stylus but surface roughness (Damodarasamy and Raman, 2003) can be checked by optical techniques which are quite expensive. Now-a-days machine vision is used to evaluate and analyze the microscopic defects in surface of the materials. The other methods of surface roughness study is shown in **Fig. 1**.

2. MATERIALS AND METHODS

Human vision can be replaced with machine vision with capturing, compressing and extraction of image in high speed precision manufacturing areas as a mainstream automation tool (Badashah and Subbaiah, 2011). Machine vision (Luk *et al*., 1989; Al-Kindi *et al*., 1992) has the advantage of grasping the images online without accounting for factors like vibrations (advantage), noise, intensity (disadvantage) (Tsai and Tseng, 1999). There is a need for design of recognition systems with capability to adjust to changing environments automatically. Less complicated, highly flexible and more cost-effective computing architectures are required as compared to the traditional ones.

Two dimensional Fourier Transform and Wavelet Transform are applied to the extracted enhanced images in spatial frequency domain. Fourier transform is used for stationary profiles and for non-stationary profiles Wavelet transform is used. The experimental setup is shown in **Fig. 2**.

2.1. Feature Extraction using Wavelet Ransforms

Fourier Transform and wavelet decomposition techniques (family of orthogonal wavelets) are used to extract the features from the image of the surface under test. The features such as the major peak frequency and the principal component magnitude squared value are extracted using Fourier transform. The energy details of the sub band images (Ramamoorthy and Radhakrishnan, 1993), such as, energy total, energy horizontal, energy vertical and energy diagonal are extracted using the wavelet (Db4) multi resolution decomposition algorithm.

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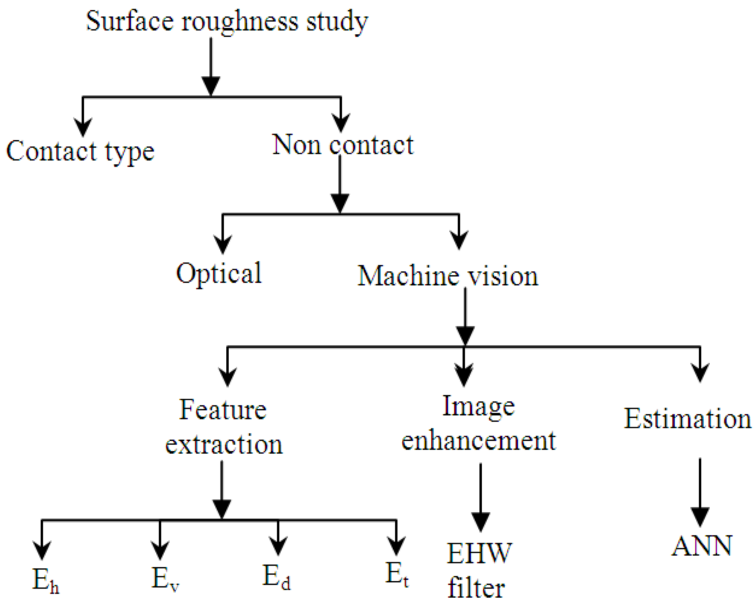

Fig. 1. Surface roughness study

Fig. 2. Experimental setup (CVRDE)

Fig. 3. Multi resolution decomposition using Microwind

2.2. Image Enhancement using EHW Filter

Image degradation occurs due to noise delivered from unavoidable source. The most common noise is impulse noise (Kartik *et al*., 1997; Cheikh *et al*., 1998; Astola and Kuosmanen, 1997; Dougherty and Astola, 1994). Enhancement of the image can be done using filtering technique. The processing elelment simulation of evolvable hardware for image enchancement is shown in **Fig. 3 and 4**. Linear filter are very less resistive to impulse noise. Hence the Median filter, a Non Linear filter has been used for enhancement and implemented using Evolvable Hardware.

2.3. Surface Roughness Estimation using Neural Network

From literature survey, regression technique is one of the better methods for surface roughness estimation. But it involves higher complexity and calculation for a little increase of accuracy. As an alternate neural network with back propagation algorithm (**Fig. 5**) based estimation can be used for surface estimation with higher accuracy and constant resource (Since the topology of the network is constant. Only bias and weights are change with some algorithm).

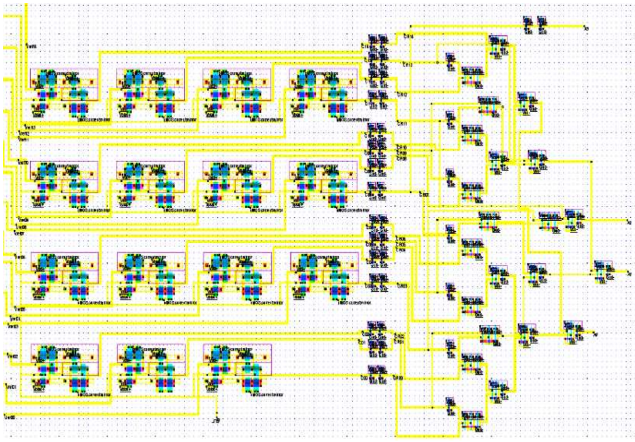

Fig. 4. Processing elements structure of EHW in microwind

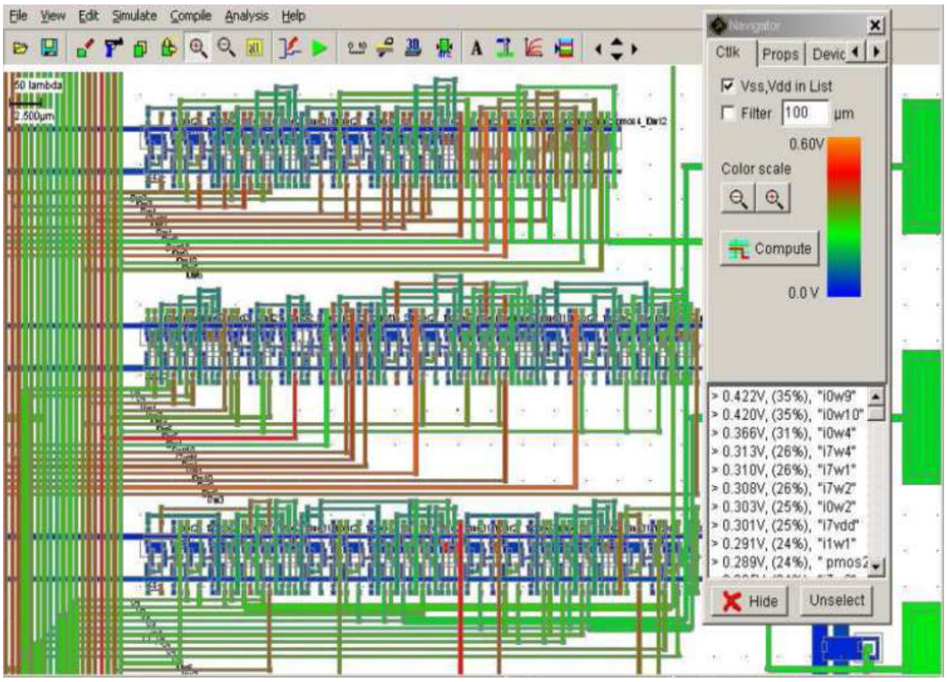

Fig. 5. Neural logic (Hidden Layer neurons and their multiplier) structure using microwind

2.4. Objectives of this Work

The major objectives of this research work are:

- In this study, to overcome the problem of high primitive gate level evolvable hardware structure, a function-level evolution (Negoita *et al*., 2008) is proposed. Domain knowledge is used to select high level computational units that signify directly in the chromosome
- To extract the features of the image using wavelet and fourier transform independently
- Training A Neural Network (ANN) (Samhouri, 2005) and use it for approximating the surface roughness R_t of industry related components manufactured using processes such as grinding and milling. ANNs have the ability to recognize patterns that are similar, but not identical; it can store information and generalize it. As this would

introduce huge parallelism, the ANNs exhibit increased computational power that can be used to deal with intricate problems. In this research, back-propagation neural network is used for estimating the surface roughness of the machined surfaces

- A comparison of surface finish attained using proposed scheme with that of using classical and conventional stylus approach

3. RESULTS AND DISCUSSION

The resource utilized by the proposed algorithm (**Fig. 6**) is economical in each and every stage of the proposed algorithm. Though there is trade off at the early stage of the filter design, it remains almost constant and independent of the number of coefficient in the entire implementation of the filter. The minimum number of coefficient will not be of 2 to 6 for a efficient filtering process (Gabbouj, 1996).

The **Table 1 and Fig. 6** shows the resource utilized and the **Table 2 and Fig. 7** shows the processing time by the existing architecture and the proposed architecture. It is clear from both the cases that the proposed architecture outperforms the existing architecture of DSP implementation. It is also clear from the **Fig. 8 and 9** the power requirement is predictable and minimum.

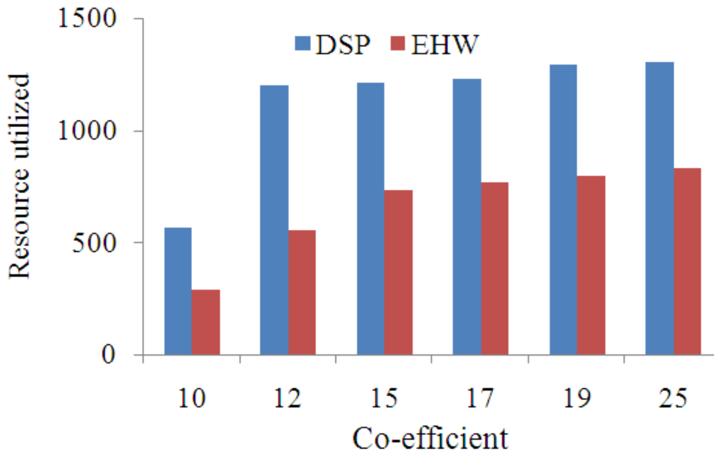

Fig. 6. Comparison of resource utilization of existing DSP based processor and proposed architecture

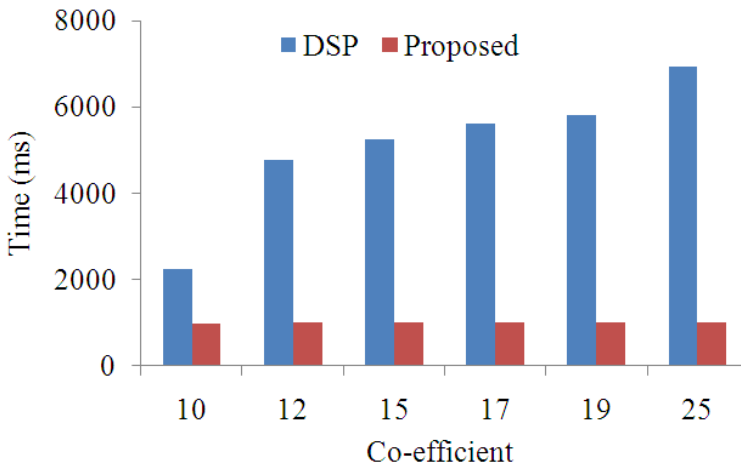

Fig. 7. Comparison of processing time of existing DSP based processor and proposed architecture

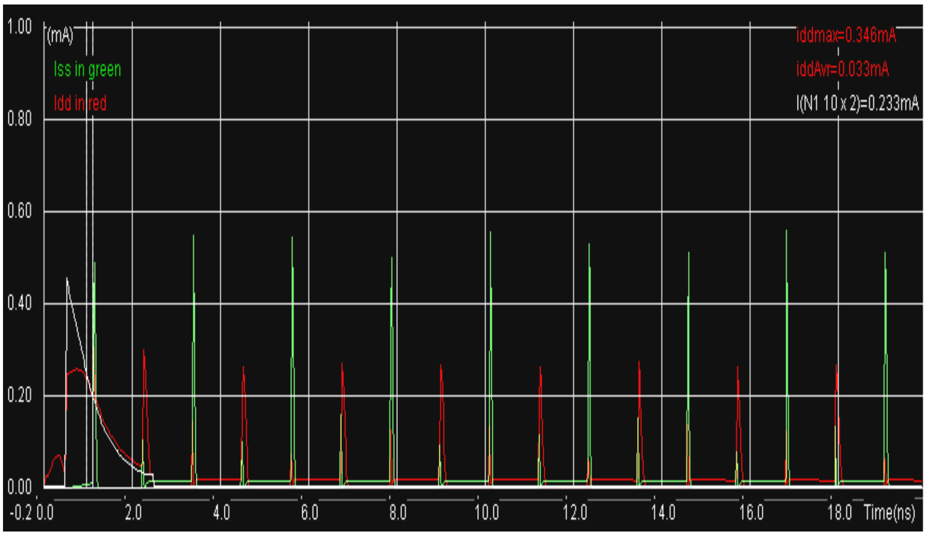

Fig. 8. Power fluctuation of proposed circuit

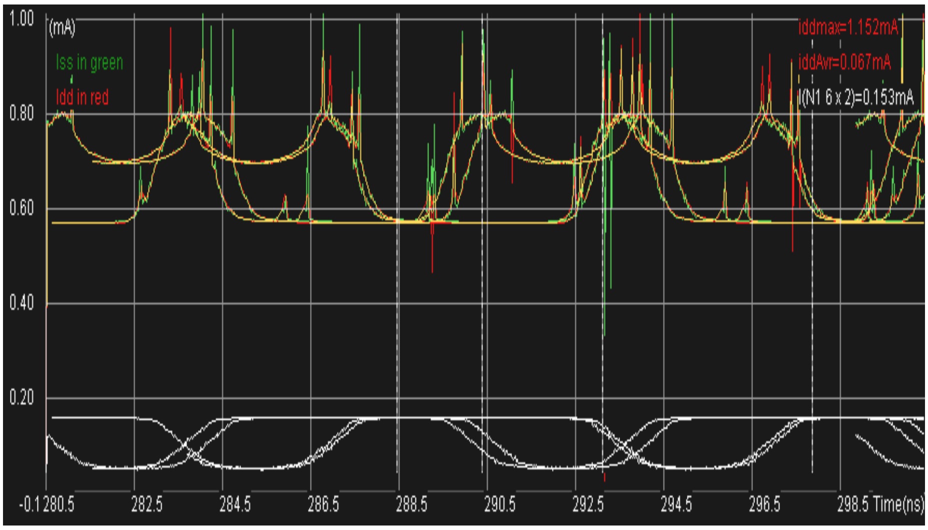

Fig. 9. Power fluctuation of DSP circuit

Table 1. Comparison of resource utilization of existing DSP based processor and proposed architecture

Co-eff	DSP	EHW
10	563	286
12	1200	551
15	1213	732
17	1226	766
19	1290	799
25	1301	832

Table 2. Comparison of processing time of existing DSP based processor and proposed architecture

	Processing time	
DSP	Proposed	Speed up%
2250	986	228.1
4762	999	476.6
5263	1001	561.7
5620	1003	560.3
5814	1004	579.0
6944	1010	687.5

4. CONCLUSION

In this study, a vision application capable of performing selective image processing and analysis has been implemented. The filter outperforms conventional designs in terms of performance measure, high speed computation and low power consumption. It is easily scalable and can be mapped with Digital Logic operators with lesser non-linear operation. Hence, the schemes (based on EHW filter, Wavelet and ANN) can successfully replace conventional ones.

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