CHAPTER 5

WAVELET TRANSFORM BASED FEATURE EXTRACTION

The wavelet transform provides an appropriate basis for image handling because of its beneficial features. The assets of the wavelet transform are:

- The ability to compact most of the signal's energy into a few transformation coefficients, which is called energy compaction.
- The ability to capture and represent effectively low frequency components (such as image backgrounds) as well as high frequency transients (such as image edges).
- The variable resolution decomposition with almost uncorrelated coefficients.
- The ability of a progressive transmission, which facilitates the reception of an image at different qualities.

5.1 Subband Refinements in Wavelet Transform

In the wavelet Transform operation, all the subbands of the lower resolution image must be refined (i.e., a rate added).

$$\sigma^2{}_{wgm} = \Pi_{m=1}^{M} (\sigma_m^2) N_m / N \qquad (5.1)$$

Let (i) M=7 [the number of subbands] and

(ii) The number of dyadic decomposition stage be two as shown in figure 5.1

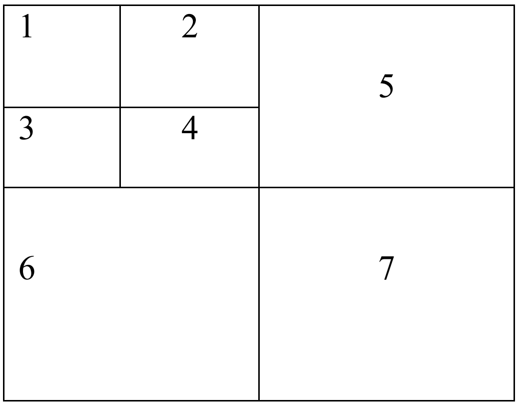


Figure 5.1 Decomposition stage

From figure 5.1 $\frac{N1}{N}$ = ----- $\frac{N4}{N} = \frac{1}{16}$ and

$$\frac{N5}{N} = \text{-----} \quad \frac{N7}{N} = \frac{1}{4} \tag{5.2}$$

Thus, in (5.2)

$$\sigma^2_{wgm} = [\sigma^2_1\, \sigma^2_2\, \sigma^2_3\, \sigma^2_4\,]^{1/16}\ \ [\sigma^2_5\, \sigma^2_6\, \sigma^2_7]^{1/4}$$

$$= [\sigma^2_{wgm(base)}]^{1/4}\, [\sigma^2_{wgm(enh)}]^{3/4}$$

Where

$$\sigma^2_{wgm(base)} \triangleq (\sigma^2_1\, \sigma^2_2\, \sigma^2_3\, \sigma^2_4)^{1/4}$$

and $\sigma^2_{wgm(enh)} \triangleq (\sigma^2_5\, \sigma^2_6\, \sigma^2_7)^{1/3}$

Thus, the resolution rate is low for subbands 1 to 4 and high for all subbands, represented as $R_i^{(1)}$ and $R_i^{(2)}$ respectively.

$$\therefore\ R_i^{(1)} = R + \frac{1}{2}\log_2\left(\frac{\sigma 2i}{\sigma 2wgm(base)}\right) \qquad i = 1,2,3,4$$

$$R_i^{(2)} = R + \frac{1}{2}\log_2\left(\frac{\sigma 2i}{\sigma 2wgm}\right) \qquad i = 1 \text{ to } 7$$

After simplification,

$$R_i^{(2)} = R_i^{(1)} + \frac{1}{2}\log_2\left(\frac{\sigma 2wgm(base)}{[\sigma 2wgm(base)]1/4\ \ [\sigma 2wgm(enh)]3/4}\right) \tag{5.3}$$

Eqn. (5.3) specifies the relation that $\sigma^2_{wgm(enh)}$ shall be less than $\sigma^2_{wgm(base)}$, so that, $R_i^{(2)} > R_i^{(1)}$ for i = 1 to 4. This necessitates that all the subbands of the lower resolution image must be refined i.e., have a rate added to them and this is carried out in this research.

5.2 FEATURE EXTRACTION RESULTS

The result obtained by applying the wavelet based feature extraction algorithm is presented. The original milled image is shown in Figure 5.2 , Figure 5.3 to 5.10 presents the decomposed image waveform details obtained at different stages of the wavelet tree decomposition.

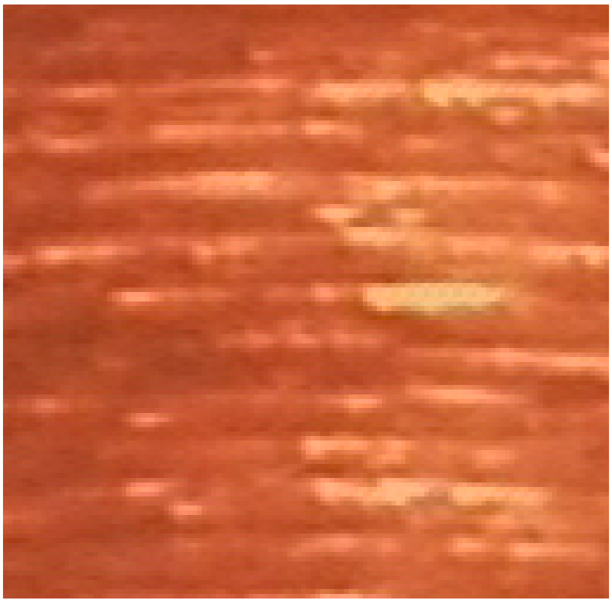


Figure 5.2 Original Enhanced milled image

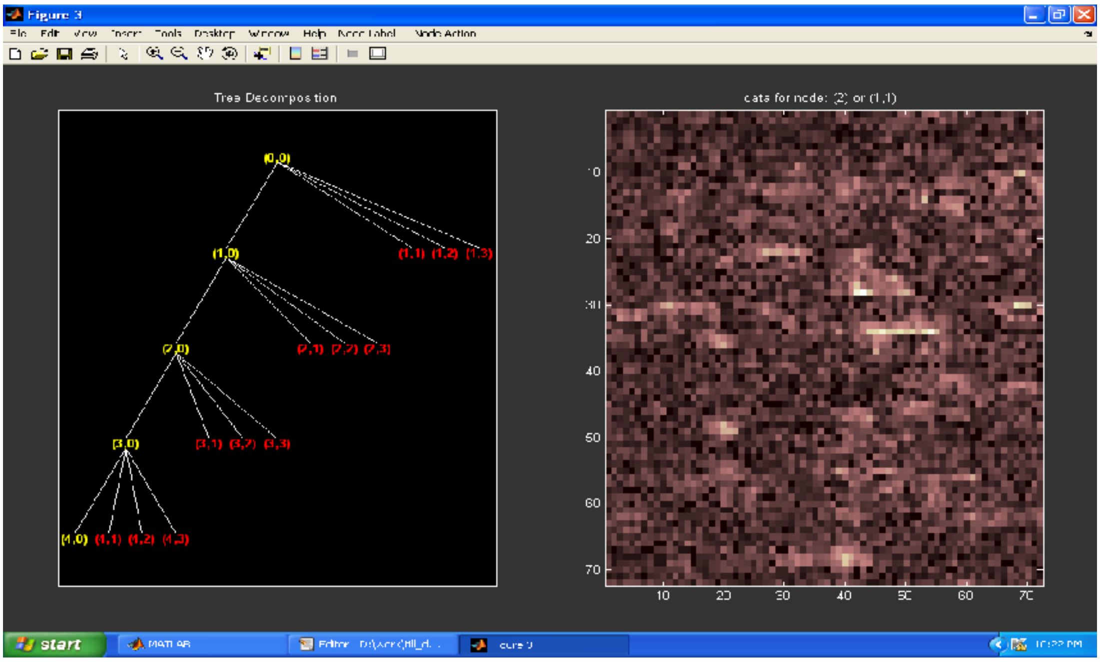


Figure 5.3 Wavelet decomposition tree [left figure] and data for node (1, 1) [right figure]

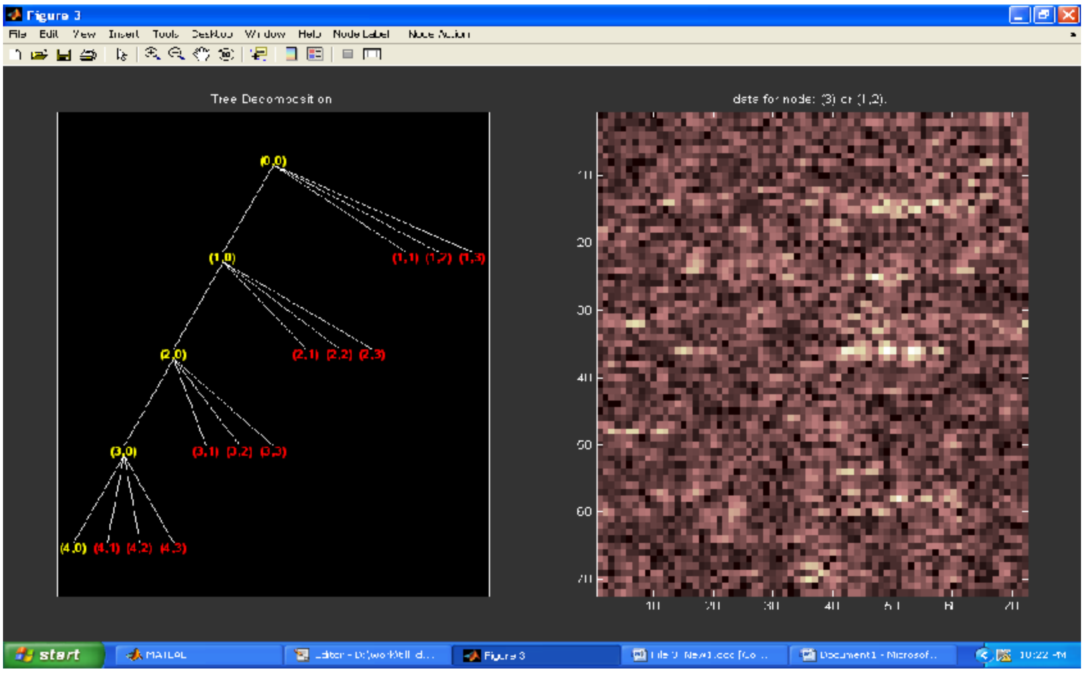


Figure 5.4 Wavelet decomposition tree [left figure] and data for node (1, 2) [right figure]

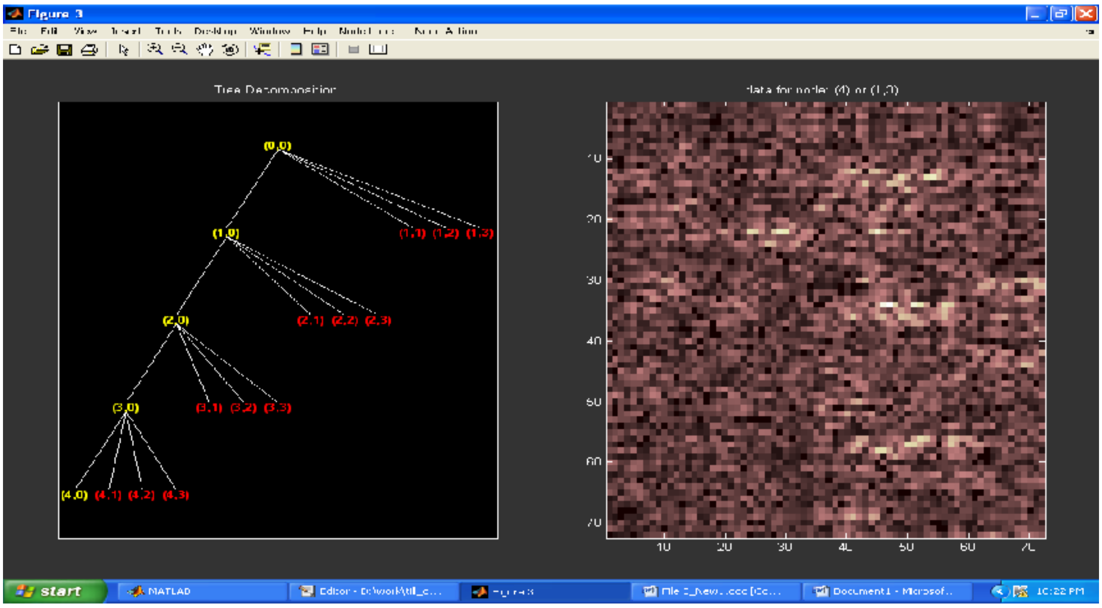


Figure 5.5 Wavelet decomposition tree [left figure] and data for node (1, 3) [right figure]

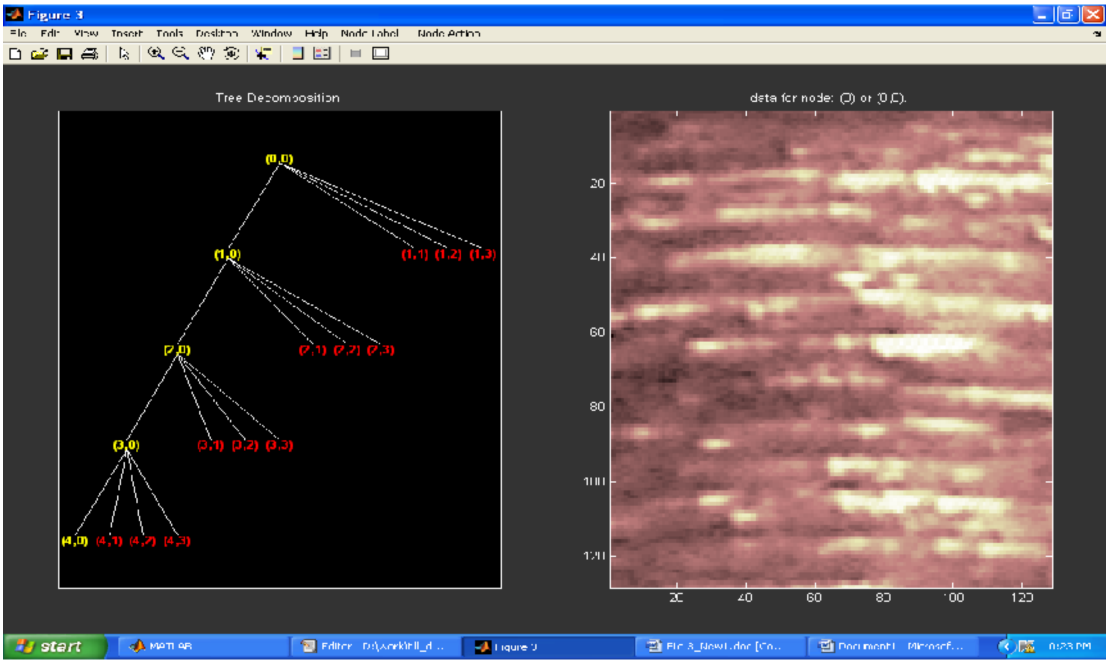


Figure 5.6 Wavelet decomposition tree [left figure] and data for node (0, 0) [right figure]

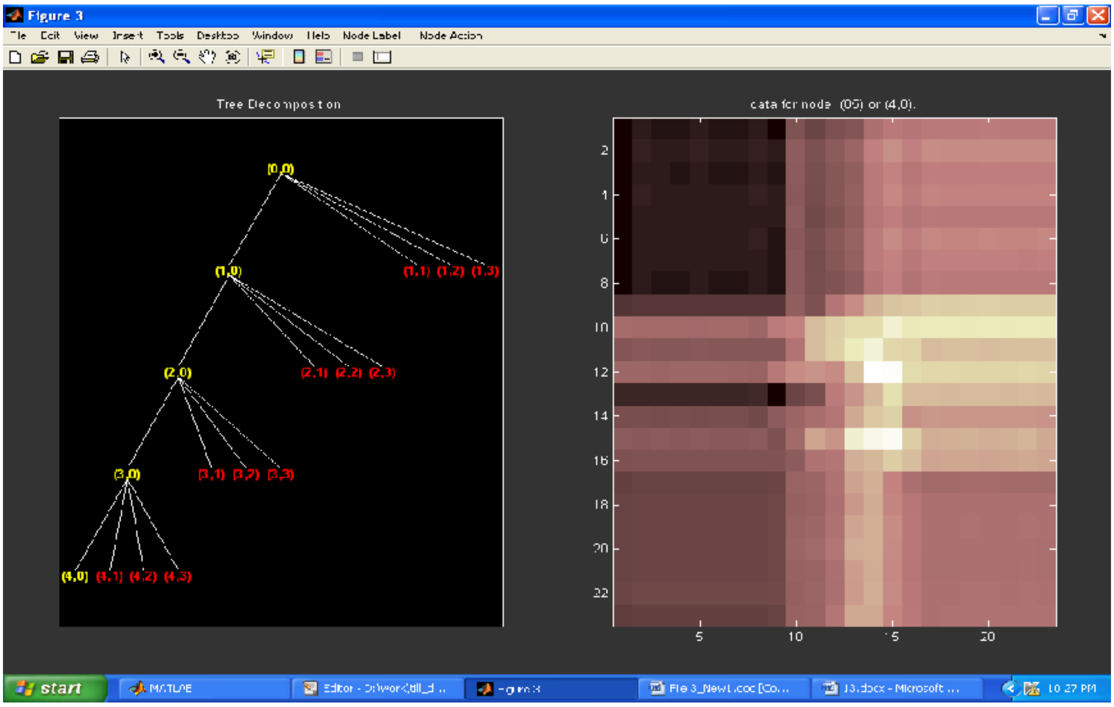


Figure 5.7 Wavelet decomposition tree [left figure] and data for node (4, 0) [right figure]

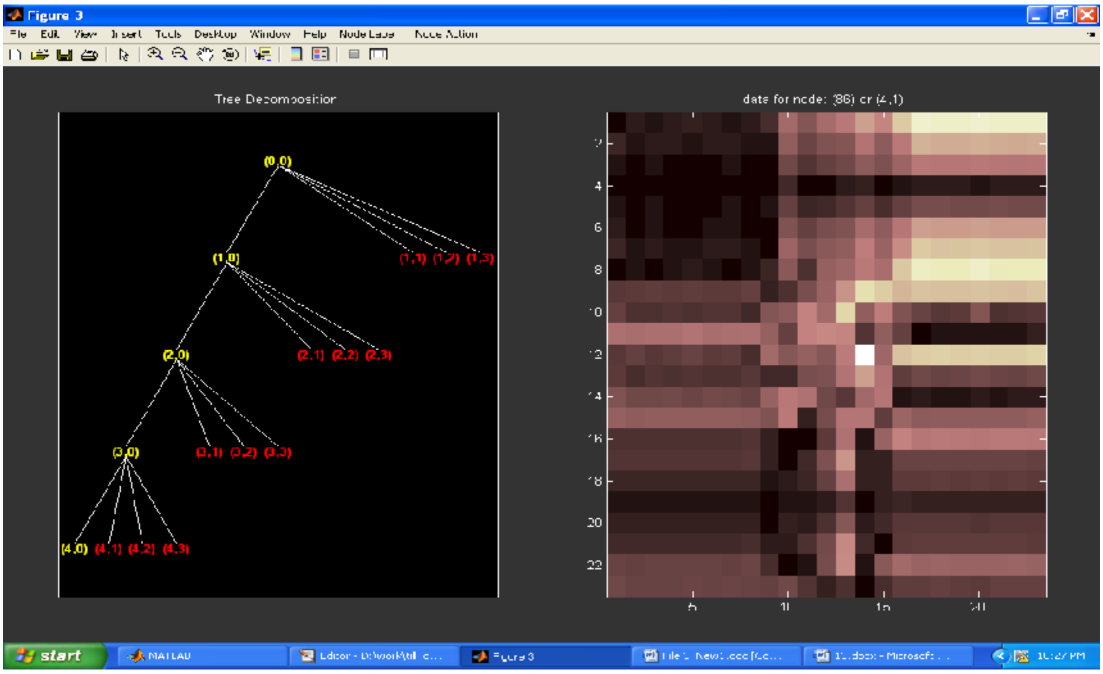


Figure 5.8 Wavelet decomposition tree [left figure] and data for node (4, 1) [right figure]

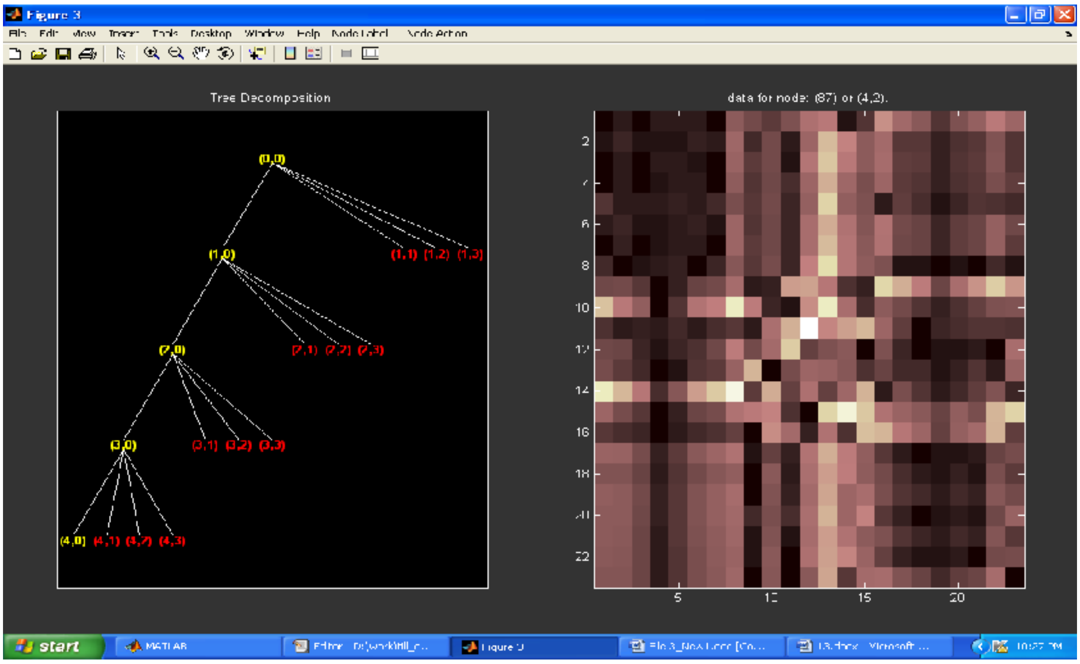


Figure 5.9 Wavelet decomposition tree [left figure] and data for node (4, 2) [right figure]

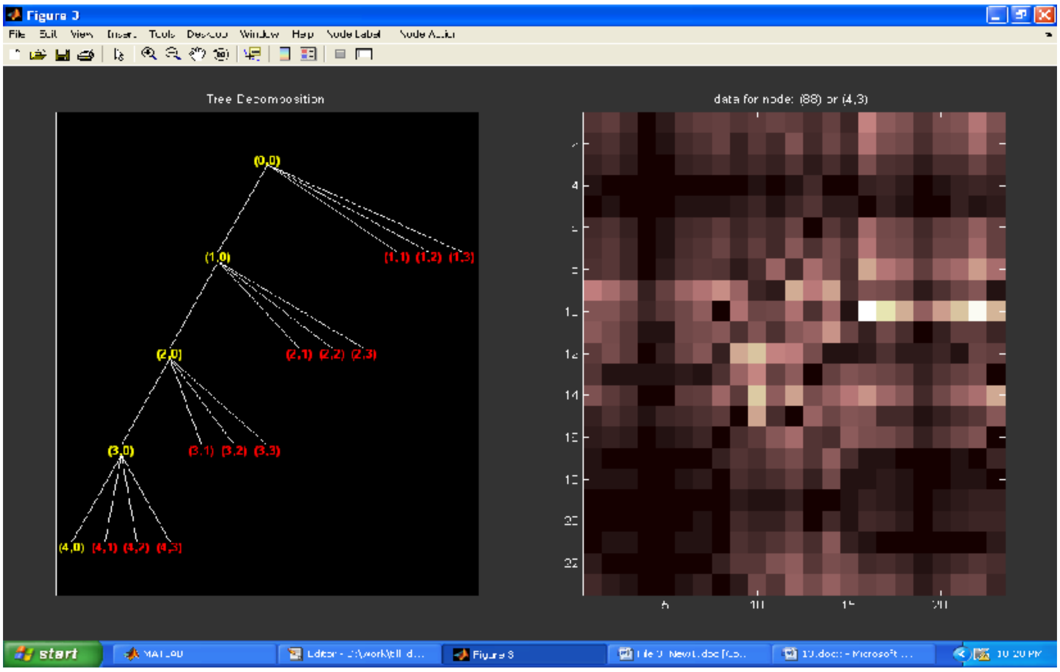


Figure 5.10 Wavelet decomposition tree [left figure] and data for node (4, 3) [right figure]

The energy details obtained for the milled image is shown in table 5.1. The last column E_{ti} in Table 5.1 is the average of E_{Hi}, E_{Vi} and E_{di} for level 'i'. These average energy values are used as input to a feature classifier network is used for predicting the surface roughness.

Table 5.1 Energy details obtained for milled images

i-values	Eai	Ehi	Evi	Edi	Eti
1	99.9507	0.0415	0.0047	0.0031	0.016433333
2	99.6876	0.013985	0.0116	0.00475	0.010111667
3	99.1891	0.242633	0.017	0.010633	0.090088667
4	99.2522	0.168425	0.011825	0.00875	0.063

5.3 ALGORITHM FOR WAVELET BASED FEATURE EXTRACTION

In this research the different feature extraction modules using DWT are developed such that the code acts as a communication interface between user and database. This database is repertoire of machined images enhanced with an evolved filter.

5.3.1 Interactive Image Reading Segment

The code interacts with the user by providing 'browse' option and offers a dialog box that lists grabbed enhanced images in the folder and enables the user to select an image with the specific extension which will be subjected to various operations for extracting feature. The selected image is validated against the same array contents and the result is conveyed to the user. On proper selection the selected image is assigned with a storage location and the stored image is read using the storage path. The image is converted to gray scale image and displayed. These are illustrated in figure 5.11.

```
DISPLAY 'browse for the image';
DISPLAY 'press any key to continue';
DISPLAY 'select image with extension .bmp"
READ machined_image;
IF machined_image_arrays_are_same THEN
display "proper selection"
ELSE
Display "improper selection";
SET image_path = READ (machined _image);
CONVERT machined _image TO machined _gray _image;
SET x= machined _gray_ image;
READ x;
SHOW x;
```

Figure 5.11 Interactive image reading segment of the code

5.3.2 Wavelet Selection, Decomposition Vector Calculation and Energy Calculation

This segment fixes the operational platform in discrete wavelet domain possessing symmetric padding extension. The user selects a wavelet function from a given set of functions. The selected function is assigned with an identifier for global use. A new class of objects using the selected function are created and displayed. The gray scale version of selected image is subjected to decomposition operation. The book keeping matrix gives the size of approximation coefficients and detail coefficients. By using the decomposition vector as input, energy levels corresponding to approximation and details coefficients are computed. This is shown in figure 5.12.

```
SELECT wavelet _mode;
SELECT wavelet _name;
ASSIGN type _name = wavelet _name;
DISPLAY type _name;
// DECOMPOSITION VECTOR CALCULATION
for i = 1 to 4
        COMPUTE WC[i] =wavelet _decomposition[x];
        COMPUTE S[i] = size _WC[i];
        CONSTRUCT decomposition _matrix[i] = [WC[i], S[i]];
        i = i + 1;
end;
// ENERGY COMPUTATION
for j = 1 to 4
        INPUT decomposition _matrix_[i];
        j = j + 1;
end
for k = 1 to 4
COMPUTE energy_ approximation_ coeff[k]=wave_ energy[wc[k],s[k]];
COMPUTE energy _ horizontal _ coeff [k] =wave _energy [wc[k],s[k]];
COMPUTE energy_ vertical_ coeff[k] = wave _energy [wc[k],s[k]];
COMPUTE energy_ diagonal _ coeff [k] = wave _energy [wc[k],s[k]];
    k = k + 1;
    end
```

Figure 5.12 Extracting energy details

5.3.3 Coefficient Extraction from Decomposition Vector and Display

This segment is fed with decomposition vector as input. It uses four functions namely approximation _coeff_ calc, detail _coeff _hor _calc, detail _ coeff _ ver _calc, detail _ coeff _dia _calc for decomposition. These functions perform extraction operation on decomposition vector and yields approximation coefficients, horizontal coefficients, vertical coefficients and diagonal coefficients. The decomposition level ranges from 1 to 4. A parameter for size 'ncolors' 'sz' is calculated. This segment also employs two more functions matrix _rescale and coeff _ deci. The matrix _rescale function scales the approximation coefficients, horizontal coefficients, vertical coefficients and diagonal coefficients by a value of 'ncolors' from present value. The coeff _deci function selectively extracts the coefficients where the selection size is derived from the value of 'sz'. This is shown in Figure 5.13.

```
for i = 1 to 4
INPUT decomposition _matrix[i];
i = i + 1;
end

// COEFFICIENT EXTRACTION
for j = 1 to 4
        COMPUTE CA[j] = approx _ coeff _calc [wc [j], s[j]];
        COMPUTE CH[j] = detail _ coeff _ hor _calc [wc[j], s[j]] ;;
        COMPUTE CV[j] = detail _ coeff _ ver _calc [wc[j], s[j]];
         COMPUTE CD[j]= detail _ coeff _ dia _calc[wc[j], s[j]];
        j = j + 1;
end
COMPUTE ncolors;
COMPUTE sz;

// MATRIX SCALING AND SELECTIVE EXTRACTION
for k = 1 to 4
        COMPUTE res _CA[k] = matrix _rescale [CA[k], ncolors];
        COMPUTE res _CH[k] = matrix _ rescale [CH[k], ncolors];
        COMPUTE res _CV[k] = matrix _ rescale [CV[k], ncolors];
```

```
        COMPUTE res _CD[k] = matrix _ rescale [CD[k], ncolors];
        k = k + 1;
end

//SELECTIVE COEFFICIENT EXTRACTION
        COMPUTE dec _ CA [1] = coeff _ deci[CA[1], sz/2];
for m = 2 to 4
        COMPUTE dec _CH[m] = coeff _deci [CH[m], sz/4];
        COMPUTE dec _CV[m] = coeff _deci [CV[m], sz/4];
        COMPUTE dec _CD[m] = coeff _deci [CD[m], sz/4];
        m = m + 1;
end
```

Figure 5.13 Coefficient extraction segment

5.3.4 Coefficient Reconstruction from Decomposition Structure

This segment performs two functions, reconstruction of coefficients from decomposition structure and scaling. The decomposition vector [wc,s] is applied as input. The computation level ranges from 1 to 4. The selected wavelet function is used here. A function, reconstruct _coeff is used to reconstruct coefficients by accepting decomposition structure, decomposition level and produces approximation coefficients, horizontal coefficients, vertical coefficients and diagonal coefficients. Using matrix _rescale function the coefficients are scaled to a size of 'ncolors'. The scaled coefficients are assigned with identifiers. This is shown in figure 5.14.

```
for i = 1 to 4
INPUT decomposition _matrix[i];
i = i + 1;
end
//COEFFICIENT RECONSTRUCTION
for j = 1 to 4
```

```
        COMPUTE recon _CA[j] = reconstruct _coeff [wc [j], s[j]];
        COMPUTE recon _CH[j] = reconstruct _coeff [wc[j], s[j]];;
        COMPUTE recon _CV[j] = reconstruct _coeff [wc[j], s[j]];
         COMPUTE recon _CD[j]= reconstruct _coeff [wc[j], s[j]];
        j = j + 1;
end
// RECONSTRUCTED COFFICIENTS SCALING
for k = 1 to 4
        COMPUTE res _CA[k] = matrix _rescale [wc [k], s[k], ncolors];
        COMPUTE res _CH[k] = matrix _rescale [ wc[k], s[k], ncolors];
        COMPUTE res _CV[k] = matrix _rescale [wc[k], s[k], ncolors];
        COMPUTE res _CD[k] = matrix_ rescale [wc[k], s[k], ncolors];
        k = k + 1;
end
```

Figure 5.14 Coefficient reconstruction segment

5.4 ENERGY MAP DETAILS FOR MILLING

The complete energy map details for three milled sample cases M10, M11 and M12 is shown in figure 5.15, figure 5.16 and figure 5.17 respectively. The original enhanced machined image for the above three sample cases is also shown in figure 5.18 (a) to (c).

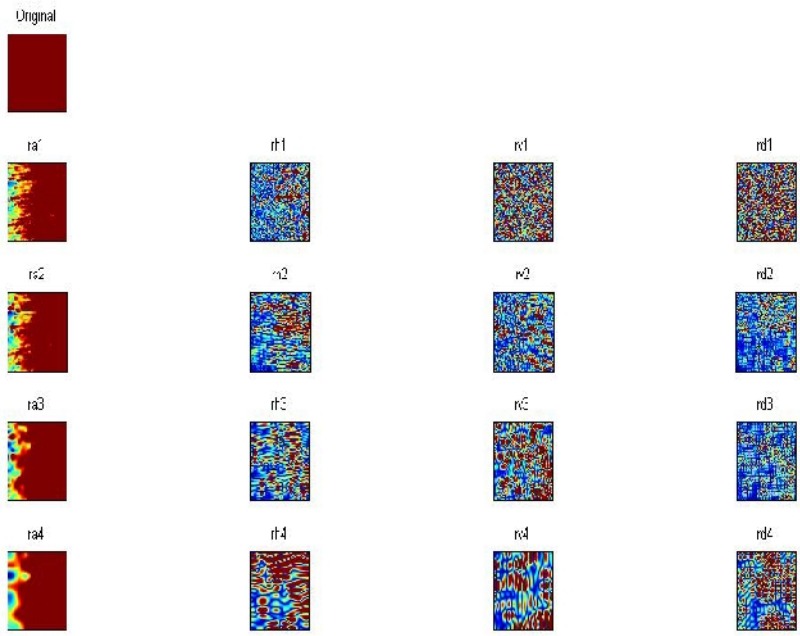


Figure 5.15 Complete energy map details for the milled image M10 (four levels Decomposition)

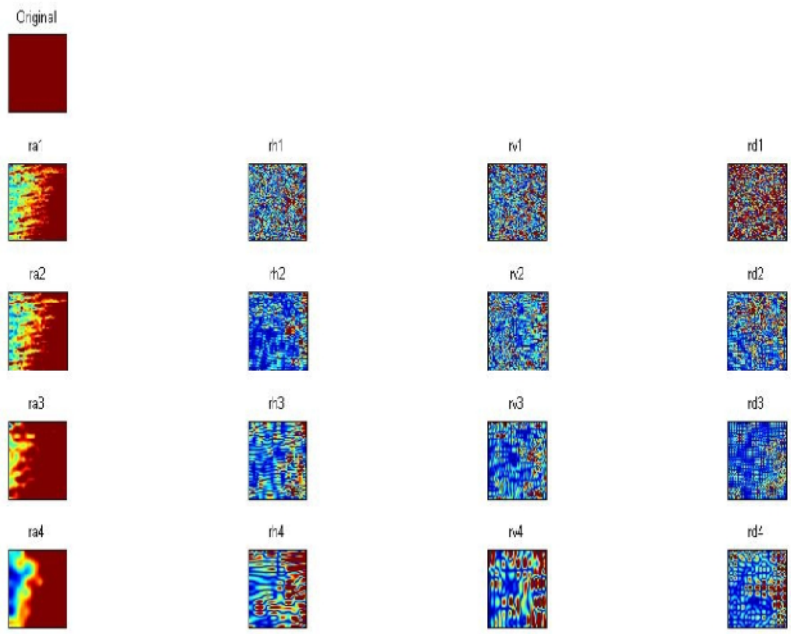


Figure 5.16 Complete energy map details for the ground image M11 (four level decomposition)

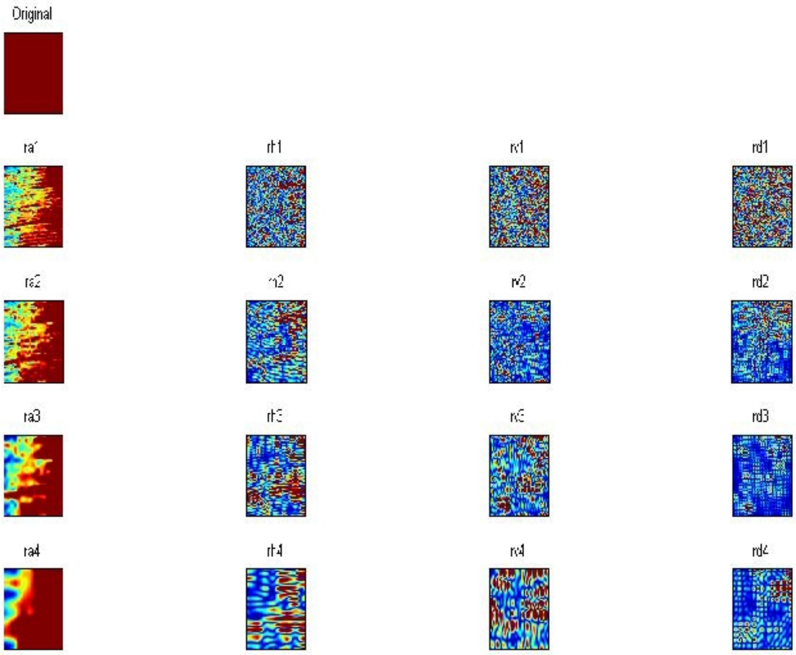
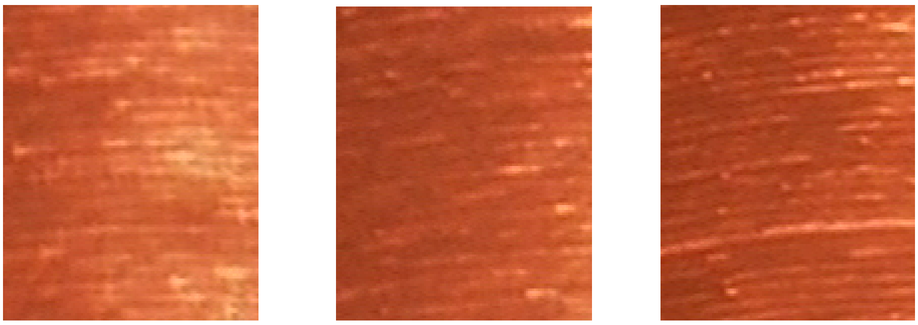


Figure 5.17 Complete energy map details for the ground image M12 (four level decomposition)



(a) M10 **(b) M11 and** **(c) M12**

Figure 5.18 Enhanced machined image for milling

5.5 ENERGY MAP DETAILS FOR GRINDING

The complete energy map details for three sample cases G10, G11 and G12 is shown in figure 5.19, figure 5.20 and figure 5.21 respectively. The original enhanced machined image for the above three sample cases is also shown in figure 5.22 (a) to (c).

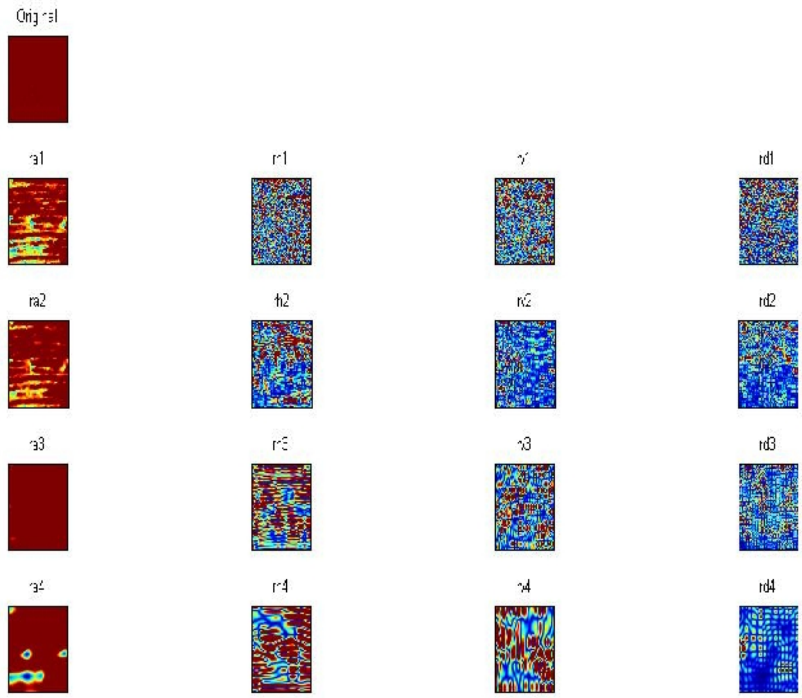


Figure 5.19 Complete energy map details for the ground image G10 (four level decomposition)

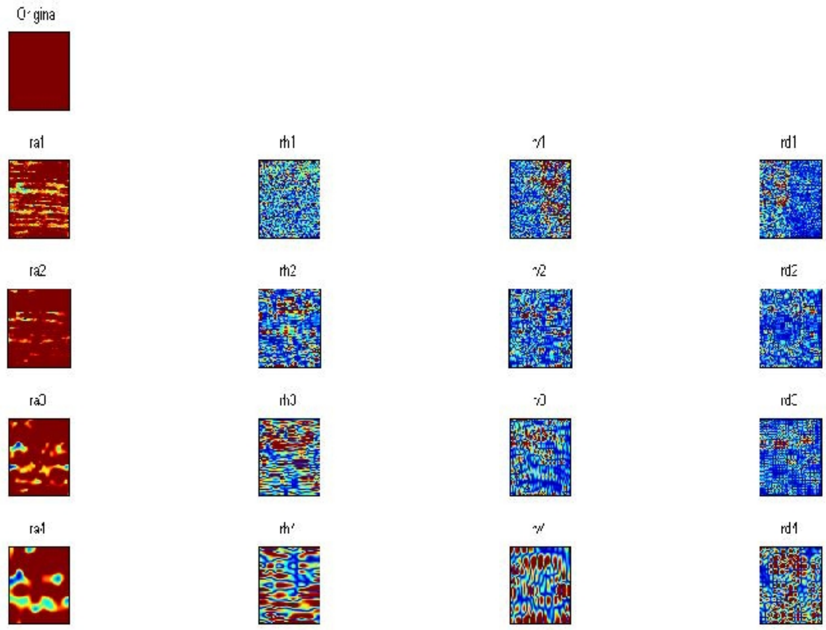


Figure 5.20 Complete energy map details for the ground image G11 (four level decomposition)

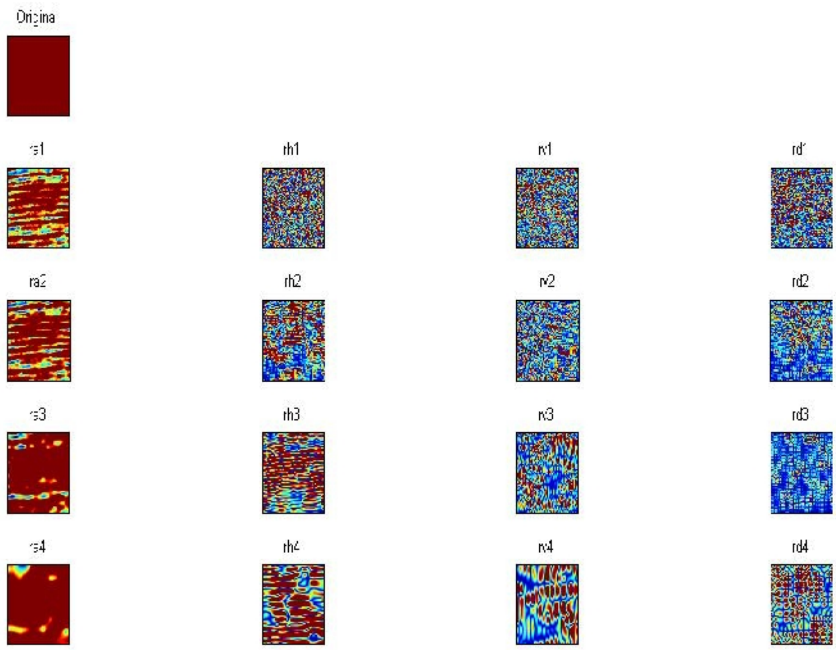
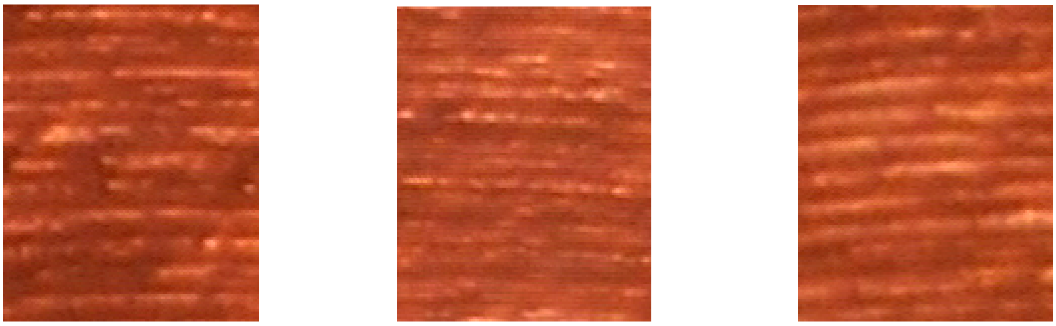


Figure 5.21 Complete energy map details for the ground image G12 (four level decomposition)



(a) G10 (b) G11 and (c) G12

Figure 5.22 Enhanced machined image for milling

5.6 VARIATION OF ENERGY VALUES WITH R_t

The variation of energy values with R_t for 12 sample cases is shown in figure 5.23 and 5.24 for milling and grinding images respectively. These variations clearly show that there is a significant correlation present between the surface roughness R_t and the decomposed energy values of the machined image.

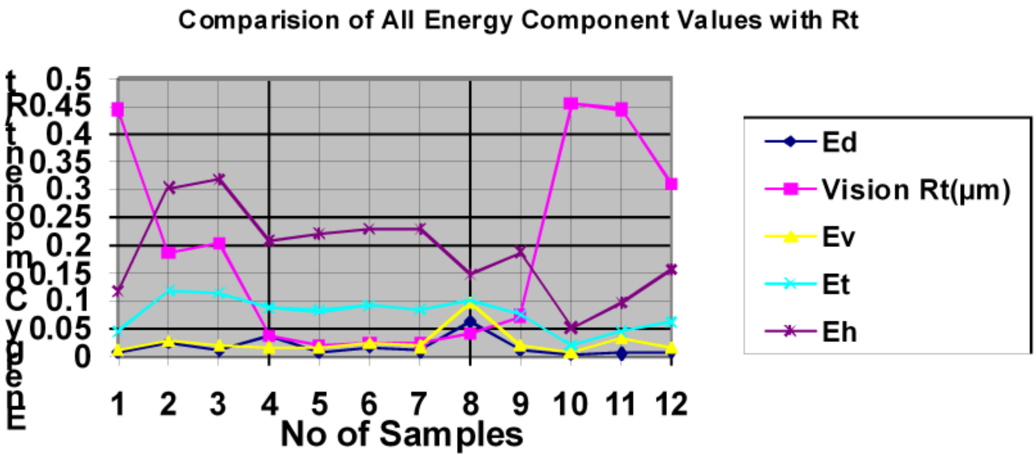


Figure 5.23 Variation of energy values with R_t for milling process

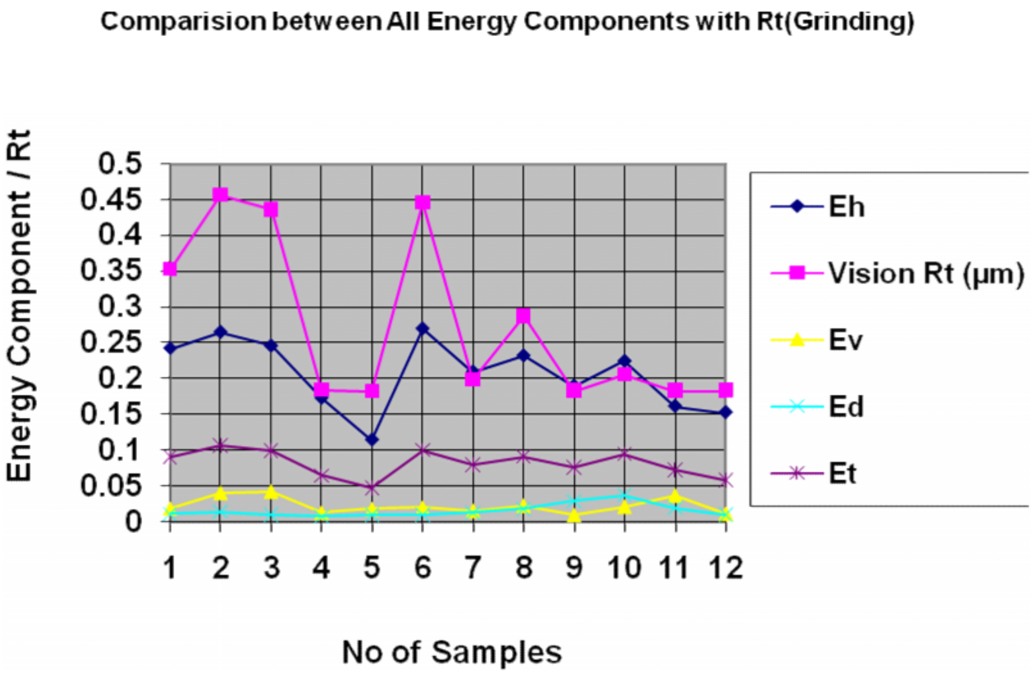


Figure 5.24 Variation of energy values with R_t for grinding process

5.7 CHAPTER CONCLUSION

The use of wavelet based feature extraction scheme is presented. A Four level decomposition is employed and it is established that there is a significant correlation present between the surface roughness R_t and the extracted energy components.