Classification of breast cancer grades using physical parameters and K-nearest neighbor method

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Abstract

Breast cancer is a health problem in the world. To overcome this problem requires early detection of breast cancer. The purpose of this study is to classify early breast cancer grades. Combination of physical parameters with k-nearest neighbor Method is proposed to detect early breast cancer grades. The experiments were performed on 87 mammograms consisting of 12 mammograms of grade 1.41 mammograms of grade 2 and 34 mammogram of grade 3. The proposed method was effective to classify the grades of breast cancer by an accuracy of 64.36%, 50% sensitivity and 73.5% specitifity. Physical parameters can be used to classify grades of breast cancer. The results of this study can be used to complement the diagnosis of breast mammography examination.

***Keywords**: breast cancer, grade, K-nearest neighbor*

1. Introduction

Breast cancer is a health problem in the world. To overcome this problem requires early detection of breast cancer. Discovered microcalsification is a sign of breast cancer. Many methods have successfully detected the presence of microcalsification [1-6]. However, the discovery of microcalsification is not enough to classify the breast cancer grades. Nezha H [7] classified breast cancer using the Quantum Clustering and Wavelet method. Shofwatul U [8] classified malignant and benign lesions using Feature Selection method. Seyyid A M [9] classified breast cancer using the K-Nearest Neighbor method with different distances. Mandeep R [10] classified malignant and benign breast cancer lesions using the Machine Learning Techniques method. Anggrek C N [11] classified normal and abnormal breast cancer using the K-Nearest Neighbor method. All the researchers mentioned above, none of them classifies breast cancer grade

To classify the grades of breast cancer typically used the methods of Tumor Node Metastase [12] and Scarff Bloom Richardson [13] are used. In this study, we proposed a new method for classifying breast cancer grades using a combination of physical parameters using the K-nearest neighbor method. The updated feature of our study is to use the physical parameters contained in the mammogram as input to the K-nearest neighbor method.

This research needs to be done to improve the prognosis of breast Cancer patient. The uniqueness of the research is by converting from a mammogram image to a numeric to determine the grades of breast cancer without a fine needle biopsy. The results of this study are used as a complement to mammography examination.

2. Materials and Methods

The steps to classify breast cancer grades are as follows: the breast is photographed using a digital mammography device, then it cuts suspicious mass and is stored using 256 heat bmp format. Then the image quality is improved to make it brighter. After that, the calculation of physical parameters using (1) to (13), then statistical tests using anova test to determine the significant physical parameters to distinguish breast cancer grades, a significant parameter and then used as an input variable from the K-Nearest Neighbor method using (14), the closest distance shows the results of grades classification of breast cancer as shown in Figure 1.

Received May 5, 2018; Revised December 1, 2018; Accepted January 27, 2019

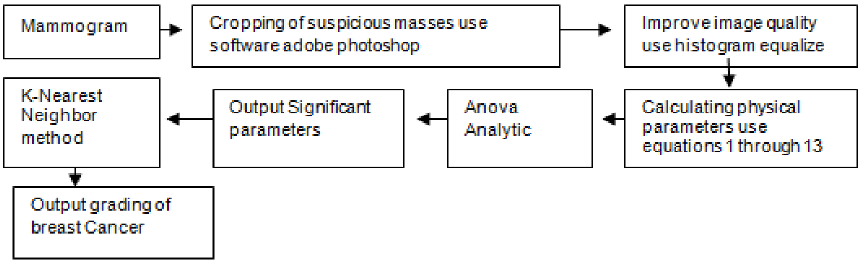


Figure 1. Research design

To classify breast cancer levels, 10 physical parameters are needed as follows:

$$\mathrm{Entropy\ (E)} = -\sum_{y_q=y_1}^{y_t}\sum_{y_r=y_1}^{y_t}[\mathrm{H}(y_q,y_r,d)]\log[\mathrm{H}(y_q,y_r,d)] \tag{1}$$

$$\mathrm{Contrast\ (C)} = \sum_{y_q=y_1}^{y_t}\sum_{y_r=y_1}^{y_t}(y_q-y_r)^2\,\mathrm{H}(y_t,y_r,d) \tag{2}$$

$$\textit{Angular Second Moment (MA)} = \sum_{y_q=y_1}^{y_t}\sum_{y_r=y_1}^{y_t}[\mathrm{H}(y_q,y_r,d)]^2 \tag{3}$$

$$\text{Inverse Difference Moment (MD)} = \sum_{yq=yi}^{yt}\sum_{yr=yi}^{yt}\left[\frac{H(yq,yr,d)}{1+(yq-yr)^2}\right] \tag{4}$$

for $y_r \neq y_q$

$$\mathrm{Correlation\ (Corr)} = \frac{\sum_{y_q=y_1}^{y_t}\sum_{y_r=y_1}^{y_t} y_q y_r \mathrm{H}(y_q,y_r,d) - \mu \mathrm{H}_m(y_q,d)\mu \mathrm{H}_m(y_r,d)}{\sigma \mathrm{H}_m(y_{qq},d)\sigma \mathrm{H}_m(y_r,d)} \tag{5}$$

with

$$\mathrm{H}_m(y_q,d) = \sum_{y_r=y_1}^{y_t}\mathrm{H}(y_q,y_r,d) \tag{6}$$

$$\mathrm{H}_m(y_r,d) = \sum_{y_q=y_1}^{y_t}\mathrm{H}(y_q,y_r,d) \tag{7}$$

$$\mathrm{Mean\ (MN)} = \sum_{y_q=y_1}^{y_t} y_q \mathrm{H}_m(y_q,d) \tag{8}$$

$$\mathrm{Deviation\ (D)} = \sqrt{\sum_{y_q=y_1}^{y_t}[y_q - \sum_{y_p=y_1}^{y_t} y_p \mathrm{H}_m(y_p,d)]^2 \mathrm{H}_m(y_q,d)} \tag{9}$$

$$\mathrm{H}_{diff}(i,d) = \sum_{y_q=|y_q-y_r|=i}^{y_t}\sum_{y_r=y_1}^{y_t}\mathrm{H}(y_q,y_r,d) \tag{10}$$

$$\mathrm{Entropy\ of\ H_{diff}\ (EH)} = -\sum_{i=i_1}^{i_t}\mathrm{H}_{diff}(i,d)\log \mathrm{H}_{diff}(i,d) \tag{11}$$

$$\mathrm{AngularMoment\ \ of\ H_{diff}\ (MAH)} = \sum_{i=i_1}^{i_t}[\mathrm{H}_{diff}(i,d)]^2 \tag{12}$$

$$\mathrm{Mean\ of\ H_{diff}\ (MHD)} = \sum_{i=i_1}^{i_t} i\,\mathrm{H}_{diff}(i,d) \tag{13}$$

with $H(y_q,y_r,d)$, d, y each is the probability of a pair of gray-level, the distance between the pixel and gray level value, respectively [14]. K-Nearest Neighbor is a method to classify using the distance of the nearest neighbor [15-20], expressed in (14). Many researchers use the KNN method to classify breast cancer as has it done by [21-25].

$$D = \sqrt{\sum_{i=1}^{i=n}\left(T_i - U_i\right)^2} \tag{14}$$

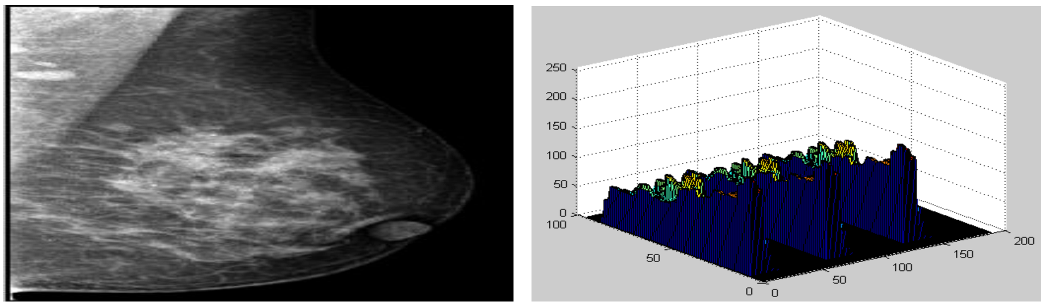
with D, T and U respectively are the closest neighbors distance, training data, data to be tested.

The study was conducted at the Sanglah central public hospital of Bali, Prima Medika Bali hospital, and Doctor Soetomo Hospital Surabaya. This research has been approved by the research ethics committee of medical faculty of Udayana University and Sanglah central public hospital Denpasar, with approval number: 1204/UN.14.2/KEP/2017. Mammography images taken from Kodak brand mammography type dry view 6800 laser imager with setting KV=30, MAS=25, brightness=7, latitude=11, contrast=-4, movie size=18x24 cm. Total trial data of 87 mammograms consisting of 12 mammograms of grade 1,41 mammogram grade 2 and 34 mammogram grade 3. Experimental design that we use is cross section. Annova was used to find significant physical parameters in differentiating grade 1, 2 and 3. Significant variables were incorporated into KNN method to classify grading of breast cancer. Physical parameters are parameters contained in the mammographic image converted into entropy, contrast, angular second moment, inverse differential moment, mean, deviation, entropy of difference second order histogram, angular second moment of difference second order histogram and mean of difference secondorder histogram expressed in (1) through (13).

3. Results and Discussion

3.1. Results

Suspicious mass is shown by arrows such as Figures 2 (a), 3 (a), 4 (a), then it cropped and stored by the 256 heat bmp format. Graph of the results of the reduction of the background image with the original image as shown in Figures 2 (b), 3 (b), and 4 (b), it turns out that there are significant differences in grades 1, 2, and 3. We took grade 1 images from the radiology installation room database and grade 1 status we got from the medical record of Doctor Soetomo Hospital Surabaya. In Figure 2 (a) there is a microcalsification.

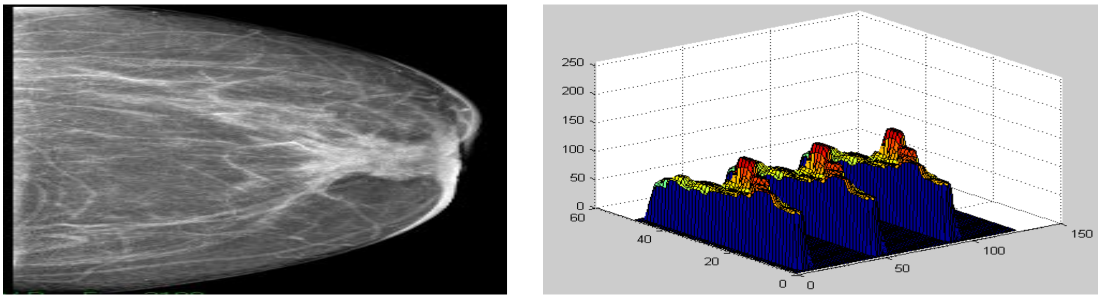


(a) (b)

Figure 2. (a) Grade 1 (b) Subtract the background image form the original image grade 1 [14]

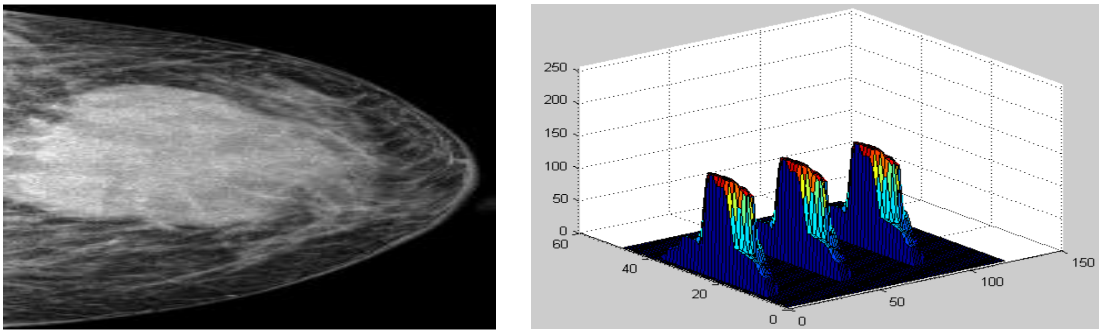
We took the grade 2 image from the radiology installation room database and the grade 2 status we got from the medical record of Doctor Soetomo Hospital Surabaya. In Figure 3 (a) there is shrinking of the skin around the nipples. We took the grade 3 image from the radiology installation room database and the grade 3 status we got from the medical record of Doctor Soetomo Hospital Surabaya. In Figure 4 (a) there is a very large density.

To classify grades of breast cancer using 10 physical parameters, not all physical parameters are significant for classifying grades of breast cancer. Annova statistical test is done to find a significant variable by looking at significant values smaller than 0.05. From the results of the study, only contrast variables that have significant values smaller than 0.5, as shown in Table 1 (see in Appendix). By: d is the distance between pixels; grade 1 (n=12) was taken 12 patients with level one malignancy; garde 2 (n=41) was taken 41 patients with level two malignancy; grade 3 (n=34) was taken 34 patients with level three malignancy.



(a) (b)

Figure 3. (a) Grade 2 (b) subtract the background image form the original image grade 2 [14]



(a) (b)

Figure 4. (a) Grade 3 and (b) subtract the background image form the original image grade 3 [14]

To determine the value of accuracy, sensitivity and specificity in this study required TP value means that if the actual grade 1 data turns out to be true grade 1, FNa means that if the actual grade 1 data turns out to be incorrect grade 1 but grade 2, FNb means the actual data Grade 1 turns out to be a non-grade 1 class, but grade 3, FP1 means that if the actual grade 2 data turns out to be incorrect grade 2, grade 1. TN1 means that if the actual grade 2 data is true the grade results actually state grade 2. FN1 means if the data actual grade 2 turns out that the result of the incorrect classification is not grade 2 but grade 3. FP2 means that if the actual grade 3 data turns out to be incorrect grade 3 but grade 1, FN2 means that the actual grade 3 data is not grade 3 but grade 2, TN2 means that the actual grade 3 data turns out to be true grade 3 classification. The formula for determining accuracy, sensitivity and specificity is as follows:

$$\text{Accuracy} = \frac{TP + TN1 + TN2}{TP + FP1 + FP2 + FNa + TN1 + FN2 + FNb + FN1 + TN2}$$

$$\text{Sensitivity} = \frac{TP}{TP + FNa + FNb}$$

$$\text{Specifity} = \frac{TN2}{TN2 + FP2 + FN2}$$

from the results of the study obtained the results of TP, FNa, FNb, FP1, TN1, FN1, FP2, TN2 as in Table 2.

Table 2. Results of K-Nearest Neighbor

		Actual Data		
		Grade 1 (12 mammogram)	Grade 2 (41 mammogram)	Grade 3 (34 mammogram)
Classification Results	Grade 1	TP = 6	FP1 = 4	FP2 = 2
	Grade 2	FNa = 3	TN1 = 25	FN2 = 7
	Grade 3	FNb = 3	FN1 = 12	TN2 = 25

The accuracy, sensitivity and specificity values are as follows:
accuracy = 64.36%,
sensitivity = 50%,
specifity = 73.5%.
Graph Relation of grade 1, 2 and 3 to the value of contrast as Figure 5.

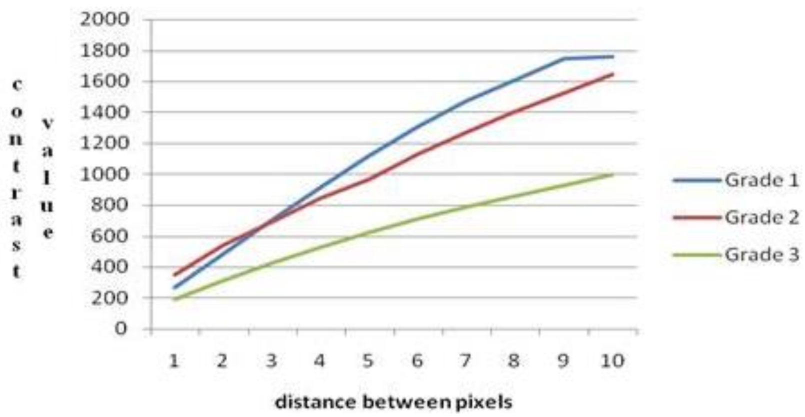


Figure 5. Contrast value of grade 1, 2, and 3

3.2. Discussion

In this paper we presented a new method for breast cancer grades classification based on a combination of physical parameters using the K-nearest neighbor method. The main motivation of this research is to develop the concept of early detection of breast cancer grades with emphasis on physical parameters with K-Nearest Neighbor. The method we propose gives good results. Evaluation was done by taking new data as many as 87 pictures from Doctor Soetomo Hospital Surabaya obtained accuracy, sensitivity and specificity are 64.36, 50 and 73.5% respectively. Our method is very stable and reliable. During our classification testing we have achieved good results regardless of the K factor value in the K-nearest neighbor algorithm. The test has successfully determined the ac`curacy, sensitivity and specificity of the method we propose. Tests have shown that the method we propose is sensitive to the type of breast cancer grades. Analysis Nine physical parameters show that not all physical parameters have a significant impact on classifying breast cancer grades. Because of this, significant parameters are needed to improve preprocessing and achieve better results. The combination of physical parameters and the K-nearest neighbor method has been shown to be a good choice for classifying breast cancer grades. The method we propose provides the ability to improve the classification of breast cancer grades.

4. Conclusion

The combination of physical parameters with K-nearest neighbor method is expected to detect early breast cancer grades. From the experimental results turned out contrast parameters as input method K-nearest neighbor able to classify the grades of breast cancer well. Future research prospects were developed using a combination of physical parameters with adaptive neuro fuzzy method, gynecological algorithm, fuzzy logic, c-mean clustering, neural network and support vector machine. The best results of these methods can be applied to digital mammography tools. So that digital mammography tool is able to detect early and predict the type of breast cancer before the biopsy.

Acknowledgment

Thanks to DPRM Ristekdikti who has funded this research, thanks also to Udayana University, Doctor Soetomo Hospital Surabaya, Sanglah central public hospital of Bali, and Prima Medika hospital that has provided facilities for this research.

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Appendix

Table 1. Average Physical Parameter Values of Grades 1, 2 and 3 with Varying Distances between Pixels from Doctor Soetomo Surabaya Hospital in 2018 [21]

	d	Grade 1 (n=12)		Grade 2 (n=41)		Grade 3 (n=34)		Significant
		Average	Standard deviation	Average	Standartd deviation	Average	Standard deviation	
Entropy	1	3.6685417	0.0881638	3.6319412	0.1573514	3.6208618	0.1525623	0.633
	2	3.7247925	0.0847231	3.672801	0.1604696	3.666451	0.1541859	0.496
	3	3.7517792	0.0857836	3.694687	0.159785	3.687972	0.156853	0.435
	4	3.7661092	0.0850587	3.706679	0.1579018	3.69521	0.1541363	0.361
	5	3.7728242	0.0836522	3.713076	0.1552709	3.699073	0.1532215	0.328
	6	3.7758875	0.0824338	3.716717	0.1533973	3.704095	0.1529091	0.34
	7	3.7757117	0.0782974	3.71747	0.1502065	3.701108	0.1508396	0.303
	8	3.7719675	0.0771117	3.717147	0.1475737	3.699568	0.1500894	0.317
	9	3.7692092	0.0742788	3.713742	0.1448325	3.696645	0.1483907	0.304
	10	3.7638058	0.0735703	3.711725	0.142265	3.692972	0.1468494	0.312
Contrast	1	265.48121	62.20458	350.38306	196.50348	189.0247	174.32289	0.001
	2	483.93363	174.75801	538.94056	293.14921	310.7809	293.39607	0.003
	3	701.66646	318.23153	695.89709	330.71914	423.77046	411.87455	0.004
	4	914.4501	474.53675	846.3778	382.35455	528.4305	527.18974	0.005
	5	1116.8115	625.24631	964.79304	464.09323	623.12277	632.24398	0.008
	6	1304.2279	763.96169	1133.7382	523.70389	707.48815	723.9107	0.005
	7	1469.4238	884.45686	1271.2085	606.08567	784.85087	807.73648	0.004
	8	1607.5084	981.88602	1403.0164	695.40234	857.93327	890.80103	0.005
	9	1746.3309	1077.6346	1528.2417	786.31147	928.13054	972.88746	0.005
	10	1757.9529	1133.6373	1647.1759	877.54774	995.00783	1051.5562	0.009
Anguler second moment	1	0.0002742	6.331E-05	0.00258	0.0121617	0.000996	0.0031795	0.615
	2	0.000235	5.368E-05	0.002369	0.0114941	0.000741	0.0023154	0.588
	3	0.00022	5.135E-05	0.002203	0.010853	0.00062	0.001843	0.579
	4	0.0002092	4.814E-05	0.00204	0.0101715	0.00054	0.0014655	0.577
	5	0.000205	4.523E-05	0.001894	0.0094979	0.000491	0.0012406	0.578
	6	0.0002025	4.615E-05	0.001754	0.008829	0.000457	0.001081	0.583
	7	0.0002008	4.441E-05	0.001623	0.0081787	0.000429	0.0009476	0.587
	8	0.0002033	4.418E-05	0.001497	0.0075266	0.000421	0.0009219	0.598
	9	0.0002042	4.231E-05	0.001379	0.0068739	0.000405	0.0008366	0.603
	10	0.0002042	4.078E-05	0.001276	0.0062613	0.000398	0.0007989	0.607
Invers differensial moment	1	0.0550017	0.0080398	0.050305	0.0112195	0.050863	0.0102625	0.388
	2	0.0435583	0.006599	0.041152	0.0088032	0.041908	0.0088899	0.691
	3	0.0366325	0.0056583	0.036585	0.0083152	0.03753	0.0086837	0.873
	4	0.03318	0.0052641	0.033432	0.0079717	0.034597	0.0091464	0.79
	5	0.030095	0.0052241	0.031184	0.0079358	0.032842	0.0091317	0.525
	6	0.0286042	0.0051924	0.029318	0.0077564	0.031019	0.0088928	0.548
	7	0.0265842	0.0056255	0.028046	0.0075968	0.029592	0.0088625	0.479
	8	0.02498	0.0051824	0.026452	0.0073192	0.028509	0.0088071	0.317
	9	0.0238067	0.0050711	0.025359	0.0068792	0.027285	0.0086237	0.313
	10	0.0234283	0.0048346	0.024368	0.0069794	0.026728	0.0085537	0.272
Mean of Hm(y,d)	1	131.62967	28.959467	145.02607	27.714486	148.54017	30.619119	0.226
	2	132.11067	29.12184	145.40824	27.738119	149.17381	30.691868	0.223
	3	132.5816	29.273948	145.74163	27.759487	149.69002	30.676374	0.222
	4	133.00409	29.415246	146.047	27.757742	150.13301	30.664421	0.222
	5	133.39093	29.545445	146.31024	27.740678	150.52887	30.66877	0.222
	6	133.75322	29.674278	146.35145	27.646034	150.86479	30.674152	0.223
	7	134.08084	29.820181	146.76085	27.663767	151.1448	30.66699	0.225
	8	134.34956	29.978102	146.95661	27.593481	151.37044	30.662581	0.226
	9	134.56753	30.137103	147.12655	27.523106	151.56755	30.652291	0.227
	10	134.73142	30.286683	147.26316	27.449828	151.7134	30.638789	0.227

Table 1. Average Physical Parameter Values of Grades 1, 2 and 3 with Varying Distances between Pixels from Doctor Soetomo Surabaya Hospital in 2018 [21] *(continue)*

d		Grade 1 (n=12)		Grade 2 (n=41)		Grade 3 (n=34)		Significant
		Average	Standard deviation	Average	Standartd deviation	Average	Standard deviation	
Deviation	1	34.260554	9.7619133	34.312329	11.739118	34.201961	10.784648	0.999
	2	34.063222	9.6913602	34.191907	11.747045	34.178546	10.497243	0.999
	3	33.87281	9.6183372	34.104492	11.766145	34.037906	10.491743	0.998
	4	33.718329	9.5646835	34.029315	11.792871	33.940052	10.525177	0.996
	5	33.59901	9.5004278	33.986836	11.803124	33.773723	10.663739	0.993
	6	33.49073	9.4028597	33.972137	11.809241	33.7171	10.70515	0.99
	7	33.376675	9.2914793	33.966377	11.819327	33.776023	10.655739	0.987
	8	33.241699	9.1846679	33.967365	11.831127	33.754651	10.701706	0.98
	9	33.132857	9.1244331	33.976051	11.835557	33.743379	10.759438	0.973
	10	33.067677	9.1209389	33.99897	11.844682	33.751424	10.812589	0.968
Entropy of of difference second order histogram	1	1.5207192	0.051969	1.544523	0.0937383	1.547077	0.0883259	0.651
	2	1.6403642	0.0628206	1.63932	0.0873686	1.643583	0.0996902	0.979
	3	1.7141417	0.0744286	1.698631	0.0893982	1.702241	0.1102782	0.887
	4	1.7665917	0.0828595	1.742473	0.0939141	1.742984	0.1194766	0.76
	5	1.8067333	0.0885038	1.776767	0.0980366	1.774627	0.1270087	0.66
	6	1.8386942	0.0924841	1.805169	0.1032635	1.800483	0.1318185	0.596
	7	1.8637192	0.0956349	1.828137	0.1076612	1.821602	0.1358604	0.563
	8	1.8797392	0.0996391	1.849734	0.1119991	1.839526	0.1396573	0.62
	9	1.9006017	0.1008531	1.867021	0.115691	1.852449	0.1419445	0.519
	10	1.9146375	0.1021066	1.881975	0.1189006	1.868959	0.1445945	0.569
Anguler second moment of difference second order histogram	1	0.03668	0.0051556	0.0341868	0.0085414	0.0353732	0.0076225	0.586
	2	0.0282383	0.0039959	0.0297332	0.0117903	0.0286021	0.0066021	0.821
	3	0.0239925	0.0037562	0.0261732	0.0110877	0.0251809	0.0065281	0.727
	4	0.021315	0.003611	0.0237566	0.010287	0.0230621	0.0065961	0.67
	5	0.0194033	0.0034894	0.0219956	0.0096175	0.0215512	0.0066765	0.61
	6	0.0180183	0.0034022	0.0206161	0.0090624	0.0203379	0.0065739	0.573
	7	0.0169567	0.003318	0.0194468	0.0083957	0.0193909	0.0065425	0.547
	8	0.0161233	0.0032688	0.0184744	0.0078957	0.0186097	0.0064878	0.532
	9	0.0154375	0.0032256	0.0176859	0.0074144	0.0179182	0.0063886	0.515
	10	0.0148642	0.0031297	0.016971	0.006786	0.01735	0.0063198	0.487
Mean of difference second order histogram	1	12.471971	1.437844	13.61416	3.055367	13.57642	2.740966	0.429
	2	16.497296	2.330525	16.91747	3.296786	17.10418	3.79908	0.868
	3	19.660166	3.426158	19.40229	3.708941	19.62252	4.608733	0.965
	4	22.319414	4.424387	21.49979	4.243049	21.63089	5.370358	0.869
	5	24.645164	5.302194	23.35188	4.84364	23.33268	6.035107	0.741
	6	26.637238	6.112734	25.03549	5.50095	24.83297	6.606327	0.66
	7	28.368256	6.793837	26.56531	6.134323	26.15693	7.135861	0.608
	8	29.839518	7.442675	28.00049	6.796493	27.37054	7.655554	0.598
	9	31.144367	8.017093	29.28278	7.442864	28.49279	8.115047	0.599
	10	32.271235	8.5010159	30.47403	8.063936	29.53199	8.580728	0.616