EAI Endorsed Transactions on Energy Web and Information Technologies Research Article **EAI.EU**

Model to estimate the salt and pepper noise density level on gray-scale digital image

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Abstract

In this research paper, we proposed a probabilistic analysis to find the relationship between entropy of image and salt & pepper noise density. For this estimation, we have employed entropy inspection of spatial domain technique. Based on the fact that entropy of image signal decreases with increase in noise density and this decreasing relationship between noise and entropy is robust to individual images traits. In this work, we exploited the entropy values of noisy image with respect to its noise density, and analyzed that such relation is robust to individual images. Further, we considered such relationships for estimation of noise level. Based on the numerical calculations and graphical representations it reveals to the fact that the error is reduced to 8.9% which can be considered as an appropriate model to estimate the salt and pepper noise density.

Received on 10 May 2018; accepted on 02 June 2018; published on 12 June 2018

Keywords: Entropy, Salt-Pepper noise, Noise density

doi:10.4108/eai.12-6-2018.154816

1. Introduction and Motivation

There has been a plethora of research work that has been carried out in image analysis and interpretation with the primary focus being on the amount of information that is available for such an analysis. The first step in any image processing is that we carry some preprocessing procedures on the input images for further processing. Before performing any preprocessing it is important to know whether the image is original or corrupted with noise. Estimating the noise density in image is very important and also little bit difficult because we do not, in most cases, do not know the source of noise (also type of noise). The estimation and filtering of noise(salt & pepper) is one of the important preprocessing steps in image process. There are many filtering algorithms, that we can use for filtering the noise, have been proposed in the past few years. The simplest one available is Median filter, one of the representative filtering algorithms. In the recent years, many variants of median filter have been proposed, such as progressive switch median filter, weighted median filter, switch median filter, large-scale correlative filter and adaptive fuzz transitive filter, etc. [6, 7, 9, 11–15]. There are few works uses hypergraph model of digital image to discriminate noisy pixels in the gray-scale image from the noise-free ones [1, 5, 8].

All the above mentioned algorithms have shown good performance in the experiments. However, the important measure while removing any type of noise is that noise processes of these algorithms need be varied according to the levels of the noise during the process of filtering. The efficiency filtering results obtained by these algorithms are seriously affected because the noise density levels cannot be estimated accurately. The estimation of noise level is one of the most important preprocessing work in the image processing application. The effectiveness and efficiency of any filtering algorithm will be improved if the parameters of the noise are accurately obtained. In salt & pepper noise the only parameter we need is the noise density in the image. Most of the present researches mainly focuses on the Gaussian noise estimation techniques.

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On the other hand very less research has been done on salt & pepper noise estimation algorithms. Most of the works of estimation of salt & pepper noise are carried by Zhang Qi and Cao Zhanhui [2, 6]. Zhang Qi [16], in his paper explains the estimation of the noise density according to the variance of coefficients of high-frequency sub-band of wavelet. Cao Zhanhui proposes the algorithm which utilizes the variable relationships of noise density and image amplitude spectrum to estimate the density. The above mentioned two algorithms can effectively estimate the noise density, but they face some problems under some conditions. The algorithm described in [16] can show better results under the low noise level. But with increase in noise density its performance will reduce, thus not effective when noise level is high. However, the experimental shown by the algorithm proposed in [2] are somehow ambiguous. The reason being that parameters that has been selected by the two algorithms do not robustly reflect the noise.

Zou Cheng [3] has considered the high frequency diagonal sub-bands of wavelet to estimate the density of salt and pepper noise and ignored the high-low and low-high frequency blocks. The high-low block contains horizontal edges and in contrast the low-high blocks shows vertical fine details of the image.âĂŃ

In this research paper, we propose a novel and unique algorithm to estimate the noise density by using entropy estimation. The proposed analysis fully utilizes the fact that with increase in noise the information level decreases. Based on the calculation it reveals to the fact that the entropy value of the image varies according to the noise density. The entropy value is used to estimate the noise density. The paper is organized as follows; the relationship between noise level and entropy has been discussed in section 2, our proposed method is in section 3, analysis of proposed method using statistical techniques: has been discussed in 4 section, and the conclusions follow in section 5.

2. The relationship of entropy value and noise density

Entropy [4, 10] is a general concept (Information Theory) and it is used to estimate the informational level. The entropy can be defined in various ways depending upon the underlying conditions. Some types of entropy that are usually used, such as Shannon entropy, standard entropy of p order, logarithmic energy entropy, SURE entropy etc. According to the definition of logarithmic energy entropy, if L represents the total number of gray levels then Entropy is defined as:

$$E = -\sum_{i=0}^{L-1} p_i \log_2 p_i$$

and p is the probability distribution of each level [12].

$$p = p_0, p_1, p_2, \cdots\cdots p_{L-1}$$

The entropy value depends upon the randomness of the given variable. When the noise level increases, first it increases the randomness of the variable thus increasing the entropy. But this increase is for very less amount of noise percentage. The behavior of the entropy with change in noise levels has been studied, and observed that when the noise level increases the entropy of the image keeps on decreases.

3. Proposed Methodology

In figure 1, the over all process flow diagram of the proposed approach is shown. We have chosen set of arbitrary gray-scale images from the standard image corpus and computed their entropy values. The images are then corrupted with salt and pepper noise with varying noise densities from 10% to 70%. Each time on adding the noise, the corresponding entropy value is calculated and recorded. The variation of entropy with varying noise density for the given set of test images is shown in table 1, 2.

The values in table 1 and 2 clearly indicates that the entropy value decrease with increase in noise but there is no constant pattern for this change, only we know that entropy decrease when noise increase. In order to find the relationship between entropy and noise density, we calculated the first order difference of the entropy values of all the test images with varying noise density. We tested with 55 test images, table 3 shows sample of the first order difference of entropy with respect to noise density.

The behavior of the first order entropy values and noise density is shown in figure 2. The curves clearly indicates that entropy decrease with increase in noise. Using the behavior of first order entropy values we try to find the approximate curve that will exhibit the behavior of all the curves. There are so many techniques for doing this like averaging, mean, median, most likelihood and many more.

From the statistical data obtained from the experiments, we use quadratic polynomial fitting according to the minimum mean square error criteria to the fitting all the first order entropy variation. Figure 3 shows the graphical representations of the generalization of the relation. Equation 1 represents the intrinsic relationships between the noise density and the entropy value of the noise images. Here, the x denotes the second order entropy value of the noise images, f represents the noise density.

$$F(x) = p_1 x^4 + p_2 x^3 + p_3 x^2 + p_4 x + p5 \tag{1}$$

where $p_1 = -246.3$
$p_2 = -126.1$

Table 1. Change in entropy with respect to noise density

Image	Image Entropy for various noise density						
	10%	20%	30%	40%	50%	60%	70%
Img1	6.911	6.572	6.111	5.606	4.99	4.389	3.694
Img2	6.350	6.060	5.690	5.224	4.703	4.129	3.524
Img3	5.576	5.358	5.063	4.693	4.282	3.764	3.241
Img4	7.104	6.731	6.270	5.715	5.128	4.471	3.757
Img5	6.413	6.121	5.736	5.277	4.738	4.171	3.514
Img6	7.129	6.752	6.262	5.733	5.116	4.483	3.786
Img7	5.723	5.496	5.201	4.798	4.365	3.873	3.303
Img8	6.189	5.924	5.548	5.105	4.630	4.053	3.460
Img9	7.099	6.725	6.255	5.729	5.120	4.469	3.758
Img10	6.483	6.172	5.776	5.294	4.781	4.194	3.547
Img11	7.190	6.802	6.330	5.778	5.188	4.513	3.798
Img12	7.268	6.877	6.402	5.841	5.223	4.543	3.811
Img13	6.600	6.285	5.871	5.390	4.849	4.249	3.594
Img14	7.307	6.910	6.423	5.851	5.241	4.557	3.824
Img15	7.403	6.994	6.497	5.915	5.302	4.613	3.868
Img16	6.603	6.278	5.876	5.386	4.852	4.248	3.598
Img17	7.150	6.777	6.297	5.754	5.162	4.498	3.766
Img18	6.358	6.062	5.687	5.222	4.718	4.155	3.485
Img19	6.606	6.294	5.877	5.400	4.841	4.24	3.626
Img20	7.163	6.771	6.304	5.764	5.158	4.512	3.773
Img21	7.013	6.649	6.184	5.661	5.065	4.419	3.727
Img22	6.852	6.512	6.069	5.556	4.989	4.358	3.667
Img23	5.673	5.451	5.137	4.764	4.324	3.829	3.278
Img24	7.271	6.855	6.362	5.801	5.189	4.511	3.781
Img25	6.715	6.388	5.963	5.473	4.908	4.308	3.623
Img26	7.068	6.701	6.238	5.688	5.096	4.463	3.768
Img27	7.076	6.685	6.245	5.699	5.123	4.453	3.739
Img28	6.993	6.630	6.173	5.655	5.061	4.432	3.718

$p_3 = -10.2$
$p_4 = -1.012$
$p_5 = -0.00826$

The above equation indicates the relation between the first order difference entropy value and the noise density in quantitative form. This relation is extended to analyze some of the data points for calculating residuals.

4. Mathematical model formulation

The ergodic physical nature of the images can be analyzed using statistical techniques. In order to capture the degree of probability concentration and amount of randomness Hidden Markov Model transition parameters can be used. In Markov chain, there exists a positive probability measure at stage n that is independent of the probability distribution at initial stage 0. Let P be the definite random variable

Table 2. Change in entropy with respect to noise density....Continuation

Image	Image Entropy for various noise density						
	10%	20%	30%	40%	50%	60%	70%
Img29	6.997	6.636	6.169	5.66	5.056	4.400	3.715
Img30	7.092	6.710	6.253	5.724	5.117	4.466	3.773
Img31	6.918	6.568	6.100	5.597	5.005	4.399	3.696
Img32	5.992	5.742	5.397	4.984	4.504	3.985	3.392
Img33	4.171	4.125	3.989	3.771	3.506	3.170	2.777
Img34	5.515	5.320	5.016	4.665	4.250	3.769	3.233
Img35	6.045	5.785	5.432	5.013	4.535	3.995	3.403
Img36	6.474	6.173	5.773	5.302	4.789	4.197	3.552
Img37	6.594	6.273	5.867	5.388	4.842	4.239	3.591
Img38	5.962	5.712	5.368	4.959	4.498	3.963	3.380
Img39	5.116	4.963	4.718	4.404	4.024	3.590	3.082
Img40	6.142	5.874	5.512	5.084	4.593	4.045	3.434
Img41	5.886	5.649	5.316	4.917	4.454	3.942	3.357
Img42	5.646	5.434	5.127	4.754	4.32	3.828	3.274
Img43	7.043	6.683	6.215	5.692	5.094	4.464	3.739
Img44	6.908	6.556	6.109	5.599	5.024	4.388	3.69
Img45	7.324	6.93	6.434	5.877	5.251	4.566	3.842
Img46	3.822	3.66	3.453	3.212	2.933	2.636	2.308
Img47	7.081	6.701	6.245	5.712	5.130	4.467	3.732
Img48	4.605	4.352	4.060	3.736	3.371	2.984	2.561
Img49	7.127	6.755	6.279	5.739	5.146	4.483	3.775
Img50	4.276	4.064	3.802	3.515	3.189	2.837	2.448
Img51	7.080	6.717	6.247	5.718	5.108	4.458	3.750
Img52	6.912	6.563	6.106	5.603	5.036	4.394	3.734
Img53	4.689	4.428	4.120	3.785	3.416	3.019	2.592
Img54	6.795	6.449	6.019	5.511	4.944	4.327	3.651
Img55	7.116	6.741	6.27	5.735	5.134	4.482	3.756

Table 3. First order deviation of entropy with respect to noise density

	(10 - 20)%	(20-30)%	(30-40)%	(40-50)%	(50-60)%	(60-70)%
Img1	-0.3392	-0.4609	-0.5058	-0.6154	-0.6015	-0.6940
img9	-0.3732	-0.4706	-0.5262	-0.6089	-0.6510	-0.7102

with probability Mass function and Pp_i is the entropy given by

$$H(P) - \sum_{i=0}^{L-1} (Pp_i) * \log(Pp_i)$$

The ergodicity can be checked and the unknown changes in the transition parameters can be detected with the help of entropy rate. The maximum entropy principle depends on the states and observations. So the likelihood values are penalized using BayeâĂŹs approach and by using Kolmorov smirno test and Aspin

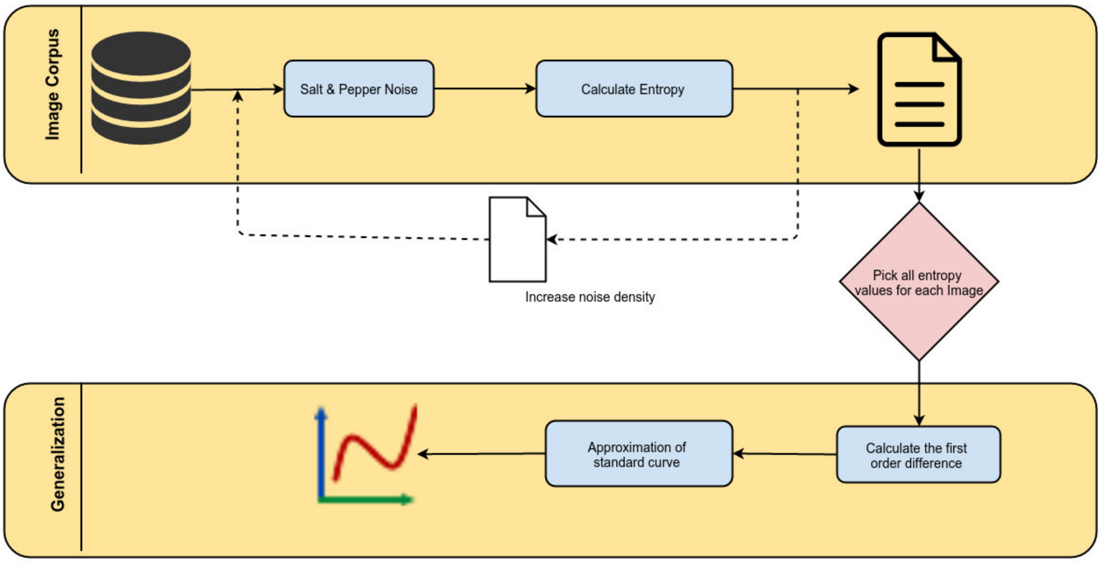

Figure 1. System Flow Diagram

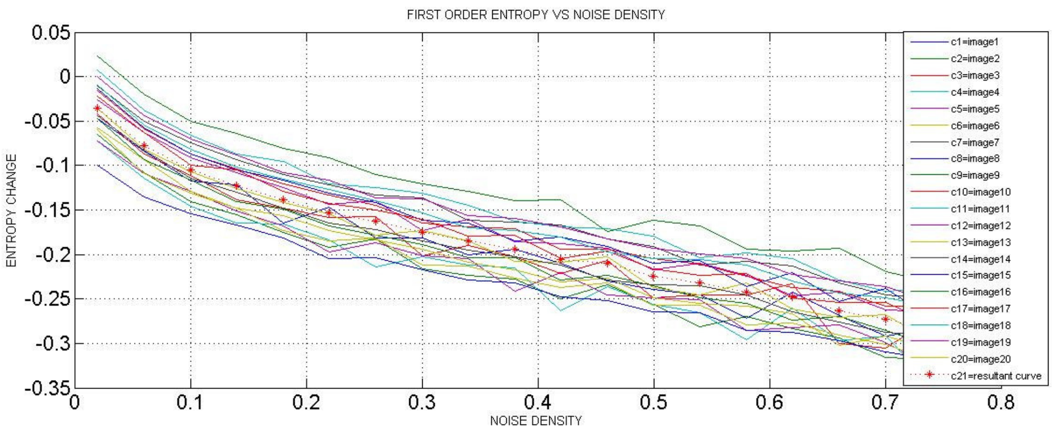

Figure 2. First order Entropy vs Noise Density

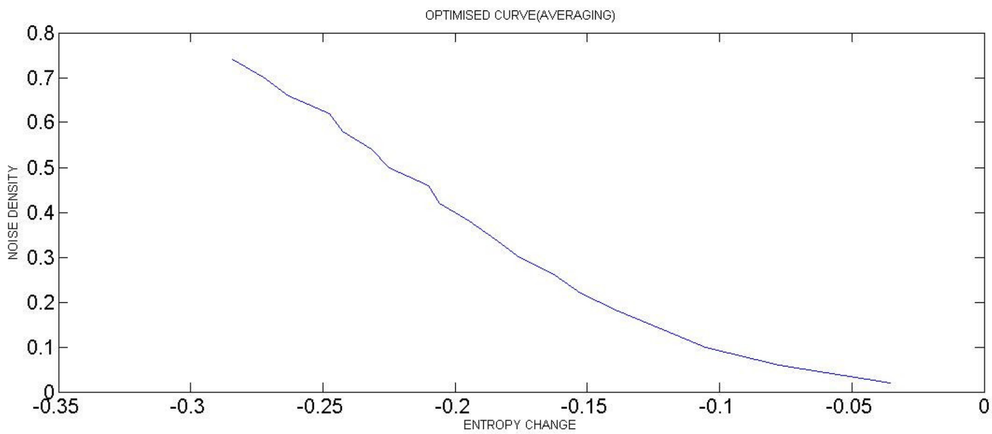

Figure 3. Generalization of data points

Welch test the uncertainties can be eliminated. By using statistical techniques for different images and based on the various types the values obtained are as shown in table 4. Here TYPE_A denotes the first order entropy difference between noise 10 and 20% densities of test images, TYPE_B denotes the first order entropy difference between noise 20 and 30% densities, TYPE_C denotes the first order entropy difference between noise 30 and 40% densities, TYPE_D denotes the first order entropy difference between noise 40 and 50% densities, TYPE_E denotes the first order entropy difference between noise 50 and 60% densities, TYPE_F denotes the first order entropy difference between noise 60 and 70% densities.

Using the behavior of first order entropy, the correlation coefficient has been obtained and its value is 0.9767652, the error estimated is 8.9% and this first order entropy changes has been depicted in figure 4.

5. Conclusions

In this paper, the relationship between the entropy values of images and the noise for the salt & pepper noise is being analyzed. It reveals to the fact that the entropy value diminishes more and more while the density of salt and pepper noise in the noisy image becomes larger and larger, and such relation is robust to individual image traits. By using using Lagrange interpolating polynomial to describe the variation of second order entropy with noise density curve fitting is obtained. Using the behavior of first order entropy, the correlation coefficient has been obtained and its value is 0.9767652, and the error estimated is 8.9%. Hence based on the numerical calculation and graphical relation, our proposed technique and analysis can be considered as an approach with minimum residual for salt & pepper noise density estimation.

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Table 4. Noise Density with respect to first order change in entropy

	TYPE_A	TYPE_B	TYPE_C	TYPE_D	TYPE_E	TYPE_F
Min.	0.04557	0.1362	0.2181	0.2655	0.2973	0.3286
1st Qu.	0.26033	0.3490	0.4165	0.4763	0.5373	0.5923
Median	0.33915	0.4297	0.5028	0.5662	0.6047	0.6766
Mean	0.31310	0.4027	0.4695	0.5275	0.5823	0.6385
3rd Qu.	0.37294	0.4677	0.5310	0.5968	0.6511	0.7121
Max.	0.41507	0.4973	0.5826	0.6255	0.6896	0.7448
Variance	0.00589	0.0068	0.0075	0.0085	0.0091	0.01009

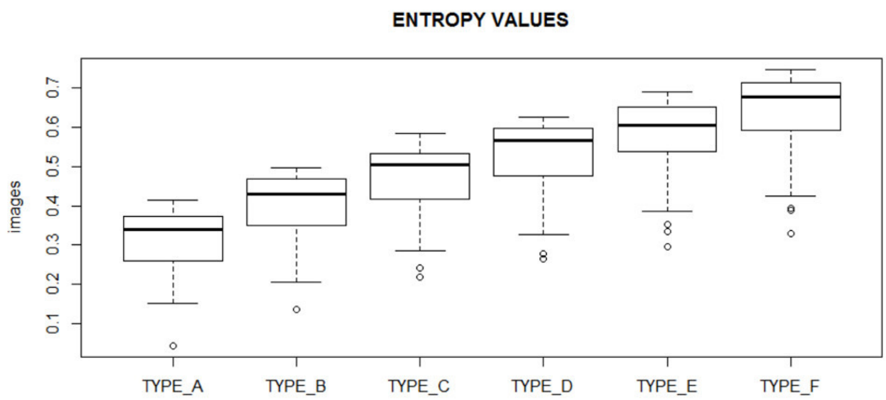

Figure 4. Change in entropy with increased noise density