Hybrid Vector Measures of Compressed Medical Images

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ABSTRACT

Lossy compression is very important for archiving and transmission of medical images in complex hospital information systems. To increase its effectiveness and applicability suitable distortion or processed image quality measures are necessary. Diagnostic accuracy should be preserved and its good measures are searched. Suitable distortion characteristic, in quality and quantity sense, could be available by applying vector measures (VM) like Hosaka plots, Eskicioglu charts etc. Generally, VMs have accepted complexity, significant correlation with subjective quality evaluation but they are unsuitable for image quality comparisons. The solution is scalar equivalent of VM as final quality score for comparisons and acceptance fixing. This equivalent should be built with a criterion of the highest correlation with diagnostic accuracy of analysed images. We incorporated diagnostic accuracy estimation (DAE) into process of hybrid vector measure (HVM) construction. Vector of image features consists of point accuracy errors, local structured errors and random errors. Weights of linear combination of six features considered as a scalar equivalent are computed using linear regression to fit to the mean opinion scores of professional observers from subjective tests. Colour bars are graphical form of vector component's presentation. Concluding, HVM is a good diagnostic accuracy measure: the correlation level between HVM and DAE is over 0.98.

Keywords: image quality evaluation, vector distortion measures, distortion characteristics.

1. INTRODUCTION

lossy compression techniques are used to increase archiving effectiveness but acceptable distortion level is still actual question to answer. Diagnostic accuracy should be preserved. How to measure the processed image quality is important question. Good measures and methods of diagnostic accuracy estimation are searched. Firstly, subjective diagnostic accuracy evaluation realised by doctors' body, followed by statistical analysis of test results (e.g. ROC-based analysis[1]) should be mentioned. But principle disadvantages are the following: time and organisation complexity, high cost and difficulty of practical applications. Subjective assessments do not provide constructive methods for performance improvement and the results obtained may vary depending on the test conditions. Much more simple and the most often used computable objective distortion measures, such as mean squared error (*MSE*) or signal-to-noise-ratio (*SNR*), let us to avoid the difficulties described above. But they do not correlate properly with psychovisual quality evaluation and degradation level of diagnostic information in some cases. The reason is simple, for example *MSE* are good distortion indicators for random errors, but not for structured, correlated or other compression-technique-dependent errors. Better distortion characteristic, in quality and quantity sense, is available by applying vector measures like Hosaka plots.[2] This method allows us to measure a number of reconstructed image features and compare it with the corresponding features in the original image. A difference between these two feature vectors is a vector error measure. Other vector measures, e.g. Eskicioglu charts[3] are univariate. It means that error vectors are extracted independently from original and reconstructed images. Generally, vector measures have accepted complexity, better correlation with subjective quality evaluation but they are unsuitable for comparisons because of their not identical in meaning graphical presentation. The solution is scalar equivalent of vector measure as final quality score for comparisons and acceptance fixing. This equivalent should be constructed with a criterion of the highest correlation with diagnostic accuracy of analysed images. Construction of objective scalar measure on the base of several distortion factors, which capture different distortion features is presented by Miyahara.[4] Picture Quality Scale (*PQS*) is a methodology for the determination of objective quality metrics to evaluate a quality of coded still images. This approach is based on the perceptual properties of human vision and extensive engineering

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experience with the observation of actual image disturbances resulting from the image coding. Two basic disadvantages of *PQS* are as follows: it is fitted to the distortions mainly caused by old JPEG DCT-based coder and there is not proposed any graphical form to widen the knowledge about error characteristics in image quality evaluation. Additionally, it is not provided for medical applications.

We propose a new method that incorporates diagnostic accuracy estimation into construction process of vector quality measure. The features of this measure are as follows:

- diagnostic accuracy estimation as element of vector measure optimisation; it is the subjective quality estimation by psychophysical questionnaires with numerical ratings and description in diagnostic preserving terms;
- graphical presentation of six-dimensional vector measure of image quality and diagnostic accuracy; reconstruction accuracy, general quality and noisy areas are depicted; the good disturbances characteristics can help in more particular image quality study;
- scalar measure as linear combination of extracted image features; this measure is dedicated to quantitative distortion evaluation and acceptable compression level estimation.

Vector of image features consists of random errors (chi-square measure and frequency weighting normalised *MSE*), structured errors (edge distortions and local error correlations), and point accuracy errors (mean and maximum image point difference). Coefficients of linear combination of six features are computed using linear regression to fit to the mean opinion scores of quality- and diagnostic accuracy-oriented observers from subjective tests. Colour bars are graphical form of vector component's presentation.

2. MEASURES OF IMAGE QUALITY

We considered the following quality measures as a base for construction of new vector measure. Firstly, we tested chosen scalar computable measures of global and local distortions, well known from different applications of image quality evaluation.[3,5] Next, we took into account Hosaka plots as vector quality measure and checked the possibility to construct its scalar equivalent. Hosaka plots were often used as good compressed image quality measure.[6] Moreover, five factors of *PQS* were considered as a good measure of various distortions appearing in lossy compression. Finally, we described briefly gold standard (DAE) estimation used for selection of the best factor base and calculation of its the most suitable combination. Hybrid vector-scalar and diagnostic accuracy-quality measure for compressed images is built from this background.

2.1. Objective scalars

Given the original image $f(x,y)$ and a distorted, compressed-reconstructed image $\hat{f}(x,y)$, we tested several computable objective scalar measures as follows:

- Average Difference:
$$AD = \frac{1}{MN}\sum_{x,y}\left|f(x,y)-\hat{f}(x,y)\right| \quad (1)$$
- Correlation Quality:
$$CQ = \frac{\sum_{x,y} f(x,y)\cdot \hat{f}(x,y)}{\sum_{x,y} f(x,y)} \quad (2)$$
- Maximum Difference:
$$MD = \max_{x,y}\{|f(x,y)-\hat{f}(x,y)|\} \quad (3)$$
- Image Fidelity:
$$IF = 1-\frac{\sum_{x,y}[f(x,y)-\hat{f}(x,y)]^2}{\sum_{x,y}[f(x,y)]^2} \quad (4)$$
- Mean Square Error:
$$MSE = \frac{1}{MN}\sum_{x,y}[f(x,y)-\hat{f}(x,y)]^2 \quad (5)$$

- Peak Signal to Noise Ratio: $$PSNR = 10\log_{10} \frac{MN \cdot [\max_{x,y}\{f(x,y)\}]^2}{\sum_{x,y}[f(x,y) - \hat{f}(x,y)]^2} \quad (6)$$

- Chi-Square Measure: $$\chi^2 = \frac{1}{MN}\sum_{x,y}\frac{\left[f(x,y) - \hat{f}(x,y)\right]^2}{f(x,y)} \quad (7)$$

2.2. Hosaka plots

Shortly, Hosaka plots are calculated by applying the following operations: quad-tree segmentation, estimation of mean and standard deviation in each class of blocks, and difference vectors computation and presentation. Example of Hosaka plot is presented in figure 1. The areas of noise level and reconstruction fidelity were calculated and used as proposition of scalar equivalent of such vector measure.

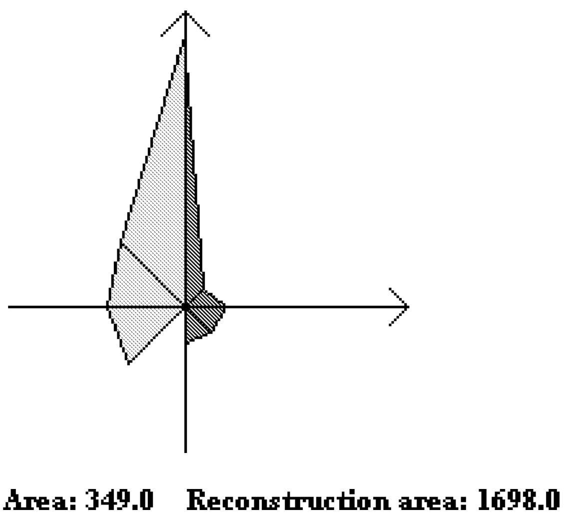

Figure.1. Example of weighted Hosaka plots. MR image, 0.4 bpp, SPIHT[7] compressed is evaluated. Lighter noise level- and darker reconstruction fidelity areas are depicted.

2.3. Picture Quality Scale

The *PQS* constructs computable scalar value of image quality on the base of five different distortion factors: two factors of random disturbances and three factors of structured and localised errors. Firstly, the image signal is transformed into one which is proportional to the visual perception of luminance (most medical images are greyscale) using the Weber-Fechner's Law and the contrast sensitivity. Secondly, they apply spatial frequency weighting to the errors. Next, objective quality factors, which quantify a majority of image degradation, are computed. Finally, space of distortion factors is reduced by principal component analysis and linear combination of reduced space components approximates the results of subjective tests. *PQS* was used for coder comparisons and efficiency evaluation.[8,9] We tested a correlation between *PQS* factors and DAE. Also combination of five factors optimised by linear regression to increase this correlation was used.

2.4. Gold standard estimation

The results of subjective tests were established as a pattern of correct image quality estimate. Because of medical applications the diagnostic accuracy evaluation of images is made. Also we utilised additionally psychophysical quality estimation (PQE) to increase reliability of quality measure evaluation. We organised the following subjective test to infer gold standard for objective measure assessment:

- independent observations of each specialist in similar comfortable conditions,

- all compressed images by *i*-technique are grouped and displayed together,
- independent classification and evaluation of one group images,
- 7 - levels description scale in comparative terms,
- quality and diagnostic accuracy evaluation.

Rating scale with descriptions was established in the following way (related to original image, its diagnostic accuracy or quality):

7 - better than original
6 - unnoticeable (changes)
5 - slightly noticeable
4 - noticeable (small quality degradation)
3 - annoying quality degradation
2 - glaring, significant quality degradation
1 - unacceptable image quality degradation

3. VECTOR MEASURE OF MEDICAL IMAGE QUALITY

We propose a new quality measure for lossy compressed medical images to estimate acceptable compression ratio, compare images compressed by different coders, analyse the character of image disturbances, and to be applied in construction process of image coders. Vector quality measure contains six factors (elements) which can be divided into three groups:

- Point accuracy errors
- Local structured errors
- Random errors

3.1. Point accuracy errors

- V_1 (average pixel error)

According to equation (1):

$$V_1 = AD = \frac{1}{MN}\sum_{x,y}\left|f(x,y) - \hat{f}(x,y)\right| \tag{8}$$

This factor characterises mean point error and hence reconstruction accuracy. Because it is mean difference between values of original image $f(x,y)$ and reconstructed image $\hat{f}(x,y)$, V_1 as integral-manner measure does not capture individual picks of reconstruction quality but characterises generally this process and shows a level of pixel reconstruction accuracy.

- V_2 (maximum pixel error)

According to equation (3):

$$V_2 = 10 \cdot MD = 10 \cdot \max\{|f(x,y) - \hat{f}(x,y)|\} \tag{9}$$

Maximum difference in pixel is important for preserving small, diagnostically important structures, which can not be changed in archiving process. This differential-manner measure is good supplement of V_1 and both are constructed in original and reconstructed image data domain.

3.2. Local structured errors

Two factors of local structured errors were taken from *PQS* because of their high correlation with DAE. To provide a more uniform perceptual scale, the images are transformed using $g(x,y) = k \cdot f(x,y)^{1/2.2}$, which closely approximates Weber-Fechner's Law for contrast sensitivity. The frequency weighted error $e_w(x,y)$ is just contrast adjusted error $e_g(x,y) = g(x,y) - \hat{g}(x,y)$ filtered with $S_a(u,v) = s(\omega)O(\omega,\theta)$, where $s(\omega) = 1.5e^{-\sigma^2\omega^2/2} - e^{-2\sigma^2\omega^2}$, $\sigma = 2$, $\omega = \frac{2\pi f}{60}$, $f = \sqrt{u^2 + v^2}$ and $O(\omega,\theta) = \frac{1 + e^{\beta(\omega-\omega_0)}\cos^4 2\theta}{1 + e^{\beta(\omega-\omega_0)}}$, $\theta = \tan^{-1}(u/v)$, $\beta = 8$, $f_0 = 11.13$ cycle/degree.

These factors are defined in the following way.

- V_3 (correlated errors in 5×5 window)

$$V_3 = \frac{1}{MN} \sum_{x,y} v_3(x,y), \tag{10}$$

where

$$v_3(x,y) = \sum_{(k,l)\in W} | r(x,y,k,l) |^{0.25} \tag{11}$$

and

$$r(x,y,k,l) = \frac{1}{y-1}\left[\sum e_w(i,j)e_w(i+k,j+l) - \frac{1}{y}\sum e_w(i,j)\sum e_w(i+k,j+l)\right] \tag{12}$$

This factor characterises local spatial correlation and is defined as summation over the entire image of local error correlations. The sums are computed over the set of pixels where (*i*,*j*) and (*i*+*k*,*j*+*l*) both lie in the 5×5 window centred at (*x*,*y*) and *W* is the set of lags to include in the computation.

- V_4 (preserving high contrast edges)

$$V_4 = \frac{1}{N_K} \sum_{x,y} v_4(x,y), \tag{13}$$

where

$$v_4(x,y) = I_M(x,y) | e_w(x,y) | (S_h(x,y) + S_v(x,y)), \tag{14}$$

horizontal masking factor: $S_h(x,y) = e^{\{-0.04 A_h(x,y)\}}$, $A_h(x,y) = \frac{| f(x,y-1) - f(x,y+1) |}{2}$, and vertical masking factor $S_v(x,y)$ is defined similarly. $I_M(x,y)$ is an indicator function which selects pixels close to high intensity transitions. N_K is the number of pixels whose 3×3 Kirsch edge response is greater or equal to threshold value $K = 400$.

Factor V_4 considers psychophysical effect, which affects the perception of errors in the vicinity of high contrast transitions. It is visual masking, which refers to the reduced visibility of disturbances in activity areas.

3.3. Random errors

- V_5 (integral square with frequency weighting defined by CCIR)

$$V_5 = 1000 \cdot \frac{\sum_{x,y} v_5(x,y)}{\sum_{x,y} f^2(x,y)} \tag{15}$$

where $v_5(x,y) = [e_f(x,y) * w_{TV}(x,y)]^2$ and $e_f(x,y) = f(x,y) - \hat{f}(x,y)$. This factor is defined similarly to normalised mean square error with frequency weighting defined by CCIR 567-1, where $W_{TV}(f) = \frac{1}{1+(f/f_c)^2}$, $f = \sqrt{u^2+v^2}$, $f_c = 5.56$ cycles/degree. Factor V_5 is also used in *PQS*. Together with next factor, they characterise energy of a difference between original and reconstructed images. Random disturbances introduced by coder or random errors of original image reduced by coder can be well described by these factors.

- V_6 (integral square normalised by pixels value)

$$V_6 = 10 \cdot \chi^2 = \frac{10}{MN} \sum_{x,y} \frac{\left[f(x,y) - \hat{f}(x,y)\right]^2}{f(x,y)}. \tag{16}$$

This metric without frequency weighting gives additional information about random errors, respectively to equation 7.

3.4. Definition of Hybrid Vector Quality Measure.

The *HVM* is defined as linear combination of these six factors with the weights calculated to increase correlation with DAE and psychovisual quality evaluation. Linear regression and training medical image data sets were used to approximate image quality pattern. Hence, we verified the following formula of *HVM* definition:

$$HVM = \sum_{i=1}^{6} \alpha_i V_i \,, \tag{17}$$

where α_i are fitted to DAE or PQE by linear regression.

Graphical form of *HVM* is prepared to visualise separate group of distortions from three categories mentioned above. It is simply three rectangles growing down because of negative meaning of distortions defined by three couples of factors. *HVM* plot is presented in figure 2.

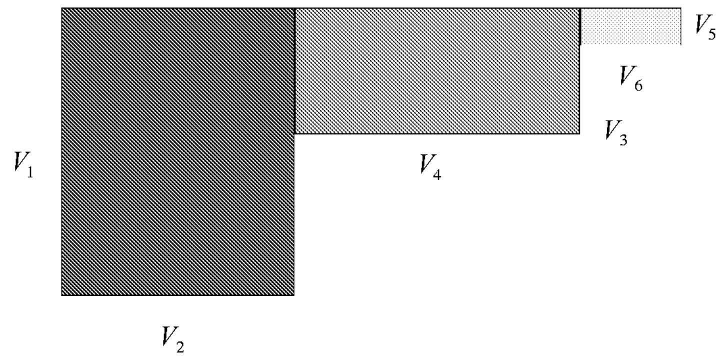

Figure 2. Graphical form of *HVM*. Six factors are included into three groups: red one informs about point errors, green field represents structured errors and yellow rectangle is a sign of random errors.

4. QUALITY EVALUATION TESTS

We used MR, CT and US images in quality evaluation tests. They are compressed by three lossy coders: wavelet-based SPIHT and MBWT,[10] and similar to JPEG DCT-based coder.[11] A difficulty of considered problem and a weakness of objective measures is visible in table 1. Popular *MSE* or *MD* measures did not correlate well with subjective rating and evaluated image quality after DCT compression as the worst. Oppositely, as you can see in table 2, higher quality of DCT-coded images was clear for all observers. The results of another test are presented in table 3. Potentially effective objective measures were used to estimate a quality of compressed images. We did such test to estimate correlation between these measures and DAE or PQE. The summary of DAE and PQE are presented in table 4. Next, important correlation coefficients between different objective measures and DAE and PQE are shown in table 5. The examples of experimental *HVM* plots are drawn in figure 3.

Table 1. An example of image quality evaluation test. US image is lossy compressed and image quality is computed in objective way (*MSE*, *MD*, *PQS*) and as an average of notes from subjective opinions (greater value means better quality).

Compression technique	Compression ratio	*MSE*	*MD*	Average note of 7 observers
SPIHT	22:1	64.12	45	3.14
MBWT	22:1	63.25	38	3.43
DCT	22:1	83.07	54	4.86

Table 2. Particular notes of observers for the results presented in table 1 (the same US image is coded, compression ratio is 22:1 for each case). Only image quality was evaluated (good psychovisual perception was a criterion, diagnostic accuracy was omitted) by students of electronics.

Observer	Evaluation notes			Image selection in quality order (1-2-3)
	SPIHT(A)	MBWT(B)	DCT(C)	
1	3	5	6	C B A
2	1	1	2	C B A
3	4	4	5	C A B
4	3	4	5	C B A
5	4	2	5	C A B
6	4	4	5	C B A
7	3	4	6	C B A
Average	*3.14*	*3.43*	*4.86*	-

Table 3. Image quality evaluation: comparison of different objective quality measures. Quality of compressed MR image was evaluated by applying: *PSNR*, *MD*, *MSE*, *AD*, *CQ*, *IF*, *HOS-R* - area of reconstruction fidelity in Hosaka plots, *HOS-N* - area of noise level in Hosaka plots, *PQS*. Three compression techniques (SPIHT, MBWT, DCT) were used. The values of successive measures are presented.

Measure\CR	10:1	15:1	20:1	25:1	30:1	35:1	40:1
χ^2 (SPIHT)	0.409	0.569	0.725	0.938	1.118	1.243	1.404
χ^2 (MBWT)	0.401	0.551	0.717	0.883	1.065	1.267	1.478
χ^2 (DCT)	0.450	0.646	0.858	1.812	1.877	2.653	1.844
PSNR (SPIHT)	42.41	39.56	37.67	36.33	35.25	34.37	33.73
PSNR (MBWT)	42.83	39.95	38.03	36.62	35.58	34.67	33.94
PSNR (DCT)	39.49	37.13	35.46	34.14	33.14	32.27	31.72
MD (SPIHT)	13	20	30	31	39	46	50
MD (MBWT)	10	16	24	29	32	49	47
MD (DCT)	21	38	36	42	49	56	53
HOS-R (SPIHT)	472	744	349	488	475	339	740
HOS-R (MBWT)	406	3	171	199	147	910	3521
HOS-R (DCT)	1103	553	9310	38999	65362	126490	26720
HOS-N (SPIHT)	179	718	1698	3003	4295	5568	7982
HOS-N (MBWT)	199	312	912	2136	1917	5405	6061
HOS-N (DCT)	253	64	437	13631	2058	9233	7232
PQS (SPIHT)	2.25	1.26	0.45	-0.34	-0.80	-1.22	-1.66
PQS (MBWT)	2.34	1.39	0.52	-0.20	-0.80	-1.18	-1.65
PQS (DCT)	1.61	0.59	-0.19	-0.92	-0.84	-1.11	-2.10
MSE (SPIHT)	3.73	7.19	11.11	15.13	19.4	23.78	27.57
MSE (MBWT)	3.39	6.65	10.25	14.18	17.98	22.28	26.29
MSE (DCT)	7.33	12.61	18.64	25.10	31.52	38.52	43.97
AD (SPIHT)	1.386	1.862	2.227	2.609	2.858	3.095	3.313
AD (MBWT)	1.347	1.813	2.181	2.518	2.798	3.069	3.31
AD (DCT)	1.788	2.265	2.703	3.368	3.694	4.176	4.26
CQ (SPIHT)	78.84	78.71	78.58	78.45	78.31	78.18	78.05
CQ (MBWT)	78.86	78.75	78.62	78.56	78.49	78.32	78.17
CQ (DCT)	78.91	78.81	78.71	78.52	78.66	78.48	78.28
IF (SPIHT)	0.999	0.997	0.996	0.995	0.993	0.991	0.990
IF (MBWT)	0.999	0.998	0.996	0.995	0.993	0.992	0.990
IF (DCT)	0.997	0.995	0.993	0.991	0.989	0.986	0.984

Table 4. The results of subjective quality evaluation tests. The table contains average values of scores in terms of rating scale. Seventeen persons took part in this evaluation: 2 doctors, 8 medical engineers and 7 students of electronics, experienced in image processing and analysis.

Observers	Compression method	Compression Ratio						
		10:1	15:1	20:1	25:1	30:1	35:1	40:1
Doctors (D)	SPIHT	5.5	4.5	3.5	3	2.5	1.5	1.5
	MBWT	5.5	4.5	4.5	3	2.5	1.5	1.5
	DCT	5.5	3.5	2.5	1	1	1	1
Medical engineers (E)	SPIHT	5.875	5.375	4.625	4.375	3.25	2.75	2.5
	MBWT	5.75	5.5	4.75	4.25	3.75	3.375	2.875
	DCT	6.12	5.5	3.08	2.0	1.42	1.08	1.08
Students (S)	SPIHT	6	5.15	4.286	3.57	2.857	2	1.57
	MBWT	5.86	4.714	4.43	3.714	3	2.43	1.714
	DCT	5.86	5	4.57	3.43	2.43	1	1

Table 5. The correlation between gold standard, taken from subjective quality evaluation tests, and objective computable factors. The correlation coefficient values are presented. The opinions of medical doctors are treated as DAE.

Factors	*DAE(D)*	*PQE(E)*	*PQE(S)*
F_1^{PQS}	0.8985	0.9421	0.9536
F_2^{PQS}	0.8394	0.9201	0.8913
F_3^{PQS}	0.7225	0.8552	0.7158
F_4^{PQS}	0.9673	0.9340	0.9566
F_5^{PQS}	0.9611	0.9560	0.9544
PQS	0.9507	0.8831	0.9441
χ^2	0.8808	0.9388	0.8682
PSNR	0.9628	0.9264	0.9174
MD	0.9485	0.8963	0.9072
HOS-R	0.4949	0.6436	0.4700
HOS-N	0.7686	0.7643	0.7260
HOS-R+HOS-N	0.5521	0.6915	0.5239
MSE	0.9133	0.9600	0.9197
AD	0.9514	0.9683	0.9347
CQ	0.7540	0.6689	0.8672
IF	0.9107	0.9517	0.9186
PQS (optimised)	0.9695	0.9662	0.9660
PQS+AD+PSNR	0.9749	0.9672	**0.9923**
HVM	**0.9810**	**0.9751**	0.9840

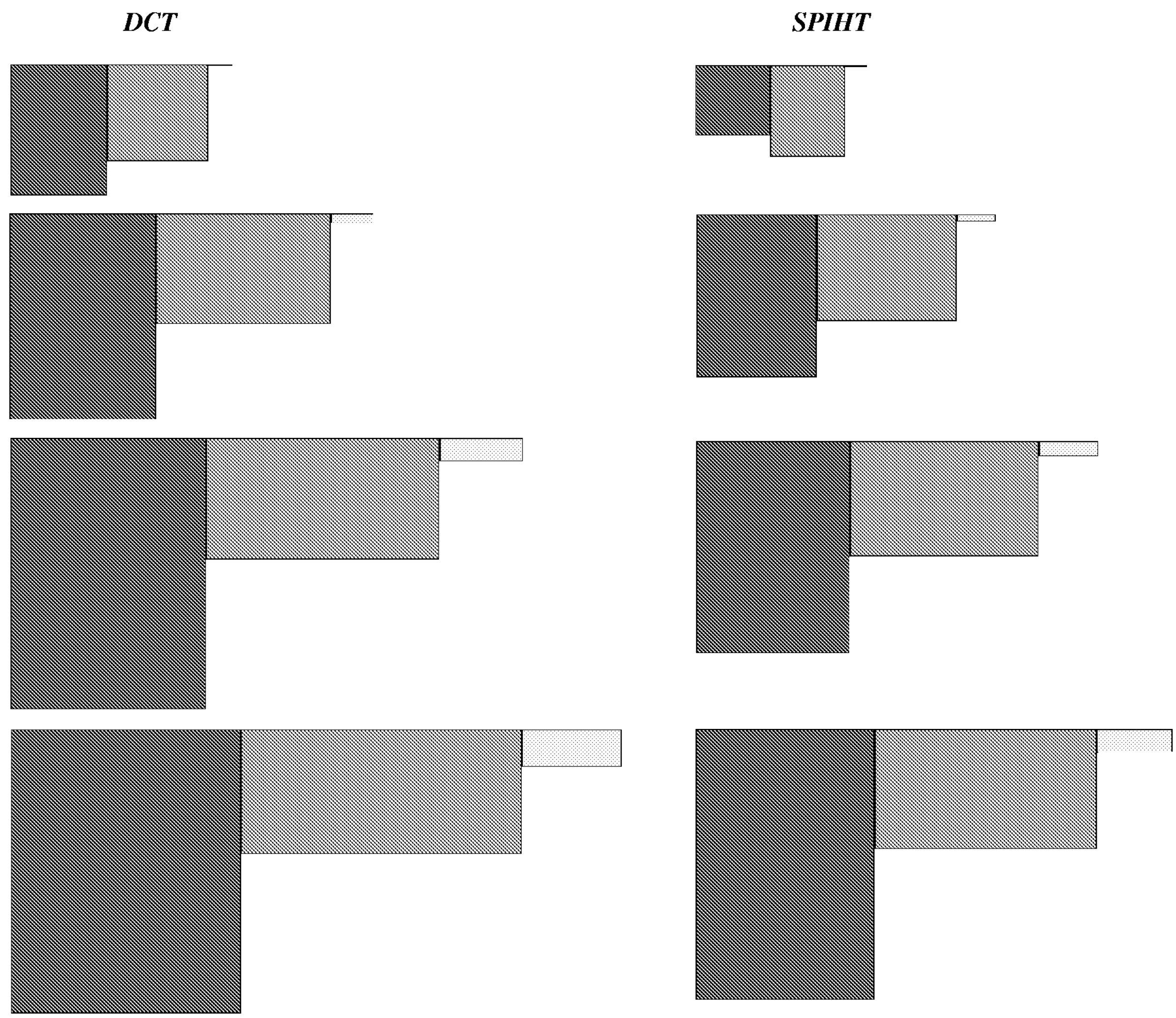

Figure 3. The *HVM* plots for compressed MR image. Two coders: DCT-based (left) and SPIHT (right) were used. The plots are drawn for four compression ratios: 10:1, 20:1, 30:1, 40:1 (top to bottom, respectively).

5. CONCLUSIONS

It is clearly shown that the level of correlation between several objective quality measures and subjectively established gold standard is various. This indicates that elaboration of computable objective distortion measure, as good approximation of psychophysical diagnostic accuracy is very difficult. Nevertheless, it is very important for archiving and transmission of medical images in databases and complex hospital information systems. *HVM* gives wide information about error characteristics and correlates with the results of subjective tests. Additionally, it is not complex, easy for applications and useful in comparison tests. Presented vector measure is better approximation of diagnostic accuracy and quality of medical images then *PQS* and its graphical form gives more important information about errors and disturbances in compressed medical images than Hosaka plots.

Proposed quality measure is a good diagnostic accuracy approximation, which could be potentially accepted by doctors and applied in practice. The correlation level between *HVM* and DAE is over 0.98. *HVM* can be also used as processed image quality evaluation (correlation coefficient with psychovisual image quality estimation is over 0.97).

The *HVM* is hybrid in a sense of regarding of both: image diagnostic accuracy and quality. Additionally, it is simultaneously vector and scalar measure of image quality. More tests for different medical image modalities and coders with more reliable gold standard estimation will be arranged to confirm its usefulness.

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