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Picture-wise just noticeable difference prediction model for JPEG image quality assessment

Применение пороговой модели прогнозирования заметных различий при оценке качества сжатых изображений в формате JPEG

Примена модела предикције прага уочљивих разлика у процени квалитета слика са JPEG компресијом

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ABSTRACT:

Introduction/purpose: The paper presents interesting research related to the performance analysis of the picture-wise just noticeable difference (JND) prediction model and its application in the quality assessment of images with JPEG compression.

Methods: The performance analysis of the JND model was conducted in an indirect way by using the publicly available results of subject-rated image datasets with the separation of images into two classes (above and below the threshold of visible differences). In the performance analysis of the JND prediction model and image quality assessment, five image datasets were used, four of which come from the visible wavelength range, and one dataset is intended for remote sensing and surveillance with images from the infrared part of the electromagnetic spectrum.

Results: The paper shows that using a picture-wise JND model, subjective image quality assessment scores can be estimated with better accuracy, leading to significant performance improvements of the traditional peak signal-to-noise ratio (PSNR). The gain achieved by introducing the picture-wise JND model in the objective assessment depends on the chosen dataset and the results of the initial simple to compute PSNR measure, and it was obtained on all five datasets. The mean linear correlation coefficient (for five datasets) between subjective and PSNR objective quality estimates increased from 74% (traditional PSNR) to 90% (picture-wise JND PSNR).

AUTHOR NOTES

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Conclusion: Further improvement of the JND-based objective measure can be obtained by improving the picture-wise model of JND prediction.

KEYWORDS: just noticeable difference, JPEG compression, peak signal-to-noise ratio, subjective and objective image quality assessment.

Р е з ю м е :

Введение/цель: В данной статье представлено интересное исследование, связанное с анализом пороговой модели прогнозирования заметных различий (JND) на изображениях и ее применением для оценки качества изображений со сжатием JPEG.

Методы: Анализ производительности модели JND был проведен косвенным способом с использованием общедоступных баз изображений с результатами субъективных тестов, при разделении изображений по двум категориям (выше и ниже порога заметных различий). При анализе производительности модели прогнозирования JND и оценке качества изображения использовались пять баз изображений, четыре из которых относятся к видимому диапазону длин волн, а одна база изображений, предназначенная для дистанционного наблюдения, была из инфракрасной части электромагнитного спектра.

Результаты: В данной статье показано, что применение моделей JND может использоваться для оценки субъективных показателей качества с большей точностью, что приводит к значительному улучшению характеристик традиционного соотношения пикового сигнала к шуму (PSNR). Среднее значение коэффициента линейной корреляции (по пяти базам) между субъективными и объективными оценками качества PSNR увеличилось с 74% (традиционный PSNR) до 90% (PSNR с моделью JND на уровне изображения). Выигрышный результат, достигаемый за счет внедрения модели JND на уровне изображения в объективной оценке, зависит от выбранной базы и результатов исходной простой меры PSNR, был получен по всем пяти базам.

Выводы: Дополнительное улучшение объективной меры, основанной на JND, может быть достигнуто за счет улучшения наглядной модели прогнозирования JND.

К л ю ч е в ы е с л о в а : порог заметных различий, сжатие JPEG, пиковое соотношение сигнал, шум, субъективная и объективная оценка качества изображения.

ABSTRACT:

Увод/цель: У раду су представљена интересантна истраживања која се односе на анализу перформанси модела предикције прага уочљивих разлика (JND) на нивоу слике и његову примену у процени квалитета слика са JPEG компресијом.

Метод: Анализа перформанси JND модела спроведена је на индиректан начин кроз занимљиву идеју да се користе јавно доступне базе слика са резултатима субјективних тестова, са поделом слика на две класе (изнад и испод прага уочљивих разлика). У анализи перформанси предикције JND модела и при процени квалитета коришћено је пет база слика, од којих четири потичу из видљивог опсега таласних дужина, док је једна база са сликама из инфрацрвеног дела електромагнетног спектра намењених даљинском осматрању и надзору.

Резултати: У раду је показано да се применом JND модела са већом прецизношћу могу естимирати субјективни скорови квалитета, што води значајном побољшању перформанси традиционалног вршног односа сигнал/шум (PSNR). Добитак остварен увођењем JND модела на нивоу слике у објективну процену зависи од изабране базе и резултата полазне једноставне PSNR мере, а остварен је на свих пет база. Средња вредност коефицијента линеарне корелације (за пет база) између субјективних и PSNR објективних естимација квалитета је са 74% (традиционални PSNR) порасла на 90% (PSNR са JND моделом на нивоу слике).

Закључак: Додатно унапређење JND засноване објективне мере може се добити унапређењем модела предикције JND.

KEYWORDS: праг уочљивих разлика, JPEG компресија, вршни однос сигнал, шум, субјективна и објективна процена квалитета слике.

INTRODUCTION

With the rapid development of systems for digital processing, transmission and display of images and videos, there has been a growing interest in efficient image/video compression techniques (Lu et al, 2021). Among the techniques intended for image compression, the JPEG technique (Wallace, 1992), (Pennebaker & Mitchell, 1993) has been the most widely accepted for more than 25 years. The original JPEG development team members emphasize that the longevity of this technique is a consequence of well-

defined mandatory conditions that it had to meet and fundamental components such as fast discrete cosine transform, psychovisual quantization, modeling, encoding, a royalty-free baseline, progressive modes, lossless compression support and real-time implementation (Hudson et al, 2017), (Hudson et al, 2018). The JPEG technique still meets the average user demand, so it is to be expected that it will be present in the coming decades.

Image compression techniques, along with the elimination of coding and spatial redundancy, use some of the characteristics of the human visual system (HVS), i.e. use visual redundancy. One of the characteristics is related to the just noticeable difference (JND) threshold. JND, as a perceptual threshold in image processing, is used in perceptual image compression (Tian et al, 2020), (Wang et al, 2019), and can also be used in objective image quality assessment (Toprak & Yalman, 2017), (Seo et al, 2021). The first and most significant JND threshold/point refers to the transition between a pristine and an image with visible distortions, or rather the transition from perceptually lossless to perceptually lossy encoding (Huang et al, 2018). Research on JND has intensified in recent years thanks to publicly available image and video datasets with the results of subjective tests, among which there are three JND-based image datasets with JPEG compression (Jin et al, 2016), (Liu et al, 2018), (Ahar et al, 2018). These three datasets are intended for different purposes – compression of natural images (Jin et al, 2016), compression of panoramic images (Liu et al, 2018) and compression of high dynamic range images (Ahar et al, 2018). JND-based subjective quality analyses also have been conducted on JPEG 2000, H.265 and VVC compressed images, and on H.264 and H.265 compressed videos (Bondžulić et al, 2021).

The MCL-JCI dataset described in (Jin et al, 2016), as a dataset of natural scene images, contains information on the JND points of JPEG compressed images and was used to predict JND points in (Fan et al, 2019), (Lin et al, 2020), (Liu et al, 2020), (Bondžulić et al, 2021). The mean absolute error (MAE) of the PSNR between the predicted and ground truth JND distributions was used as a prediction accuracy measure. The deep learning approaches (Fan et al, 2019), (Lin et al, 2020), (Liu et al, 2020) yielded the MAE for the first JND point of 0.69 dB, 0.58 dB and 0.79 dB, respectively. Recent research published in (Bondžulić et al, 2021) has shown that based on only one feature derived from a source non-compressed image (mean gradient magnitude, MGM), the PSNR of the first JND point of an image with JPEG compression can be reliably predicted (linear correlation coefficient between PSNR of the predicted and ground truth first JND points is greater than 92%, while the MAE between them is 1.21 dB). The proposed approach does not require complex vision or masking models and determines the optimal JPEG quality factor through a simple rate-distortion function using the computationally efficient PSNR metric for objective quality assessment. The high degree of correlation can be explained by a good prediction of image complexity using MGM, which is essential in determining the degree of compression and bandwidth allocation (Yu & Winkler, 2013).

The research in this paper aims to further confirm the success of the prediction of the first JND points for a given image using a simple and fast approach (Bondžulić et al, 2021) and to show that the information of position of the first JND points can be used to reliably evaluate quality of images with JPEG compression. Prediction success and reliable evaluation were confirmed on five subject-rated image datasets containing images with JPEG compression.

PREDICTION OF THE FIRST JND POINT FOR JPEG COMPRESSED IMAGES

The quality factor (QF), whose values range from 0 to 100, has been used to control the quality of JPEG compressed images. Higher QF values correspond to better quality images. Although one can choose a QF from 0 to 100, with an increment equal to one, recent research has shown that observers can distinguish a finite number of image quality levels (four to eight), and that the relationship between perceptual distortions and a bit-rate/distortion level is not a continuous but a step function (Jin et al, 2016). The steps of this function represent the JND points. The first among them, and at the same time the most important JND

point, refers to the maximum difference between the original and the test image that the HVS will not notice (Li et al, 2020), (Bondžulić et al, 2017). This transition point between the original image and the images with visible degradations also represents the transition from perceptually lossless to perceptually lossy encoding. The second JND point is obtained by detecting noticeable differences from the first JND point (anchor), i.e. lower JND points are used as anchors to determine higher JND points.

Figure 1 shows the original uncompressed image from the MCL-JCI dataset (Jin et al, 2016), its stepwise distribution of JND points and the regions of the original image and images corresponding to JND points. The results of subjective tests were given through the stair quality function (SQF), which represents the normalized cumulative sum of the JND function, and was obtained by analysing and post-processing raw JND data. The height of the SQF function for a boundary point with QF=100 is equal to one and defines the maximum possible quality. The first drop in quality corresponds to the first JND point (JND #1), and its height corresponds to subjective quality. This point corresponds to the image with QF=35, and its subjective quality is SQF=0.92. The position of the first JND point depends on the image content and for 50 source images from the MCL-JCI dataset these positions were obtained for a wide range of QF values, from 25 to 70 (Jin et al, 2016).

The regions in Figure 1 show visible differences between the images corresponding to the higher JND points (JND #2 and JND #3) and the region of the original image.

Prediction of the first JND point for JPEG compressed images can be achieved in the PSNR, QF, and bits per pixel (bpp) domains, but researchers suggested using the PSNR domain to predict the first JND point (Liu et al, 2020), (Bondžulić et al, 2021).

The procedure for determining the estimation of the ground truth PSNR value (PSNR JND #1) proposed in (Bondžulić et al, 2021) is carried out in several steps. In the first step, if it is a color image, the conversion from the RGB color format to a grayscale image is performed (Gonzalez & Woods, 2018):

$$f(n, m) = 0.299R(n, m) + 0.587G(n, m) + 0.114B(n, m). \quad (1)$$

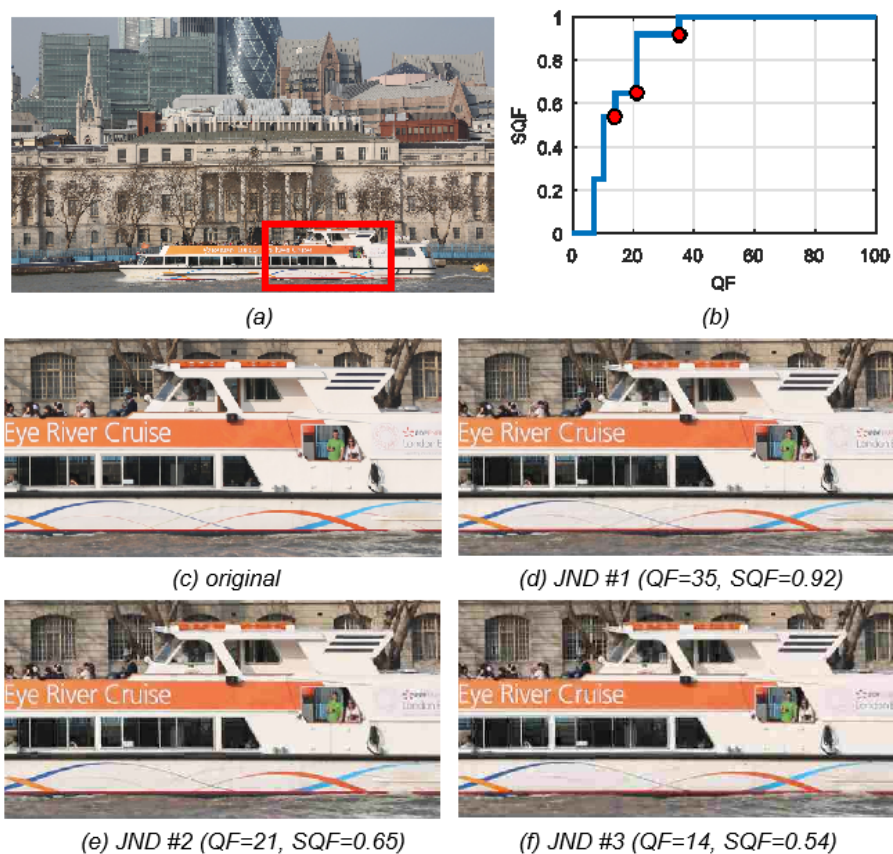


FIGURE 1

(a) (b) original image rich in detail and its SQF function, (c) (d) (e) and (f) regions of the original image and compressed images corresponding to the JND points

In the second step, the responses g_x and g_y of the grayscale image to the 2D Sobel filters are determined:

$$g_x(n, m) = f(n+1, m-1) + 2f(n+1, m) + f(n+1, m+1) - [f(n-1, m-1) + 2f(n-1, m) + f(n-1, m+1)] \quad (2)$$

and

$$g_y(n, m) = f(n-1, m+1) + 2f(n, m+1) + f(n+1, m+1) - [f(n-1, m-1) + 2f(n, m-1) + f(n+1, m-1)] \quad (3)$$

From the resulting g_x and g_y oriented gradient components, the MGM information is easily obtained according to:

$$MGM = \frac{1}{NM} \sum_{n,m} \frac{1}{g_{\max}} \sqrt{g_x^2(n, m) + g_y^2(n, m)},$$

(4)

where $g_{\max}$ is the experimentally determined maximum magnitude value, taken as $g_{\max}=4.472$ for grayscale images with a dynamic range 0 to 1 (image . which is an 8-bit unsigned integer array with a range of 0 to 255 is linearly scaled to a dynamic range of 0 to 1 with a double-precision 64-bit format) (Bondžulić et al, 2021).

The PSNR JND #1 prediction is determined based on the MGM information as:

$$PSNR(MGM) = \begin{cases} 2115.5MGM^2 - 377MGM + 46.4, & MGM \leq 0.0896 \\ 29.58, & MGM > 0.0896 \end{cases}, \quad (5)$$

and this mapping function is shown in Figure 2.

The optimal values of the coefficients in Eq. (5) were determined based on the results of subjective tests on the MCL-JCI dataset (Bondžulić et al, 2021).

Figure 2 shows that, with increasing MGM, the value of PSNR prediction decreases, where for $MGM=0.0896$ the mapping function reaches its minimum value ($PSNR_{\min}=29.58$ dB). This can be explained by the influence of contrast and texture that are important for visibility masking estimation because in the regions that contain more non-uniform contents more distortion can be tolerated than in the regions with homogeneous content. Furthermore, block-based JPEG coding suppresses high-frequency components. In the homogeneous regions with gradual color/intensity change, the blocking artifact is visible to observers. In contrast, the distortion is less obvious in the textured regions (Jin et al, 2016).

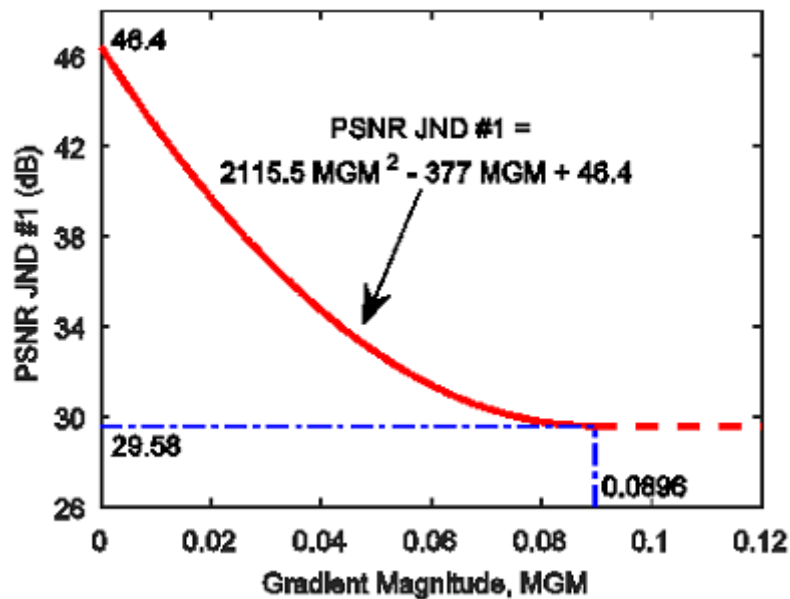


FIGURE 2

PSNR prediction of the first JND point based on the mean gradient magnitude

JND PREDICTION AND IMAGE QUALITY ANALYSIS

The described model (Bondžulić et al, 2021) was used without any additional adjustments to determine the PSNR estimates of the first JND points of the reference images from the four datasets. For example, the adopted JND model is trained on high spatial resolution images (1280x1920 pixels), and will be tested on images that are of significantly lower resolution.

Figure 3 shows the scatter plots of subjective (mean opinion score – MOS/difference MOS – DMOS) and objective (PSNR) quality scores. Each point on the scatter plots corresponds to one test image with JPEG compression. Scatter plots are shown for four image datasets, three of which are publicly available – LIVE (Sheikh et al, 2006) (with 29 original images), CSIQ (Larson & Chandler, 2010) (with 30 original images) and VCL@FER (Zarić et al, 2012) (with 23 reference images). The fourth image dataset, marked with LWIR, will be publicly available soon, and can be obtained by sending an inquiry to the authors who created it (Merrouche et al, 2018). A subset of 100 images with JPEG compression was taken from the LWIR dataset containing images from the infrared part of the electromagnetic spectrum. The LWIR dataset test images were created from 20 original images, and their quality was reduced using five degradation levels (five quality factors). In subjective tests, the scores of 31 observers were collected.

On the scatter plots, JPEG images are represented by two symbols, where the first symbol (o) corresponds to the images in which the PSNR of the test image is above the PSNR JND #1 (this is the first class of images, which should consist of high quality images, and in which there is no loss of visual information). The second symbol (D) corresponds to the images for which the PSNR of the test image is below the PSNR JND #1 (this is the second class of images that should consist of lower quality images). A similar idea of dividing images into two classes was used in (Ponomarenko et al, 2015).

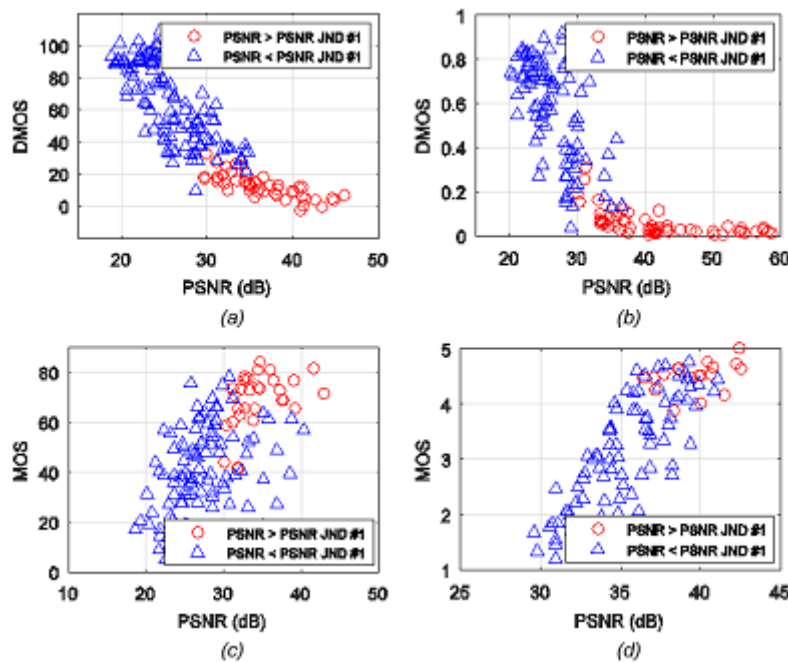


FIGURE 3

Scatter plots of subjective and PSNR objective image quality scores for JPEG images from four datasets: (a) LIVE (175 images), (b) CSIQ (150 images), (c) VCL@FER (138 images) and (d) LWIR (100 images)

Figure 3 shows that the proposed approach for the first JND point estimation proved to be excellent on the LIVE and CSIQ datasets. By applying the PSNR of the first JND point, images of excellent visual quality were detected – they correspond to lower values of subjective DMOS scores. Slightly worse results of the proposed first JND point estimation model can be seen for the images from the VCL@FER dataset.

The surprising result of the proposed approach can be seen on the LWIR image dataset. Although it is a dataset of images from the invisible (infrared) part of the electromagnetic spectrum, the proposed approach of the first JND point estimation has proven to be very successful in detecting JPEG compressed images with high quality – they correspond to higher values of subjective MOS scores. In this way, the validity of the

proposed PSNR estimation of the first JND point was indirectly confirmed, using the results of subjective quality tests of available image datasets.

Figure 4 shows two source images from the LWIR dataset and their JPEG compressed versions for which the PSNR value is above the PSNR JND #1. The test images are of excellent and good visual quality, i.e. there is no visual difference between the pair of images shown in Figures 4(a) and 4(b) (MOS=5), while the observers noticed slight differences between the pair shown in Figures 4(c) and 4(d) (MOS=4).

For the two selected examples, the degrees of image compression are approximately equal and are 21.7 (Figure 4a) and 23.3 (Figure 4b).

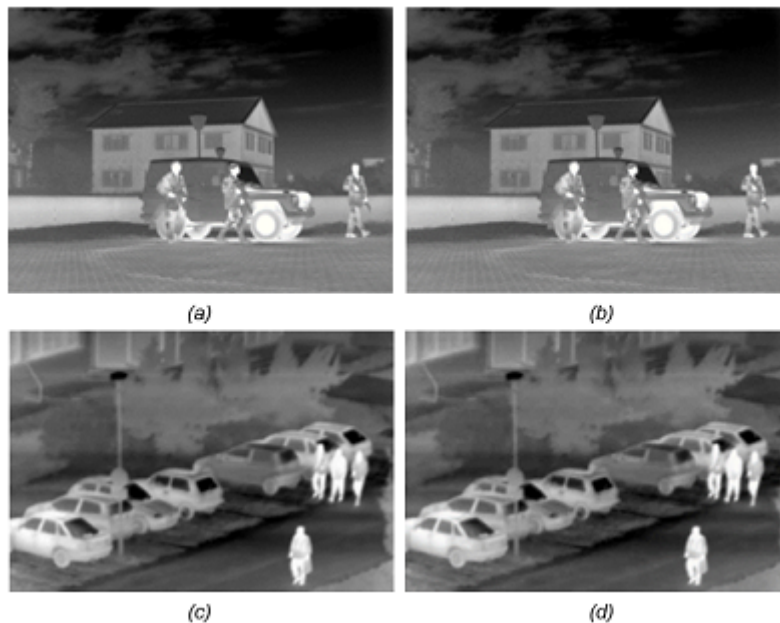


FIGURE 4

(a) original image (image size is 608 kB), (b) test image with JPEG compression (PSNR=42.47, PSNR JND #1=39.92, MOS=5, image size is 28 kB), (c) original image (image size is 256 kB) and (d) test image with JPEG compression (PSNR=40.03, PSNR JND #1=38.18, MOS=4, image size is 11 kB)

IMPACT OF JND PREDICTION ON IMAGE QUALITY ASSESSMENT

The described approach of the PSNR estimation of the first JND point is derived from the results of subjective tests of the MCL-JCI dataset (Jin et al, 2016) in which 50 original images are used. The degree of agreement between SQF subjective and objective quality scores on this JPEG image dataset is worse than the degree of agreement between subjective and objective quality scores on publicly available image datasets such as LIVE, CSIQ, VCL@FER and similar (Bondžulić et al, 2020). A very low degree of agreement between the SQF subjective and PSNR objective quality scores on this image dataset can be observed through the large spreading on the scatter plots shown in Figure 5. The scatter plots are shown for PSNR objective quality scores. The degraded images originating from the same original image are on the scatter plot in Figure 5(a) connected by lines of different colors. On the scatter plot in Figure 5(b), the images corresponding to the JND points derived from subjective tests are marked with different symbols (from JND #1 to JND #7).

Additionally, in Figure 5(a), it can be seen that the slope of the lines corresponding to the images originating from the same original image is approximately the same. The spreading in the space of subjective and objective quality scores is a consequence of the different content of the original images. Similar conclusions related to the PSNR performance in video quality assessment were reached by the authors in (Huynh-Thu & Ghanbari, 2008), (Bondzulic et al, 2016). The goal of designing objective quality assessment

measures is that the results of the assessment, among other things, do not depend on the content of the original images.

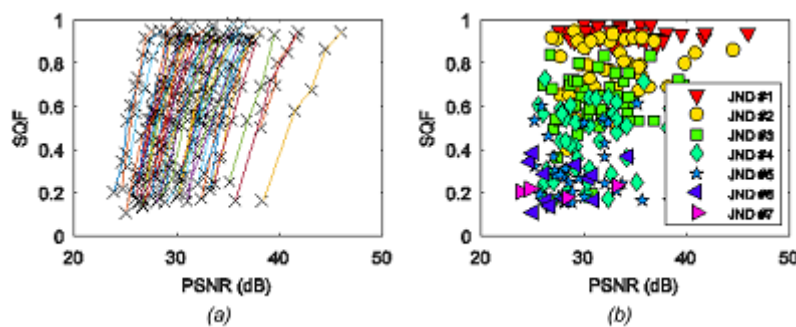


FIGURE 5

Scatter plots of subjective and PSNR objective quality scores of MCL-JCI JPEG compressed images: (a) the scatter plot is shown regarding the images originating from the same original image and (b) the scatter plot with marked JND point

Figure 6(a) shows the curves of the JND points from the two source images, between which are the other JND points of the scatter plot between the SQF and PSNR scores on the MCL-JCI image dataset.

Figure 6(b) and 6(c) show the original images corresponding to the curves of Figure 6(a), i.e. the left and right boundaries on the scatter plot. It can be concluded that the points on the scatter plot are located between the JND points of the image with uniform regions and visible boundaries between them (right scatter border), and the image with a pronounced uniform region in the upper third of the image (with intensity saturation), and rich in details in the rest (left scatter border).

From Figure 5 it can be seen that the vertices of the curves start from the images corresponding to the first JND points. In order to make the result of the PSNR objective quality evaluation independent of the content of the original images, it is reasonable to define the differential PSNR as the difference between the PSNR and the estimation of the PSNR JND #1:

$$DPSNR = PSNR - PSNR_{JND \#1}. \quad (6)$$

DPSNR values can be both positive and negative. Positive values correspond to good quality images ($PSNR > PSNR_{JND \#1}$), while negative values correspond to lower quality images. Also, DPSNR is a picture-wise JND measure of objective image quality assessment.

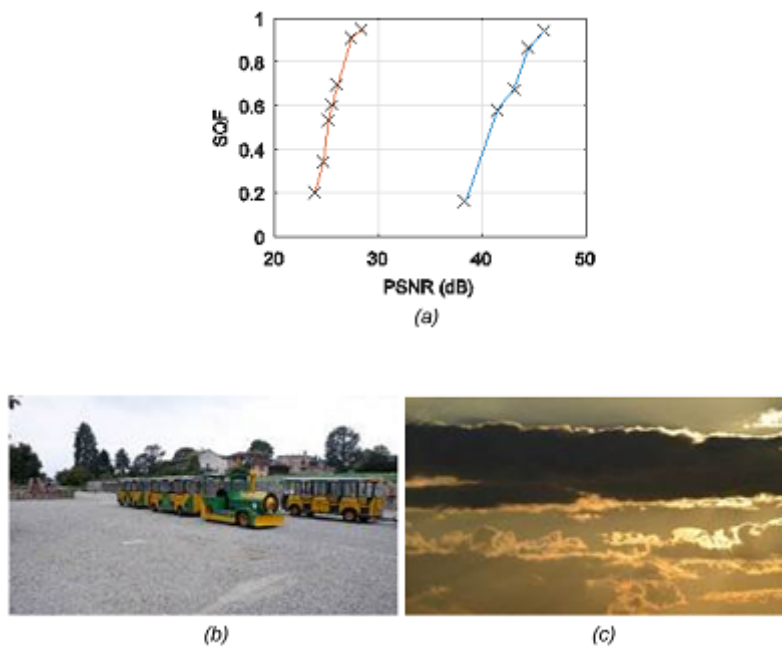


FIGURE 6

(a) the relationship between SQF and PSNR for the two source images of the MCL-JCI dataset, (b) the original image corresponding to the left boundary of the JND points and (c) the original image corresponding to the right boundary of the JND points of the MCL-JCI image dataset

The scatter plots of subjective and DPSNR objective quality scores on the four analyzed image datasets are shown in Figure 7. Significantly less spreading of scores is observed in relation to the spreading of the scores of the PSNR objective measure (Figure 3).

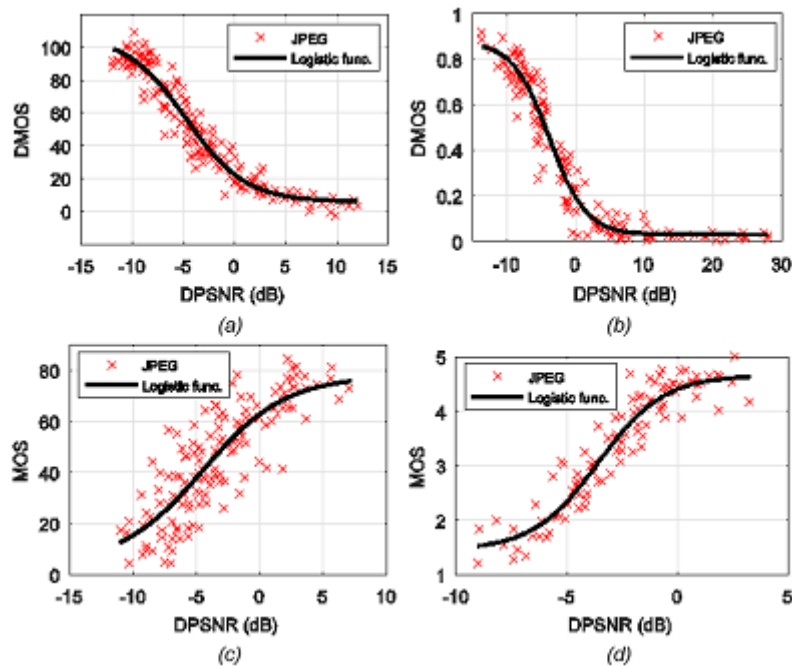


FIGURE 7

Scatter plots of subjective and DPSNR objective quality scores of images with JPEG compression on four datasets: (a) LIVE, (b) CSIQ, (c) VCL@FER and (d) LWIR

Table 1 provides the quantitative indicators of the degree of agreement between the subjective and PSNR/DPSNR objective quality scores for the four analyzed image datasets. The linear correlation coefficient (LCC), Spearman's rank-order correlation (SROCC), mean absolute error (MAE), root mean square error (RMSE) and outlier ratio (OR) between the subjective and objective quality scores after nonlinear regression using a logistic function with four parameters were used as quantitative indicators (ITU-T, 2004), (Bondžulić et al, 2018). In addition to the performance of these two objective measures, the performance of the HVS-based objective measures is given: PSNR-HVS (Egiazarian et al, 2006), PSNR-HVS-M (Ponomarenko et al, 2007) and WNMAE (Huang et al, 2018). PSNR-HVS and PSNR-HVS-M measures are sub-band models that take into account the contrast sensitivity function. Additionally, PSNR-HVS-M takes into account the between-coefficient contrast masking of the discrete cosine transform basis functions (Ponomarenko et al, 2007). WNMAE is a traditional pixel-wise model based on JND. Through this measure, HVS's physiological (color and light sensitivity) and psycho-physiological (texture and edge sensitivity) characteristics were implemented. The two best results for each dataset and for each quantitative indicator are in Table 1 marked in bold.

TABLE 1
Performance comparison of objective measures on four datasets

Dataset	Measure	LCC	SROCC	MAE	RMSE	OR [%]
LIVE	PSNR	0.8879	0.8809	11.3594	14.6532	12.5714
	DPSNR	0.9649	0.9565	6.5225	8.3637	1.1429
	PSNR-HVS	0.9585	0.9478	7.1802	9.0760	1.1429
	PSNR-HVS-M	0.9752	0.9650	5.5549	7.0493	0.0000
	WNMAE	0.9143	0.9113	9.9537	12.9013	5.7143
CSIQ	PSNR	0.8906	0.8879	0.0964	0.1391	31.3333
	DPSNR	0.9707	0.9510	0.0547	0.0735	19.3333
	PSNR-HVS	0.9577	0.9400	0.0603	0.0880	22.6667
	PSNR-HVS-M	0.9733	0.9512	0.0501	0.0702	20.0000
	WNMAE	0.8971	0.8962	0.0946	0.1352	34.0000
VCL@FER	PSNR	0.6041	0.6040	13.6027	16.7039	69.5652
	DPSNR	0.8269	0.8262	9.2646	11.7856	52.1739
	PSNR-HVS	0.8741	0.8775	7.8178	10.1823	48.5507
	PSNR-HVS-M	0.9408	0.9388	5.5695	7.1051	33.3333
	WNMAE	0.6252	0.6279	13.2803	16.3580	71.7391
LWIR	PSNR	0.8377	0.8146	0.4362	0.5650	59.0000
	DPSNR	0.9481	0.9238	0.2596	0.3290	45.0000
	PSNR-HVS	0.8238	0.8018	0.4573	0.5865	63.0000
	PSNR-HVS-M	0.8389	0.8135	0.4492	0.5631	65.0000
	WNMAE	Not applicable				

The performance of the DPSNR objective measure is significantly better than the performance of the PSNR, for all five quantitative indicators and on four datasets. It can be noticed that the performance of the DPSNR is the worst on the VCL@FER image dataset, where the original PSNR has the worst results.

The DPSNR performance is at the top on the LIVE and CSIQ datasets, along with the PSNR-HVS-M measure. Two sub-band models provide the best results on the VCL@FER image dataset, while the performance of the proposed DPSNR approach is best on the LWIR dataset of images from the infrared part of the electromagnetic spectrum. The performance of the WNMAE objective measure is slightly better than the performance of the worst ranked PSNR objective measure.

A careful reader may notice that in comparing the results of objective measures between different datasets (Table 1) one should be careful because different grading scales in subjective experiments have been used

on different datasets (see Figures 3 and 5). The dynamic range of the grading scale affects the MAE and the RMSE. In this case, the LCC and SROCC values are relevant for comparing the results between the datasets.

The performance of objective measures was additionally analyzed on the MCL-JCI image dataset, which was used to train the estimation algorithms of the first JND point. Figure 8 shows the scatter plots of the SQF subjective and PSNR objective quality scores with image division into two classes, using PSNR JND #1 values estimated using the approaches described in (Bondžulić et al, 2021) and (Lin et al, 2020).

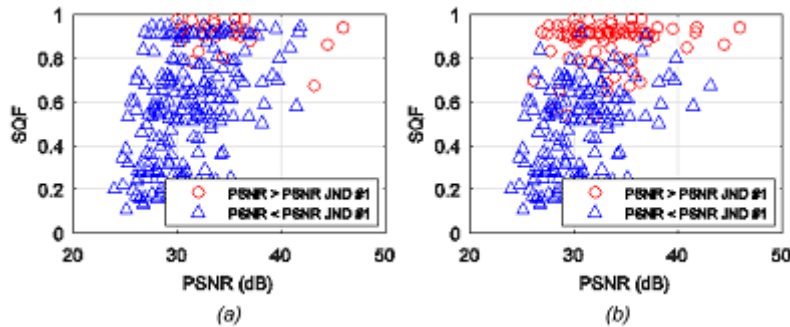


FIGURE 8

Scatter plots of SQF subjective and PSNR objective scores on the MCL-JCI image dataset with division of images into two classes, where the estimates of PSNR JND #1 were determined based on: (a) approach (Bondžulić et al, 2021) and (b) approach (Lin et al, 2020)

From Figure 8 it can be concluded that, by applying the approach (Lin et al, 2020), more JND #1 points are detected than by applying the approach (Bondžulić et al, 2021) (additionally, see Figure 5(b)). It can also be observed that using this approach, several other (higher) JND points that are above the threshold of visible differences (PSNR JND #1) were detected.

The values of the DPSNR objective measure were determined on the basis of two estimates of PSNR JND #1 – the approaches described in (Bondžulić et al, 2021) and (Lin et al, 2020). The scatter plots of the SQF and DPSNR scores on the MCL-JCI dataset and the corresponding logistic functions are shown in Figure 9, while the quantitative indicators of the degree of their agreement are given in Table 2.

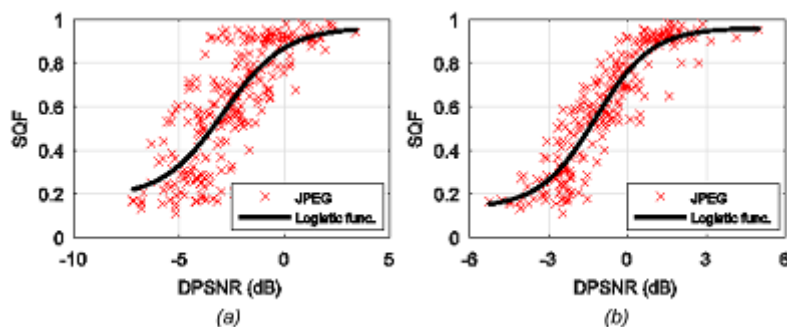


FIGURE 9

Scatter plots of subjective and DPSNR objective scores on the MCL-JCI image dataset where the estimates of PSNR JND #1 were determined based on: (a) approach (Bondžulić et al, 2021) and (b) approach (Lin et al, 2020)

From Figure 9 and from Table 2, it can be noticed that there is a significantly higher degree of agreement between the SQF and DPSNR objective quality scores determined using the PSNR JND #1 estimates based on the approach from (Lin et al, 2020). This result could be expected because this approach has a mean absolute PSNR JND #1 estimation error of 0.58 dB on the MCL-JCI image dataset, while the approach described in (Bondžulić et al, 2021) has a higher estimation error (1.21 dB). In this case, although the

poor performance of the baseline PSNR measure (LCC=0.4721), using PSNR JND #1 the performance of DPSNR was significantly increased and exceeded the performance of other measures (LCC=0.9194).

TABLE 2
Performance comparison of the objective measures on the MCL-JCI dataset

Dataset	Measure	LCC	SROCC	MAE	RMSE
MCL-JCI	PSNR	0.4721	0.4486	0.1907	0.2288
	DPSNR (Bondžulić et al, 2021)	0.7973	0.7930	0.1222	0.1566
	DPSNR (Lin et al, 2020)	0.9194	0.9144	0.0779	0.1021
	PSNR-HVS	0.7679	0.7506	0.1328	0.1662
	PSNR-HVS-M	0.8584	0.8456	0.1026	0.1331
	WNMAE	0.4783	0.4665	0.1899	0.2279

Although the introduction of the objective measure DPSNR has significantly improved the degree of agreement between subjective and PSNR objective quality scores, there is still room for improvement, and the degree of improvement will depend on the accuracy of PSNR JND #1 estimation.

The position of the threshold of visible differences introduced in the quality assessment through PSNR JND #1, in this paper improved the performance of PSNR on the class of images with JPEG compression. This is a consequence of reducing the dependence of objective estimates on the content of the source signal. We expect that with reliable estimation of the position of PSNR JND #1 for other image classes (types of degradation), the performance of PSNR of individual classes will be improved, as well as the performance on a global level (reducing the dependence of estimates on the type of degradation).

CONCLUSION

The paper analyzes the reliability of one approach/model for the peak signal-to-noise ratio estimation of the visible differences (JND #1 point) of images with JPEG compression. Reliability was confirmed in an indirect way by using the results of subjective tests of five available image datasets, i.e. it has been shown that by applying a peak signal-to-noise ratio of the first JND point, high quality images can be detected. As the proposed approach was derived on one of the analyzed image datasets, and the success was confirmed on the four remaining ones, it can be concluded that the findings derived from subjective tests on one dataset can be successfully used on other related datasets.

The paper additionally shows that the performance of the peak signal-to-noise ratio as a measure of objective quality assessment can be improved by taking into account the PSNR values of the first JND point. Improvement was achieved on image datasets with JPEG compression, through a significant increase in the degree of agreement between subjective and objective quality scores. Also, it has been shown that improving the accuracy of the estimation of the first JND point has a positive effect on the degree of agreement between subjective and objective assessments. Therefore, future work will be focused on improving the accuracy of the PSNR estimation of the threshold of visible differences, both for images with JPEG compression and for images with other types of degradation.

To the best of our knowledge, this is the first attempt to use JND information in quality assessment at the picture-wise level. Previous models have used pixel-based or sub-band JND visibility thresholds. The additional significance of the paper is reflected in the idea to indirectly analyze the success of the JND model through two-class image separation without conducting subjective tests, i.e. using already available subject-rated image datasets. Finally, the results are presented on JPEG compressed images originating from the

visible and from the infrared part of the electromagnetic spectrum, which is of interest for remote sensing and surveillance applications.

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