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Visual Information Evaluation With Entropy of Primitive

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ABSTRACT In this paper, we overview the recent work on entropy of primitive (EoP), including its concept, design, extension, and mathematical analysis in evaluating the visual information of natural images. The design philosophy of EoP is establishing an entropy model that quantifies the visual information based on patch-level sparse representation, due to the close relationship between sparse representation and the hierarchical cognitive process of human perception. Furthermore, based on the concept and definition of EoP, we also demonstrate several applications, including just noticeable difference estimation and visual quality assessment. The future research directions of visual information evaluation are also envisioned, where we can perceive both promises and challenges.

INDEX TERMS Entropy of primitive, sparse representation, visual information, quality assessment, just noticeable difference.

I. INTRODUCTION

The evaluation of visual information perceived by the human visual system (HVS) is a fundamental issue that plays an important role in understanding the visual world. In the field of information theory [1], the entropy is an effective measure that quantifies the amount of information missing before reception. For natural images, a traditional way of the visual information quantification is to calculate the entropy at pixel level. For example, the histogram that characterizes the occurrence of each pixel in the image can be built for entropy calculation. However, this may not reveal the visual information perceived by HVS. It has been widely believed that natural image signals are highly structured [2]: their pixels are not independently distributed and exhibit strong dependencies that carry important information about the structure of the objects in the visual scene. As such, the hypothesis that the visual information is perceived in terms of pixels is quite questionable.

Sparse representation has been repeatedly proven to be powerful in characterizing the visual signals based on the sparsity and redundancy of their representations for many visual processing tasks [3]. In [4], the properties of spatially localized, oriented and bandpass properties of the primitives in sparse representation are exhibited to be closely relevant with the human visual system, especially the receptive fields of simple cells. As such, constantly increasing applications have been powered by sparse representation, and promising performance in image quality assessment [5]–[15], image denoising [16], image restoration [17]–[22] and image/video coding [23]–[28] has been achieved. Despite the great success of sparse representation, the visual information evaluation based on patch-level sparse representation is an emerging area.

To perform sparse representation, the typical K-SVD [29] algorithm is a popular method in obtaining the over-completed dictionary based on dictionary training. A series of matching pursuit family algorithms have also been presented to achieve sparse representation [30]. Among them, the orthogonal matching pursuit (OMP) [31] is one that works in a greedy fashion. These powerful tools enable efficient and effective visual signal representation for visual information evaluation. Benefiting from the advantages of sparse representation over the traditional pixel level representation, the Entropy of Primitive (EoP) was proposed to characterize the visual information in a more precise way. In this paper, we investigate and summarize the design and concept of EoP, explore its characteristics and possible extensions, and demonstrate its further applications. The future extensions of visual information evaluation, especially based on deep learning, which has been demonstrated to be more powerful in dealing with the rich, varied and directional information, are discussed. In summary, the paper presents the following contributions:

- We systematically analyze the concept and design philosophy of EoP in an effort to provide an accessible and intuitive overview of these approaches. In particular, the sparse representation and dictionary learning, which serve as the foundations of EoP, as well as the properties of the EoP, are reviewed. The extension of EoP by considering the coefficient energy and its convergency analysis, are also discussed.
- The applications of EoP are introduced, including the typical visual perception relevant tasks such as just noticeable difference (JND) estimation and visual quality assessment. Possible applications of EoP that worth further investigation are also discussed.
- We outline the main challenges and potential further research directions of visual information evaluation powered by the deep neural network, due to wide spectrum visual computing applications of deep learning that can automatically extract meaningful features in a data driven manner.

The rest of the paper is organized as follow. In Section 2, we provide the review of EoP as well as its properties and extensions. Section 3 introduces the applications of EoP. Current challenges and future directions of visual information evaluation are discussed in Section 4, and the paper is concluded in Section 5.

II. ENTROPY OF PRIMITIVE

A. SPARSE REPRESENTATION

The Sparseland model serves as the foundation of the sparse representation [3], and it assumes that natural visual signals $x (x \in \mathbb{R}^n)$ can be well represented by a linear combination over an over-complete dictionary, which can be written as $\forall x, x \approx \Psi\alpha$ and $\|\alpha\|_0 \ll n$. Here, $\Psi (\Psi \in \mathbb{R}^{n\times k})$ is the over-complete dictionary and the primitive is denoted as ψ_i. $\alpha (\alpha \in \mathbb{R}^k)$ is the representation vector corresponding to the coefficients in sparse representation. The notation $\|\bullet\|_0$ represents the ℓ_0 norm. Typically, we assume that $k > n$, implying the dictionary Ψ is redundant to x. To obtain the over-complete dictionary, the K-SVD algorithm [29] is typically employed. In particular, two iterative calculations are performed, including sparse coding and dictionary updating. Given the training samples which are generated by partitioning the input image into patches $x_1, x_2, \ldots, x_i, \ldots$, we can obtain the dictionary that leads to the best representation of the image under the sparsity constraint, which is formulated as follows,

$$(\Psi, \{\alpha_i\}) = \underset{\Psi,\{\alpha_i\}}{\arg\min} \sum\nolimits_i \|x_i - \Psi\alpha_i\|_2^2, \; s.t. \|\alpha_i\|_0 < \mathbb{L}. \quad (1)$$

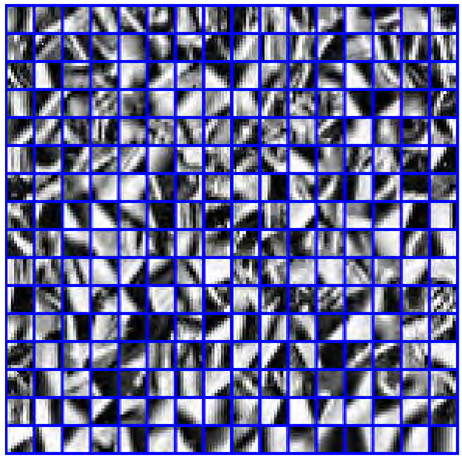

FIGURE 1. The 256 primitives learned in terms of 8 × 8 patches (*Lena*).

Here, $\mathbb{L}$ controls the sparse level. A typical dictionary learned from the *Lena* image is shown in Fig. 1.

Based on the trained dictionary Ψ and the constrains on accuracy and sparsity, sparse representation targets at obtaining the coefficients α_i that represents the visual signal, which is given by,

$$\alpha_i = \underset{\alpha_i}{\arg\min} \|x_i - \Psi\alpha_i\|_2^2, \; s.t. \|\alpha_i\|_0 < \mathbb{L}. \quad (2)$$

This can be solved by a number of approximation algorithms, among which the OMP [31] is a popular one working in a greedy way.

The sparse representation in terms of different values of L is shown in Fig. 2, where L is used to specify a specific iteration in OMP. It is clearly observed that the reconstruction quality increases with the value of L. In particular, the image reconstructed by the first layer ($L = 1$) represents the primary information. With the increasing number of the primitives used in the reconstruction, the artifacts such as blocking and blur are removed and most of the structural information can be preserved after $L = 6$. In essence, such observation is in accordance with the mechanism of HVS. In particular, based on the Internal Generative Mechanism (IGM) theory [32], [33], visual signal can be regarded by the composition of primary visual information and uncertainty. The primary visual information can be accounted by the low-level layers, and the uncertainty corresponds to the details described by the high level layer.

In [34], it is observed that the matching pursuit schemes such as OMP can decompose the image signal into multiple layers, including primary, sketch and non-structural layers. Interestingly, these layers are naturally ordered by perceptual importance, as demonstrated in Fig. 3. As such, the most significant structural information can be reconstructed by the

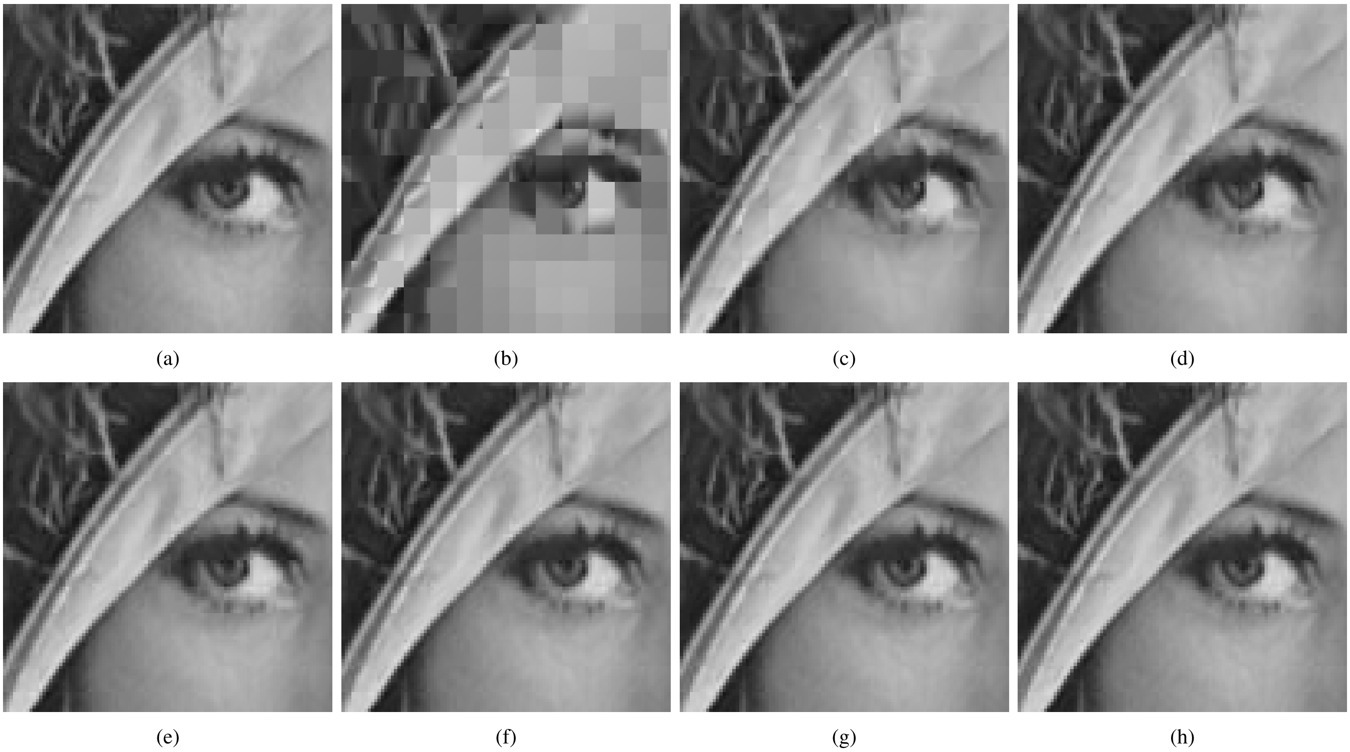

FIGURE 2. **Reconstructed *Lena* images with different number of primitives. (a) Original image. (b) $L = 1$. (c) $L = 3$. (d) $L = 5$. (e) $L = 7$. (f) $L = 9$. (g) $L = 11$. (h) $L = 13$.**

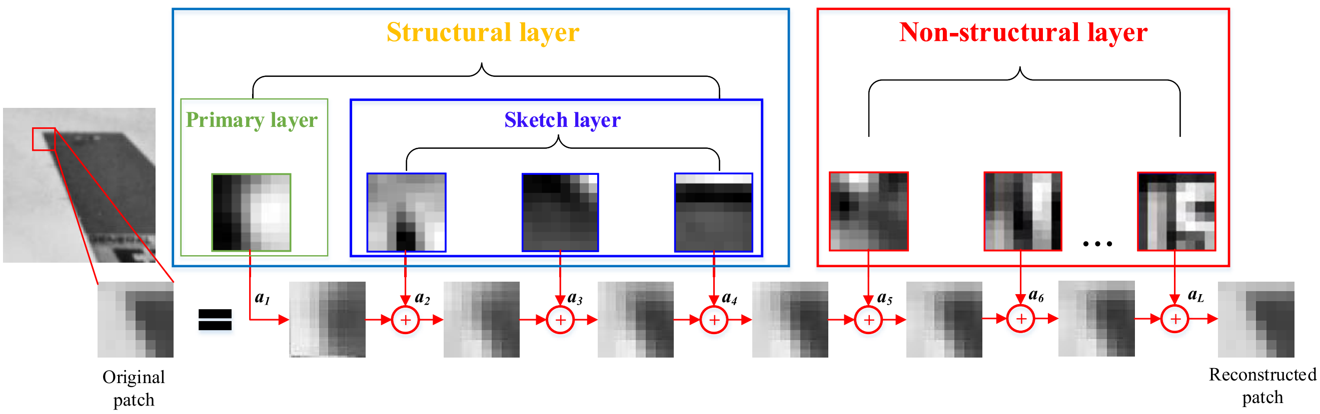

FIGURE 3. **Hierarchical image representation based on different number of primitives [34].**

first layer ($L = 1$), and the following layers reconstruct the detailed information. With the primary and sketch layers, almost all the perceptual information that is sensitive to HVS is adequately represented.

B. ENTROPY OF PRIMITIVE

The design philosophy of EoP [34] is that the visual information perceived in the natural scene shall be evaluated in terms of the patch level representation instead of the pixel level histogram. This originates from the fact that the natural images obey the natural scene statistics [35] and appear to be highly structured [2]. Moreover, due to the close relationship between the patch level sparse representation and human perception, the primitive is adopted as the basis in entropy calculation. In particular, in the sparse representation process, we assume that the total number of the i^{th} primitive used from the first iteration to the L^{th} iteration is defined as $\bar{N}_{L,i}$. The corresponding probability density functions (PDF) for the i^{th} primitive selected is given by,

$$\bar{p}_{L,i} = \frac{\bar{N}_{L,i}}{\sum_{i=1}^{k} \bar{N}_{L,i}}. \tag{3}$$

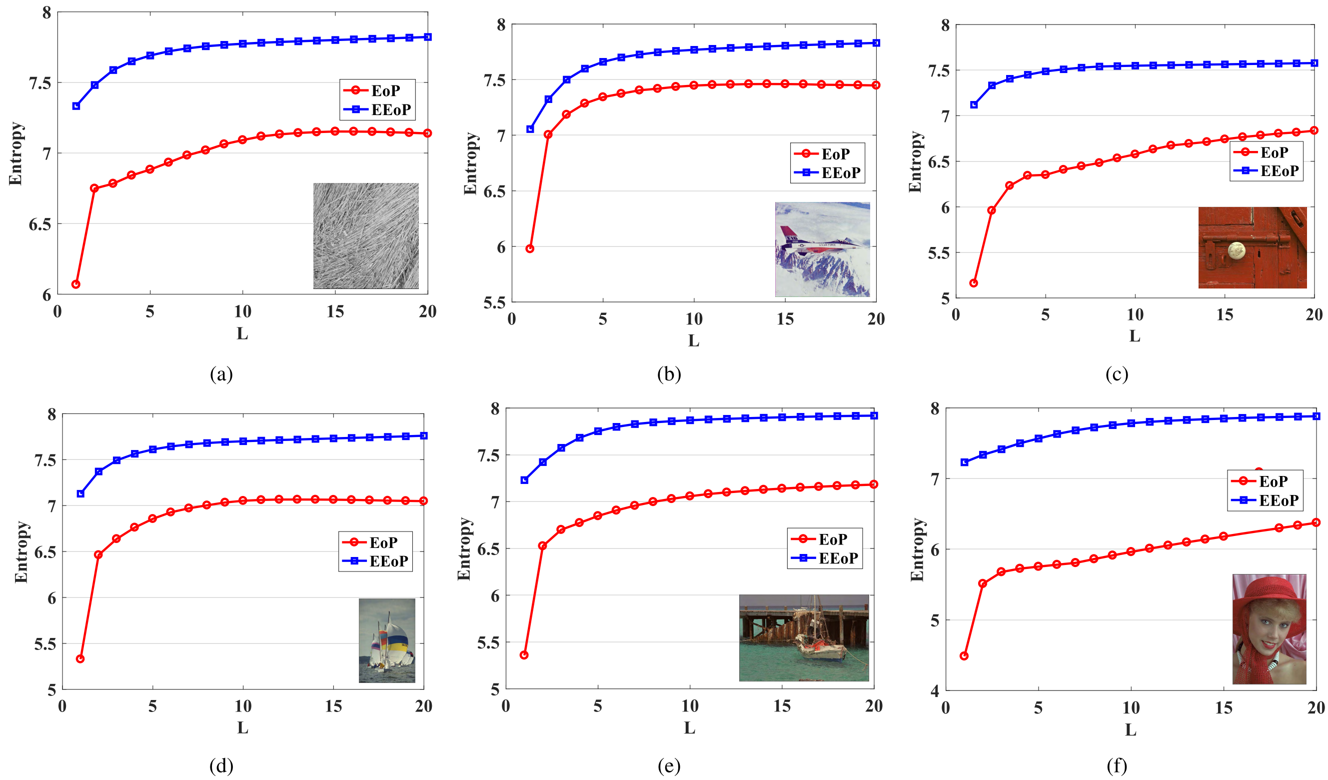

FIGURE 4. **EoP and EEoP curves in terms of the number of iterations *L*. The original image is shown in the corner of each figure.**

Based on the *Shannon* theory [1], the EoP at the L^{th} iteration can be defined as follows,

$$EoP_L = -\sum\nolimits_{i=1}^{k} \bar{p}_{L,i} \log \bar{p}_{L,i}. \tag{4}$$

As indicated in (4), the EoP is essentially defined based on the iteration index L, indicating that at each iteration of reconstruction, the visual information characterized by EoP is variant. In particular, as the visual quality becomes better along with the increase of the iteration index, it is also interesting to see that the EoP increases monotonously with L, as shown in Fig. 4. Another observation is that it converges to a saturation point, which also corresponds to the scenario that the visual quality is perceptually equivalent to the original image as the visual information becomes constant. As such, it is natural to apply the concept of EoP in JND estimation and quality evaluation, as discussed in Section III.

C. EXTENSION OF EOP

However, a major drawback of the EoP is that the coefficients in sparse representation are not taken into consideration. In particular, the PDF in EoP definition is only based on the selected primitive, regardless of the coefficient energy. To tackle this, an extension of EoP (EEoP) based on the ℓ_2 norm of the coefficients is proposed in [36]. First, a PDF considering the coefficient energy can be defined as follows,

$$N_L = \sum_{i=1}^{k} n_{L,i}, \tag{5}$$

$$p_{L,i} = \frac{n_{L,i}}{N_L}, \tag{6}$$

where $n_{L,i}$ denotes the ℓ_2 norm of the coefficients for the i^{th} primitive and the L^{th} iteration. Then, the EEoP is defined as follows,

$$EEoP_L = -\sum\nolimits_{i=1}^{k} p_{L,i} \log p_{L,i}. \tag{7}$$

In [36], the convergence of the EEoP is further verified. In particular, it is proved that the PDFs of two neighboring iterations become similar to each other as the number of iterations increases, i.e., $\lim_{L\to\infty} |p_{L+1,i} - p_{L,i}| = 0$, which can be split to the following two parts,

$$\lim_{L\to\infty} |p_{L+1,i_{\min}} - p_{L,i}| = 0, \tag{8}$$

$$\lim_{L\to\infty} |p_{L+1,i_{\max}} - p_{L,i}| = 0, \tag{9}$$

where $p_{L+1,i_{min}}$ and $p_{L+1,i_{max}}$ are the lower and upper bounds of $p_{L+1,i}$, respectively.

Some examples of the EEoP curves are shown in Fig. 4. We can observe that the curves of EEoP are more stable and robust compared to the original EoP curves. EoP is essentially based on the statistical distribution of the number of nonzero coefficients, i.e., the ℓ_0 norm, while the EEoP is essentially

FIGURE 5. Images noised by different JND models including Yang *et al.*'s [37], Liu *et al.*'s [38], Wu *et al.*'s [39] and EoP based JNDs from left to right, respectively.

based on the coefficient energy, i.e., the ℓ_2 norm. Therefore, EoP could be rather sensitive to the values close to zero and it simply ignores the coefficient amplitude. As such, a significant primitive with large coefficient value and an insignificant primitive with negligible value have the same impact on the entropy calculation in EoP. EEoP addresses this issue by taking the coefficient energy into account, thus achieving a more stable and robust representation compared to EoP. As such, EEoP is a meaningful extension of EoP, which comprehensively reflects the sparse representation process and the relationships between sparse representation and HVS.

III. APPLICATIONS OF EOP

While the fields of visual information evaluation and sparse coding are still quickly evolving, it is interesting to discuss how we could make use of EoP in real-world applications. As a powerful tool in evaluating the visual information, EoP has been successfully applied in the applications of JND estimation and visual quality evaluation. In this section, the applications of EoP will be detailed to show how EoP can play important roles in an even more extended field of scenarios. It is also envisioned that in the future more applications of the EoP or visual information evaluation methods may emerge, especially for the perceptual visual compression which relies on robust visual quality assessment algorithms.

A. JUST NOTICEABLE DIFFERENCE ESTIMATION

As the quality of the reconstructed image improves gradually with the value of L, the visual quality will reach to the saturation point such that further signal level fidelity improvement cannot further improve the visual quality. As such, it is natural to exploit the characteristics of EoP in JND estimation. In particular, given an original image X, the corresponding reconstructed image $\tilde{X}$ can be obtained by sparse representation. As such, the JND profile can be estimated by the difference between X and $\tilde{X}$, which is given by,

$$JND(X) \triangleq \left|\tilde{X} - X\right|, \tag{10}$$

where the notation $|\bullet|$ indicates the absolute operator.

To obtain the reconstruction image $\tilde{X}$, we follow the computation of EoP. In particular, the image X is used to train the dictionary using the K-SVD algorithm. Then each patch is decomposed into a linear combination of a few primitives by the OMP approach. The threshold $\tilde{L}$ can be calculated based on the definition of EoP,

$$\tilde{L} = \arg\min_{i} i, s.t. \frac{EoP_i - EoP_{i-1}}{\max_j \left(EoP_j\right) - \min_j \left(EoP_j\right)} < \varepsilon, \tag{11}$$

where ε determines the convergence condition. As such, the reconstructed image $\tilde{X}$ can be reconstructing the image with the first $\tilde{L}$ primitives, and the following primitives can be discarded. Due to the concept of EoP, we regard the reconstructed image $\tilde{X}$ as having equal quality with the original image or perceptual lossless. In this manner, the JND map can be obtained via (10).

In [34], the JND noised images are compared, as shown in Fig. 5. Though they share approximately identical PSNR value, it is interesting to see that the noise injected images with the JND derived based on EoP and sparse representation have better quality. Here, we also provide the JND maps to better show their differences, as illustrated in Fig. 6. It is also worth noting that all these JND maps contain exactly the same noise energy, as identical quantity of errors are injected into the original images. One can see that the EoP based method can concentrate the noises on the regions that have

FIGURE 6. Illustration of the JND maps including Yang *et al.*'s [37], Liu *et al.*'s [38], Wu *et al.*'s [39] and EoP based JND maps from left to right, respectively.

rich textures and details, and meanwhile keep the smooth areas with minimal distortions, yielding better visual quality. This further provides useful evidence that the JND profile guided with EoP is more effective in shaping the noise.

B. VISUAL QUALITY EVALUATION

Recently, image quality assessment (IQA) has received great interest due to its widely applications in monitoring and optimizing the multimedia systems [40]. Advanced full-reference (FR) [2], [32], [41], reduced-reference (RR) [42]–[47] and no-reference (NR) [48]–[50] IQA models have been developed to access the visual quality of natural images. Moreover, the IQA tasks have also been extended in various ways, such as screen content [51], [52], contrast [53]–[55], 3D and synthesized view [56]–[58], video streaming [59], [60] etc. Recently, various databases [61], [62] and evaluation methods [63] have also been proposed for the validation of the IQA methods.

In view of the significant importance of IQA, EoP has been adopted in IQA models in various ways. In particular, EoP serves as the measure that globally quantifies the visual information, such that the RR-IQA model can be built based on it. More specifically, inspired by the IGM theory, the RR-IQA model in [12] is derived based on the primary visual information and uncertainty. The primary visual information can be regarded as the information that can be understood in the natural scene, and this is naturally consistent with the concept of EoP. In [64], the uncertainty is represented as the discrepancy between the input signal and the best interpretation with the auto-regression model. In the context of sparse representation, by regarding sparse coding as the approximation of visual cognition process, the residuals between the input signal and the reconstructed signal with sparse representation can be treated as the uncertainty. As such, assuming the reconstructed image after the sparse representation is $\tilde{X}$, the uncertainty is defined as the entropy of the difference signal between the original and reconstructed one,

$$F_L(X) = E(X - \tilde{X}_L). \tag{12}$$

Here, E denotes the entropy calculation and again L denotes the iteration in the sparse representation process.

The RR-IQA model is finally defined as the combination of primary information and uncertainty, which are both characterized with sparse representation. In particular, with two images X and Y, which correspond to the original image and the distorted version, the quality measure is defined as

$$Q = EoP_L(X) \cdot F_L(X) - EoP_L(Y) \cdot F_L(Y). \tag{13}$$

As such, the features extracted from the original image X are transmitted and compared with those of Y, such that one value is required to be transmitted to the receiver side, which greatly facilitates the application of the RR-IQA model. The experimental results of the RR-IQA model are listed in Table 1, where the RR-IQA methods such as RRVIF [42], OSVP [43], ROCB [44] and WNISM [45], and the FR-IQA metrics such as PSNR and SSIM [2] are compared. The performance is evaluated based on Pearson linear correlation coefficient (PLCC), Spearman's rank correlation coefficient (SRCC), Kendall's rank correlation coefficient (KRCC), Root mean-squared error (RMSE) and mean absolute error (MAE). It is observed that the RR-IQA model achieves promising performance in terms of both prediction accuracy and monotonicity.

TABLE 1. Performance Comparisons of Visual Quality Prediction Based on LIVE Image Dataset.

	PLCC	SRCC	KRCC	RMSE	MAE
SSIM [2]	0.9042	0.9104	0.7311	11.669	9.228
PSNR	0.8723	0.8756	0.6865	13.360	10.509
RRVIF [42]	0.7543	0.7246	0.5438	17.937	13.675
OSVP [43]	0.8201	0.8218	0.6275	15.633	12.261
ROCB [44]	0.8866	0.8822	0.6966	12.636	9.853
WNISM [45]	0.7512	0.7599	0.5697	18.035	14.020
EoP Based [12]	**0.9146**	**0.9157**	**0.7418**	**11.050**	**8.731**

In addition, the concept of EoP has also been extended in various ways, such that they can be successfully applied in the IQA model. In [13], the ℓ_1 norm instead of ℓ_0 norm is used in the calculation of EoP, and it is interesting to observe that the EoP curve with such modification is more consistent with the perceptual quality measure SSIM [2]. As such, the perceptual stereoscopic image quality assessment method is derived. In [14], the visual primitives are classified into DCprimary, sketch and texture, and the corresponding entropy of classified primitives (EoCP) are calculated. In this manner, the differences of EoCP are used as the feature distance to characterize the perceptual loss. In [15], the EoCP is also applied in the stereoscopic IQA scheme, where the EoCP as well as the mutual information of classified primitives (MIoCP) are used in the quality prediction. In particular, the MIoCP is obtained by the two-view images to indicate the binocular cue.

As a natural extension of EoP, in the future EEoP may also play important roles in visual perception tasks, especially for the near-threshold JND profile estimation and supra-threshold IQA algorithm development. Moreover, it is also envisioned that more ways will be found with EoP and EEoP to benefit various IQA tasks, such as 3D synthesized view, contrast, as well as other relevant IQA topics.

IV. OUTLOOK

It is apparent that the sparse representation based visual information evaluation possesses many favorable properties. However, as one of the first attempt in this research topic, although it has demonstrated promising performance in various visual computing tasks, accurate and efficient visual information quantification is still in its infancy stage. While artificial intelligence is still quickly evolving, deep neural network has been shown to be advanced methods in learning discriminative prior models for natural images [65]. As such, it is natural to investigate the visual information evaluation in the context of deep neural network, which has also been verified to be highly correlated with the cognitive process of the human visual system [66], [67].

In particular, powered by the deep neural network, the current approach can be improved from the following perspectives. Firstly, the deep features instead of the primitives are extracted for visual information evaluation, which provide a more intuitive way in combining the psychological process in the HVS and visual information processing. Secondly, with the flexible representation of the deep neural networks, instead of the primitives, the features which correspond to the coefficients in sparse representation, are used in visual information evaluation. As such, the extracted information are more meaningful, leading to more robust evaluation of visual entropy. Finally, the deep neural network enables adaptive perceptual scale in computing the visual entropy, such that the perceived information can be adaptively computed with the dynamic viewing conditions and image content. However, one important issue of deep learning is that there does not exist a generic deep model that is perfectly designed and trained. As such, the accuracy of visual information evaluation may get improved gradually with the evolution of deep learning methods. This poses new challenges to visual research and opens up new space for future exploration.

Another meaningful research topic is to systematically develop the evaluation framework for validating the visual information prediction methods. In contrast with other visual computing tasks, it is difficult to obtain the ground-truth of the visual information. Therefore, a widely accepted evaluation protocol is necessary in this scenario. Moreover, regarding the application of EoP, most of the efforts focus on the perceptual visual quality assessment, and much less work has been dedicated to the visual analysis tasks. In the future, how the visual information evaluation could benefit the high level visual analysis should also be further investigated.

V. CONCLUSION

In this paper, we review recent findings on visual information evaluation based on sparse representation, and bridge the relationship between visual information and primitive representation with the concept of EoP. More specifically, the design philosophy of EoP is discussed, and the distinct properties of EoP are analyzed. It has also been demonstrated that the EoP can be successfully applied in a wide spectrum of applications such as visual quality evaluation and JND estimation. In the future, it is expected that the intelligence-oriented visual information evaluation can play more important roles in the visual processing and communication, and impact the new development of future visual-related technologies.

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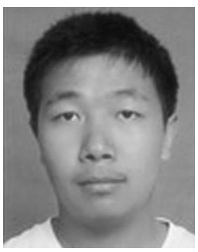

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