A Survey of Perceptual Image Processing Methods

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Abstract

Perceptual approaches have been widely used in many areas of visual information processing. This paper presents an overview of perceptual based approaches for image enhancement, segmentation and coding. The paper also provides a brief review of image quality assessment (IQA) methods, which are used to evaluate the performance of visual information processing techniques. The intent of this paper is not to review all the relevant works that have appeared in the literature, but rather to focus on few topics that have been extensively researched and developed over the past few decades. The goal is to present a perspective as broad as possible on this actively evolving domain due to relevant advances in vision research and signal processing. Therefore, for each topic, we identify the main contributions of perceptual approaches and their limitations, and outline how perceptual vision has influenced current state-of-the-art techniques in image enhancement, segmentation, coding and visual information quality assessment.

Keywords: Human Visual System, Image Quality, Contrast, Perceptual Masking, Segmentation, Noise filtering, Enhancement, Coding, Quantization

1. Introduction

The extensive use of digital visual media in our everyday life and their inherent presence around us, necessitates for the development of smarter and more efficient methods for modeling, analysis, processing and communication of visual information. Machine vision techniques progressed so much and were able to perform tasks that one could only dream of a few years ago; thanks to smarter algorithms, a huge increase in processing power, storage capabilities and communication bandwidth available in today's computers and networks. Nevertheless, these techniques fall short of our expectation when compared to the ease with which the human visual system (HVS) deals with complex scene analysis, processing and abstraction. Therefore, we are witnessing a growing interest in HVS inspired approaches for digital visual information modeling, analysis, processing and communication. The salient characteristics of the HVS can be exploited in the design of novel methods for image processing and machine vision. For example, the perceptual irrelevancy and visual masking effects can be exploited to improve image compression and filtering algorithms. On the other hand, the understanding of processing and coding visual information by the HVS may help one to develop new perceptual approaches that may overcome the limitations of existing signal processing based methods.

The HVS is a complex system dominated by a retinotopic organization, parallel processing, feedforward, feedback and lateral connections. This article, however, does not concern the structural or functional organization of the HVS. The focus is rather on the perceptual aspects of human vision. Section 2 introduces the main perceptual characteristics that have been largely exploited in the field of image processing. It briefly describes the concept of contrast, visual masking, contrast sensitivity function, and frequency selective channels. Section 3 presents an overview of image enhancement methods, including denoising techniques, contrast enhancement methods and artifact reduction approaches. Section 4 describes perceptual image segmentation algorithms and classifies them into region-based, edge-based and perceptual grouping based approaches. The improvement of image coding methods based on perceptual approaches is tackled in Section 5, focusing on perceptual lossy compression. Section 6 is dedicated to some important issues regarding quality assessment of visual information. The paper ends with some concluding remarks presented in section 7.

2. Perceptual Characteristics of the Human visual system

Over many decades, the understanding of the human visual system (HVS) has attracted the curiosity of many researchers working in image processing and machine vision. Very often, however, the models used in computer vision and image processing are simplifications derived from psycho-physical experiments. In the following subsections, we describe the basic human vision characteristics that have been largely exploited in different image processing tasks such as *contrast enhancement*, *visual masking*, *contrast sensitivity function* (CSF), and *frequency* and *orientation selectivity*. Biological interpretation of the mechanisms underlying the different visual phenomena considered in this article is beyond the scope of this article. For a more comprehensive treatment of visual perception the reader is referred to [1] and [2].

2.1. Image Contrast

Contrast is one of the most important factors to consider for image analysis and processing. However, the definition of contrast is still controversial and there is no consensus on how to define and measure objectively the perceptual contrast. For optical images, contrast refers to the ability of the human visual system to detect the luminance difference between two or more stimuli. The contrast depends on many physical and psycho-visual factors [2]. Many experiments and studies have been conducted in search for an objective contrast measure that is consistent with the perceptual sensitivity of the HVS. Weber (1834) was the first to investigate the visual discrimination ability of the

HVS. Many years later, Fechner (1861) formulated more explicitly the empirical law of Weber and proposed methods for measuring the discrimination ability of the HVS based on the notion of *Just Noticeable Differences* (JNDs). The first physical measure of contrast was then expressed as the relative variation of luminance. Another measure of global contrast was proposed by Michelson in 1927 [3]. This measure was introduced to quantify the visibility of optical fringes. While this contrast definition has no link with the HVS, it has been widely used in many studies, including psycho-visual experiments such as the measurement of contrast sensitivity function [4]. In 1944, Moon and Spencer considered the case of a target on a non-uniform surround and proposed a more realistic measure of contrast [5].

All these seminal experiments contributed much to our knowledge of how the HVS perceives global contrast in some limited environment. However, for natural and complex images local contrast measures need to be defined to account for non-stationarity and local structures of the signal. Since the early pioneering works of *Weber* and *Fechner*, many studies have been conducted and several measures of local contrast have been proposed, which aim to mimic the key psychophysical characteristics of the HVS [6]-[9]. *Peli* was the first to introduce frequency in the measurement of contrast in both complex and natural images. Following *Peli*'s reasoning, *Winkler* and *Vandergheynst* proposed an isotropic contrast measure based on directional wavelet decomposition [8] to account for the energy responses of both in-phase and quadrature components. It has been shown that this new contrast measure overcomes some limitations of *Peli*'s definition. The anisotropy selectivity of the HVS was taken into account in defining a band-limited local contrast in [10]. These studies highlighted the need for defining a contrast where both the directional and frequency selectivity are taken into account. Many other contrast measures inspired by *Peli*'s approach have been proposed [8]-[11]. However, the extension of contrast measurement to color images has attracted less attention. One of the difficulties is related to the fact that the color contrast is linked to color constancy phenomenon [12], which is not well understood. A color contrast analysis based on a model of the influence of color perception and the interactions between local and global spatial structures of the image was presented in [13]. In [14], a multilevel approach based on *Rizzi*'s method was proposed to measure perceptual contrast in color images.

Although the contributions of the chromatic channels and spatial information have been considered in the computation of local contrast, to the best of our knowledge, there is no comprehensive model that allows the prediction of global contrast from the local contrast measures; though, some attempts have been made to derive such models [11], [14]-[16]. The basic idea of these approaches is to compute a local contrast at various spatial frequencies and then derive the global contrast by using a weighting process. However, there is no finding from the HVS or underlying visual model to support such operation. The study performed in [16] revealed also the difficulty in predicting the global impression of contrast in natural images.

2.2. Visual Masking

Visual masking refers to the inability of the HVS to detect one stimulus, the target, in the presence of another, the mask. It is a perceptual phenomenon that has been studied extensively since it was first observed in the 1960's. The visibility of the target depends on many factors, in particular frequency, orientation and contrast of both the mask and the target. The modeling of this phenomenon has been carried out on some simple stimuli such as sinusoidal patterns. *Legge* and *Foley* performed extensive experiments on some simple visual scenarios [17]. They studied the threshold contrast necessary to detect the target when varying the contrast and frequency of the mask. They established an empirical power law relating the target threshold contrast to the mask contrast. Other more elaborated masking models have also been proposed [18]-[20]. A comparative study of some masking models can be found in [20]. For a more extensive discussion on this important phenomenon, the reader is referred to [17]-[20].

2.3. Contrast sensitivity function

The contrast sensitivity of the HVS does not depend only on the relative luminance between the background and the stimulus, but also on many other factors, such as spatial frequency, size, color, and orientation of stimulus. The contrast frequency sensitivity of the HVS was investigated by *Robson* and *Campbell*, among others, in the early 1960's [21],[22]. It was found that the HVS acts roughly as a band-pass filter. It was also observed that while the temporal and spatial sensitivities are independent at high frequencies, they are inseparable at low frequencies. The early studies concentrated mainly on luminance contrast sensitivity. The study of the chromatic CSF (CCSF), on the other hand, is more complex; few studies have been devoted to it, which revealed that the CCSF is rather different from the achromatic CSF [24]. Some practical methods for measuring the CCSF have also been proposed [23].

2.4. Frequency and orientation selectivity

Since the pioneering work of *Hubel* and *Wiesel* [25], many studies have been devoted to the understanding of the functional architecture of the primary visual cortex of mammalians [26]-[28]. These studies and other findings revealed the existence of neurons that are sensitive to orientation, size and spatial frequency. It is now acknowledge that the HVS possesses both orientation selectivity and spatial-frequency selectivity. To mimic this multi-channel characteristic of the HVS, some transforms have been proposed for image analysis and coding [29]-[31]. In particular, the *cortex transform* introduced by Watson was found to be effective in many applications such as image coding, image quality assessment and texture analysis [32]-[34].

2.5. Information processing in Visual System

The human visual organs use retina in the eye to collect and process visual information. The vast number of interconnected neurons in retina transforms visual stimuli into nerve impulses representing both static and dynamic temporal imagery [108]. The retina samples visual imagery at more than 126 million spatial locations using a layer of photoreceptors comprising of rods and cones [107]. Rod and cone are synapsed by bipolar and horizontal cells due to the lateral inhibition characteristic of the photoreceptor connections. This causes contrast enhancement in the visual imagery. The next layer in the retina comprised of Amacrine cells modulates the outputs of the bipolar and horizontal cells. Finally, the Ganglion cells connect the retinal output to the optic nerve. Ganglion cells are also responsible for motion anticipation [104]. Early works suggest that the retina approximates the Laplacian edge detector and adaptive low-pass filtering resulting in noise reduction [105].

There are three primary visual pathways such as P, M and K-koniocellular that terminate at the striate visual cortex (V1), and process information in parallel. Each of these areas in primary visual cortex (V's) maintains one processed and topographically correct image map of information that falls on the retina. There appears to be some cross-talk among the channels at various cortical levels. According to the concept of columnar organization, the neighboring neurons in the visual cortex have similar orientation tunings and consequently form an orientation column [106]. It has been known that the initial phases of neuron responses encode the location of visual stimuli whereas the later phases encode the stimulus orientations. Temporal edge location and its orientation at the neuronal level in the primary visual cortex may be used for the parallel-sequential image processing tasks such as segmentation under control of visual attention.

3. Image enhancement

Image enhancement is probably one of the most extensively studied problems in image processing. There are many factors that affect the quality of the acquired, transmitted or reconstructed image. Some factors are directly related to the image acquisition process, such as the illumination, whereas others are related to the physical properties of the sensor and the observed scene. The perceptual image quality is also affected by the common limitations of coding and transmission technologies. In this section, we briefly describe perceptual image enhancement in its broadest sense, with a focus on three of the most widely studied problems: image denoising, contrast enhancement and coding artifact reduction.

3.1. Image denoising

The visibility of noise in images is an important issue that has been well investigated. However, little attention has been paid to the understanding of how the HVS perceives noise in natural images. The HVS is able to discriminate very quickly between two levels of noise in a given image. Image denoising is one of the most widely studied problems in image processing. The main difficulty is how to reduce noise while preserving some important image structures such as edges and fine texture details. Although, many interesting approaches have been proposed to address this difficulty, the problem is still open. Indeed, in many cases there is still a large gap between the predictions of the theoretical models and the empirical results from human observation. The main difficulty is due to the lack of an effective measure that controls the effect of denoising on texture and fine details as perceived by a human observer. For example, the SNR (signal-to-noise ratio) does not reflect the level of denoising as perceived by a human observer. Incorporating some characteristics of the HVS appears as a promising solution to this difficult problem.

In [35] a perceptual nonlinear filter based on local contrast entropy was proposed. The idea is based on the fact that additive noise increases the local contrast entropy. Therefore, by decreasing the local entropy at the neighborhood of each pixel, a smoothing effect ensues. The performance of the method was evaluated on gray-tone images with additive white Gaussian noise (AWGN) and salt&peper noise. The results show that the method compares favorably in both objective and subjective image quality as well as in terms of computational speed, compared with classical and weighted median filters. The idea of exploiting the local contrast for noise filtering was later pursued in [36], but with a more advanced perceptual model of the HVS. This perceptual approach incorporates some characteristics from the early stages of the human visual system. A nonlinear filtering approach based on the *Holladay* principle and, *Moon* and *Spencer* contrast [37] was introduced and evaluated on gray-level images [37] . The noisy pixels were filtered using a decision rule based on the optical *Just Noticeable Contrast* (JNC) defined in *Moon* and Spencer model. The performance of the model was evaluated on some typical images contaminated by AWGN (additive white Gaussian noise), and compared with some other nonlinear filtering methods. However, the minor performance advantage does not justify the additional computational complexity. One of the main advantages of this model, though, is that the denoising level can be controlled by tuning only a single parameter. Later, the multi-resolution concept was introduced for reduction of perceptual irrelevancy based on the JNC model [38]. However, the authors did not provide any measure related to the noise visibility. Furthermore, the consistency of the method is demonstrated on a gray-level image only.

In [39] a perceptual variational framework was proposed for color image denoising. The method is based on anistropic diffusion and exploits some properties of the HVS, especially edge detection mechanisms in color perception. The image is analyzed and processed in the perceptually uniform color space CIE-La*b*. The enhancement is then formulated as an optimization problem with a color consistency constraint to avoid over-diffusion of color information. The method compares favorably with the classical *Perona-Malik* filtering technique; however, it is computationally complex and requires at each iteration the evaluation of some parameters in the scale-space. More recently, a similar method based on TV variational model and some simple characteristics of the HVS has been proposed for color image denoising [40]; here, the diffusion parameter is adaptively selected according to noise visibility. More recently, it has been shown that incorporating the perceptual saliency in a variational framework can improve image denoising performance [49]. It was reported that the proposed method prevents some artifacts, such as staircase effect, without affecting the perceptual quality of other salient features.

There are many other methods that implicitly exploit some properties of the HVS for color image denoising. In [41], the image is decomposed and processed in the perceptually color uniform space using bilateral filtering. To avoid color distortions that may result from filtering, only perceptually similar colors, as measured in the CIE-Lab space, are taken into account in the averaging operation. A new approach to color image denoising based on wavelet decomposition and the CSF was proposed in [44]. In this approach, the CSF is applied in the CIELAB color space. The method was found to outperform two other wavelet-based filtering techniques, in the presence of AWGN, using three subjective and objective metrics. Though the method seems to be interesting, it is compared to only some wavelet-based methods.

In [42] the authors introduced a perceptual learning-based approach for image denoising. The idea is to combine a blind noise parameter estimation with the BM3D (Block-Matching and 3D) denoising algorithm [43]. The input noise parameter used in the BM3D method is then estimated using a learning process based on natural scene statistics and image quality assessment. The proposed approach statistically outperforms the BM3D algorithm. However, the slight improvement in some cases does not seem to justify the additional computational complexity over the BM3D algorithm. Another adaptive perceptual approach based on non-local means (NLM) filtering was introduced in [45]. In this approach, the anisotropic weighting function for the NLM denoising filter is adapted to the local perceptual content of the image. The idea is based on the observation that image noise is highly noticeable in regions with few perceptually significant characteristics and masked in textured regions. A perceptual measure that accounts for the shape and orientation of the local structures is then computed at each pixel and used to tune the spreading factor of the weighting function. However, the method was only compared with NLM filtering. Furthermore, the relevance and the use of the perceptual measure was not clearly explained. In [46] a spatial adaptive denoising method for raw CFA (Color Filtering Array) data acquired by CCD/CMOS image sensors was introduced. It was shown that by taking into account the statistical characteristics of sensor noise and some simple features of the HVS, efficient denoising could be achieved. In this approach, the smoothing filter is adapted to the noise level and the image texture. But this method is quite complex and the results depend on many parameters and tunable thresholds. Furthermore, the results are evaluated in terms of PSNR; whereas, the method is based on some HVS characteristics. A comparison with other HVS-based methods based on some perceptual measures would have been better.

There are also other denoising methods where the characteristics of the HVS are exploited indirectly through some perceptual measures [47]-[48]. In [47], the *structural similarity* (SSIM) index was used to measure the similarity between patches used in the weighting function. However, the SSIM is a full reference image quality measure and as such cannot be used directly since the original image is unavailable. To overcome this difficulty, the noise is first estimated from the noisy observed image. Then an estimate of noise-free patches is performed by subtracting the noise from the observed image; further adjustments of some SSIM parameters are necessary before filtering is performed. While it outperforms NLM filtering, the method depends on many parameters and seems ineffective in the case of very low SNR. Furthermore, during the estimation of similar patches, it is difficult to assess how much noise still remains in the filtered image. In [48], a similar method where an image content metric based on SVD (singular value decomposition) and some local image features was introduced. It was shown that this metric is well correlated with noise, contrast and sharpness. The authors claimed that this metric could be used to optimize the parameters for any image denoising method. However, as in the previous method, the noise parameter is assumed to be known or can be estimated from the noisy image. This makes the method dependent on the noise estimation method, and hence it may fail in the case of multiplicative noise or low SNR images.

3.2. Contrast enhancement

The main objective of contrast enhancement is to improve objective or perceptual quality of a given image so that the features of the transformed image become more visible than the feature of the original image. Contrast enhancement can be expressed as an optimization problem where the objective is to maximize the average local contrast of an image. However, a mathematical formulation of contrast enhancement that doesn't incorporate some relevant properties of visual perception tends to produce unrealistic results and unpredictable visual artifacts. Historically, it is believed that *Gabor* was the first to suggest a method for contrast enhancement [50]. In the same period, *Land* and *McCann* introduced, independently, the Retinex theory [51]-[52], which has gained increasing interest in the image processing community. This theory is modeled on perception of lightness and color in human vision. Land suggested decomposing the lightness into three distinct components in order to obtain photometric invariants of the observed object surface. Two decades after the publication of the first paper on Retinex, *Land* introduced the human perceptual receptive field structures in the model [53]. Over the past two decades, many improvements have been introduced by incorporating new findings from the HVS, color science and some new image representations such as multi-scale models [54]-[57]. It is worth mentioning that Retinex has been mainly developed for tackling the color constancy problem. The Retinex model produces also contrast enhancement and illumination compensation of lightness and color. Besides Retinex theory, many perceptually based approaches have been proposed for contrast enhancement. Here we give a brief description and discussion of some representative HVS-inspired contrast enhancement methods.

Contrast enhancement (CE) methods can be classified by means of various criteria. One way to classify CE techniques is to divide them into two classes, depending on the domain where the image is analyzed and processed (spatial domain or spatial-frequency domain) and the way of transforming the contrast (direct or indirect) [58]-[59]. Direct methods involve mainly three steps. The first step involves the estimation of the original contrast. In the second step, the contrast is amplified using a mapping function [59]-[60] or an optimization function as done in [61]. Finally, the pixel intensity value is transformed according to this new contrast value.

Although much research effort has been devoted to the development of methods for contrast enhancement for gray-tone images, there has been less effort devoted to color images. Although the basic notions of color perception are relatively well understood, processing color images is not an easy task. This is due to the complex interaction between many physical and psycho-visual factors that influence color perception. Indeed, processing color images may lead to unpredictable results. Particular care must be taken when processing the color components. One of the most studied problems in color processing is color constancy. The Retinex model is one of the first appealing solutions for solving this difficult problem. Since its introduction, many methods based on Retinex theory have been developed for color contrast enhancement [61]-[63].

An interesting perceptual approach for contrast-enhancement of gray-level and color images was introduced in [64]. The contrast enhancement problem is posed as a constrained optimization problem using a perceptual criteria derived from Weber law governing the supra-threshold contrast sensitivity of the HVS. The global function to be optimized is derived from the perceived local contrast; it expresses the relative global increase of contrast. This function is maximized under some constraints such as saturation and color shift. However, for gray-level images, the method is compared only to some classical histogram-based methods. For color images, the method is compared to multi-scale Retinex, a curvelet-based enhancement method [65] and *Fattal*'s method [66]; although, the comparison is mainly based on the optimization function used in the contrast enhancement method.

In [75], a contrast enhancement method was introduced based on some basic characteristics of the HVS. The basic idea is to segment the image intensity into three regions, namely *De Vries Rose* region, *Weber-Fechner* region and the saturation region. The enhancement is then adapted to each region, thus avoiding any over-enhancement or noise amplification. The method is extended to human visual system based multi-histogram equalization approach to create a general framework for image enhancement. The authors also proposed a quantitative measure of image enhancement, restricted to gray-level images. However, the proposed objective measures do not incorporate any relevant perceptual features of the HVS. In [67], an HVS-based local contrast enhancement method for the visualization of highly contrasted images was introduced. The idea is to segment the image into light and dark regions and then process independently the luminance and color components according to this segmentation. To overcome the limitations of the dynamic range of cameras and display devices, another HVS-based method for image enhancement was proposed in [68]. The authors developed some interesting solutions inspired by the way the hue and color saturation are processed by human perception under critical illumination environments.

It is worth mentioning that *tone mapping* (TM) technique can also be considered as another indirect approach for contrast enhancement. For example, the TM methods proposed in [69]-[70] yield good results in terms of color contrast enhancement. This is mainly due to the fact that these methods try to mimic the adaptation and local contrast enhancement mechanisms of the HVS.

Perceptual contrast enhancement in the compressed domain was investigated in [71]-[72]. The developed method is based on *Peli*'s contrast measure and the contrast enhancement method developed in [58]. Enhancing contrast in the compressed domain offers many advantages. Indeed, many images and videos are available in compressed form. It is therefore more efficient to process the data in their compressed form to save computational overheads when performing the inverse transform. The other advantage is to exploit the frequency distribution of the coefficients in the design of the enhancement process. But, all the JPEG compressed domain methods suffer from coding artifact amplification, especially in homogeneous regions. In [73], a more elaborated method for enhancing gray-level and color images was developed. The idea of processing images in the compressed domain has also been extended to the Retinex model in [74]

3.3. Coding artifact reduction

In spite of the rapid development of huge capacity and high speed storage devices, lossy compression techniques of multimedia data, and especially images, are still increasingly used. However, many of the proposed lossy image compression methods suffer from some drawbacks at low bitrates [76]-[78]. In the following, we focus on the two well-known annoying artifacts, namely blocking and ringing effects. Block based compression methods suffer from blocking effect which results in visible discontinuities across block boundaries. This is mainly due is to independent processing of blocks. In JPEG it is due to independent coarse quantization of blocks. Although blocking effects are reduced in wavelet transform based compression methods, such as JPEG 2000 [76] and SPIHT [77], another annoying effect called ringing appears around contours [78]. This is due to the coarse quantization and truncation of the high frequency wavelet coefficients. This effect is generally accompanied by blurring distortion around contours and fine details [78]. Some metrics have been proposed to estimate such distortions [79]-[80] However, blocking and ringing are difficult to model and to suppress. Many ad hoc methods have been proposed in the literature to reduce these effects [81]. In this survey, we limit the discussion to some techniques based on some relatively well-understood HVS properties.

In [84], the authors proposed a deblocking approach based on HVS properties, dedicated to highly compressed images. The approach is based on a combination of edge detection, activity masking and brightness masking. Depending on the visibility level defined by a threshold, a processing step is applied on the block in order to reduce the artifact. A technique of blocking artifacts reduction based on fuzzy edge-sensitivity has been proposed in [85]. It relies on orientation and frequency selectivity, two essential characteristics of the HVS. Filtering is then applied by integrating a fuzzy logic technique. *Wong* et al. proposed a deblocking algorithm which relies on a human perceptual significance based on local phase characteristics [88]. The local phase coherence is then used to adapt the deblocking process.

In [83], *Chetouani et al.* proposed a strategy for reducing the visibility of blocking artifacts without knowledge of the method of compression. A visibility map is obtained by analyzing the visibility of the borders of adjacent regions using the CSF, Cortex transform and masking. Finally, the deblocking process is adaptively applied depending on perceptual visibility of the region. A similar approach has been proposed in [87], where the visibility map is replaced with a map computed by summing the horizontal and vertical profiles of gradient vector magnitudes. The obtained map is then used to feed a recursive filter designed to reduce the blocking artifacts. The proposed method outperforms the state-of-the-art methods in terms of perceptual quality but at the expense of an increased computational complexity.

Besides works dedicated to blocking artifact reduction, several authors focused on approaches combining reduction of ringing and blocking. For instance, *Do et al.* proposed to use the JNC and luminance adaptation as perceptual properties in order to balance the total variation regularization [86]. The latter is constrained by information extracted from the image. Recently, the same authors proposed an approach consisting of three steps: (i) blocking-ringing artifacts detection, (ii) perceptual distortion measure and (iii) blocking-ringing artifacts reduction. Several other approaches have been developed, many of them are dedicated to video, which is not the focus of this survey [82, 90]. Through this brief survey of recent works on coding artifacts reduction methods, it appears that the use of some simple HVS characteristics in the design of the algorithms and the artifact measures good results could be achieved. However, more elaborated models that can account for other relevant HVS features and other coding artifacts are still missing.

3.4. Tone mapping and enhancement of High Dynamic Range Images

Because of the technical capabilities in the 90s, the 8-bit representation of visual data has been adopted for various technologies as for capture and display devices. Consequently, the range of tones being recorded or displayed became very limited. However, the natural world provides a wide range of colors and tones to our visual system allowing thus an adaptation to obtain the best appearance. This visual appearance of natural scenes is highly dependent on perceptual effects happening in the early stages of human vision. To solve the aforementioned limitation, a concept (i.e. format) called High Dynamic Range (HDR), opposed to Low Dynamic Range (LDR), has been developed to account for a higher range of tones. This field is attracting interest from various applications. Nevertheless, it is still mandatory to narrow the dynamic range to be able to visually explore the content. This operation, known as *tone mapping*, relies on observer models that allow the transformation of the luminance of a scene into a desired display image.

TMOs (*Tone Mapping Operators*) have been first used in computer graphics community where *Trumblin* and *Rushmeier* [91] introduced a pioneering framework consisting of the combination of a scene observer model with an inverse display observer one. Theoretically, when the framework is properly constructed such operators should guarantee the realism of the displayed image. Nonetheless, visual appearance is still, to date, a very complex problem that can only be approached thanks to computational models. Several TMOs have been developed since then and can be classified as local or global operators [92]. Global operators apply the same operation to every pixel of an image while local ones adapt their scales to different areas of an image. Most of the TMOs can be generalized as a transfer function taking luminance or color channels of an HDR scene as input and processing it to output pixel intensities that can be displayed on LDR devices.

Perceptual models have been widely used in tone mapping. For global approaches, *Wards et al.* proposed a TMO based on the idea of preservation of perceived contrast relying on the *Blackwell*'s psychophysical contrast sensitivity model [93]. At the display side, the monotonic tone reconstruction avoids the change of scene contrast. Based on threshold visibility, color appearance and visual acuity, *Pattanaik et al.* proposed tone mapping operator where the stimulation measured at the retina is used for adaptation of every image pixel in addition to the supra-threshold colorfulness [94]. Dealing with color appearance, *Ferwerda et al.* [100] measured changes in threshold of this appearance by using separate TVI (threshold versus intensity) functions for rods and cones and interpolation for the mesopic luminance range. In the same vein, *Reinhard* and *Devlin* [101] based their development on a computational model of photoreceptor behavior with a chromatic transform allowing a flexibility of the white point.

In local approaches, a contrast approximation similar to *Peli*'s local band-limited contrast was used by *Reinhard* et al. [95] and *Ashikhmin et al.* [96]. In [95], a global tone mapping is applied to reduce the range of displayable luminance. In order to have different exposures for different areas of the image, a photographic dodging and burning technique is applied. The automated version presented in [98] takes advantage of low contrast region detection thanks to a center-surround function at different scales. The contrast used in the previous approaches can be easily replaced by the one defined by *Mantiuk et al.* [97] for HDR images. As stated by the authors, the pyramidal contrast representation ensures proper reconstruction of low frequencies and does not reverse global brightness levels. Moreover, the introduction of a transducer function, giving the response of the HVS for the full range of contrast amplitudes, is especially useful for HDR images.

Recently, two works have been dedicated to the evaluation of TMOs. In [102], authors conducted a psychophysical experiment in order to discriminate seven TMO approaches (3 local and 4 global) using attributes such as contrast, brightness, details reproduction in dark and bright regions, and naturalness. Similarly, in [103], authors run a psychophysical experiment involving several criteria on fourteen TMOs. The result of this work was the definition of an overall image quality function dedicated to tone mapping described as a linear combination of the used attributes.

4. Perceptual image segmentation

The objective of image segmentation is to obtain a compact representation from an image, sequence of images, or a set of features. Robust image segmentation is one of the most critical tasks in automatic image processing. Image segmentation has been an active field of research for many decades [109, 110]. Many surveys on image segmentation have appeared in the literature [110][112]. Image segmentation methods can be roughly grouped into three categories, as suggested by Fu and Mui [110]: (i) region-based segmentation, (ii) edge-based segmentation, and (iii) feature clustering. Here we focus only on perceptual approaches for image segmentation.

Perceptual image segmentation involves extraction and grouping of perceptually relevant information for complex scene segmentation [113]. Though human perception of images is heavily influenced by the colors of the pixels, the perception of each pixel also depends on neighboring pixels. Similar to any segmentation technique, perceptual image segmentation requires the extraction of low-level image features. These low level features are then correlated with high-level image semantics for efficient image segmentation. For example, the authors in [113] propose low-level image features and segmentation techniques that are based on perceptual models and principles about the processing of color and texture information. The approach is based on spatially adaptive color and texture features and has been proven effective for photographic images including low resolution, degraded, and compressed images. Such perceptual image segmentation models can also help in obtaining more robust perceptual image quality measures [114]. The authors in [114] propose a Segmentation-based Perceptual Image Quality Assessment (SPIQA) metric which quantifies image quality while minimizing the disparity between human judgment and predicted image. One novel feature of SPIQA is that it exploits inter- and intra-region attributes in an image that closely resembles how the human visual system (HVS) perceives distortions.

Another extension of perceptual image segmentation is obtained in [115] wherein Fuzzy sets are defined on the H, S and V components of the HSV color space. The model uses a fuzzy logic model that aims to follow the human intuition of color classification. Experimental results suggest that the proposed algorithm obtains improved classification over other basic color classification techniques, especially in more challenging outdoor natural scene segmentation. In summary, the primary motivation of perceptual image segmentation relates to segmentation using color and texture since imaged objects are often described at perceptual level by distinctive color and texture characteristics [116]. The authors in [116] provide thorough evaluation and review of the most relevant algorithms for image segmentation using color and texture features. Furthermore, SPIQA metric can be used for automated perceptual image segmentation and prediction of image quality simultaneously.

Most perception-based image segmentation techniques primarily involve bottom-up processing. However, top-down feedback of information can modulate the feature processing and clustering appropriately for better image segmentation as shown in Figure 1.

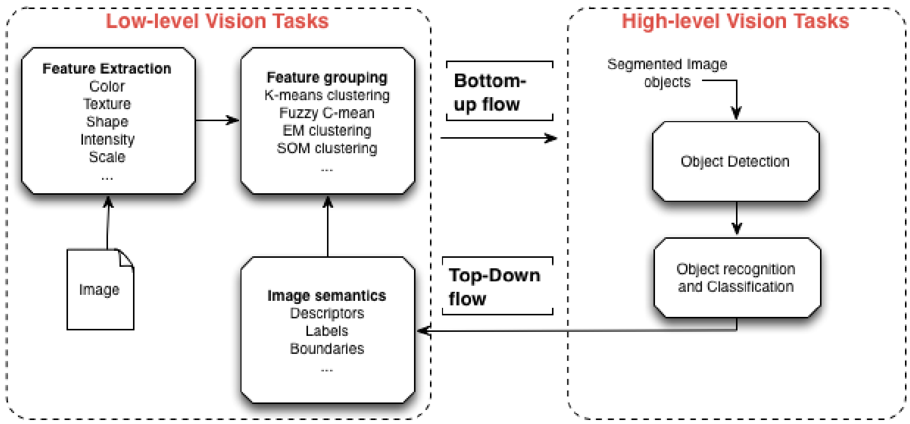

Figure 1: Schematic of Image Segmentation Steps in Visual Information Processing

Figure 1 shows an overall machine-centric visual information processing approach. The schematic includes both low level and high level visual processing tasks. The low level vision tasks involve extraction of different types of features such as color, intensity, shape, texture and scale. These features are then processed further in the visual cortex as discussed above. In the machine centric implementation, different clustering techniques such as k-means, fuzzy c-mean, self-organizing map (SOM), and expectation maximization (EM) are used to cluster the features into segments. The role of image semantics is very important in perceptual image segmentation. Image semantics in the form of descriptors, labels or boundary can help to refine image segmentation. The image segments obtained from low level vision processing are then processed for object detection, recognition and classification steps. These high level vision tasks are processed in the V1 areas with the aid of long term and short memory and attention. This information flow from retina (sensor) to V1 for object segmentation and processing is known as bottom-up information processing. Feedback from the high-level vision processing is also fed back all the way to retina for iterative multi-scale refinement of perceptual image segmentation process. The feedback flow is also known as top-down information flow. Often times effective computational modeling of visual information processing necessitates integration of bottom-up and top-down flows.

4.1. Region-based Segmentation

The region-based segmentation algorithms stem from the fact that quantifiable features inside a structure in an image appear homogeneous. The region-based segmentation algorithms aim to search for the image pixels with similar feature values. Robust region based segmentation in noise is challenging. In the HVS, there are two major stages for information processing, segmentation and recognition [117]. The first stage is early vision that involves focusing of attention in visual system to obtain the necessary information. The subsequent processing step in visual system then segments out potential candidates from noisy backgrounds for high-level processing. The second stage of recognition is identification. After information is preprocessed for segmentation in the first stage, much smaller amount of information is sent up in the visual stream for identification. During identification stage, knowledge from higher-level cortex is fed back to revise the information processing in early vision. Many theories of object segmentation involve comparing visual information with several characteristic views of object stored in memory. Such theories implicitly assume that stages of visual processing have solved visual segmentation among other tasks. Different biologically inspired models have been suggested in literature for image segmentation.

Human visual perception can be very resilient in segmenting objects from noisy images. Burgi and Pun proposed a human perception inspired static image segmentation method in noise [118]. In this method the authors use the idea of asynchronous processing such that strong luminance elicits reactions from the visual system before weaker ones. The method involves transformation of a static image into a data flow in which information flow attracts attention for object segmentation and detections. However, this method has been evaluated on a very limited set of gray-tone images. Furthermore, the results depends on many tunable parameters. The other weakness of the proposed method is due to the fact that the asynchrony analysis relies on only the pixel intensity and does not incorporate other relevant spatial features. Reference [119] discusses a model of human pre-attentive texture perception that can predict the salience of texture boundaries in gray-scale image. The model attempts to simulate outputs of V1 area of visual cortex for image segmentation.

A novel framework for joint processing of color and shape information in natural images is proposed in [120]. Based on the information processing in the HVS, this work proposes a hierarchical non-linear spatio-chromatic operator which yields spatial and chromatic opponent channels. The authors extend two popular object recognition methods such as the hierarchical model of visual processing and a SIFT bag-of-words approach to incorporate color information along with shape information. They use the framework in scene categorization and segmentation.

4.2. Edge-based segmentation

Edge detection techniques involve characterization of abrupt intensity changes in scenes caused by physical processes in the world. An important goal of edge detection is the reduction of image information for further processing. Early works on edge detection attempted to characterize intensity changes using different types of derivative operators, and at different resolutions (scales) [121]. In one such work, a theory of multiscale edge detection is presented [122]. The authors analyze natural image intensity at different scales using second derivative of a Gaussian filters. The intensity changes due to edge are then represented by oriented primitives called zero-crossing segments. Evidence is given that the zero-crossing representation is complete. They also show that edges in images are spatially localized and these edges arise from surface discontinuities caused by reflectance or illumination boundary changes. Consequently, the zero-crossing segments in different color components are not independent, and rules are deduced for combining them into a description of the image. This description is called the raw primal sketch. The theory explains several basic psychophysical findings, and the operation of forming oriented zero-crossing segments from the output of center-surround filters acting on the image forms the basis for a physiological model of simple cells. Subsequent works investigate the effect on edge extraction when the theory of HVS based thresholding [123] is made to operate on the intensity domain of a grey scale image. The performance of the systems is also quantitatively analyzed using the 'entropy' metric.

Later works on edge based segmentation are motivated by models of the HVS and involves detection of visually relevant luminance features [124]. The technique detects edges (sharp luminance transitions) and narrow bars (luminance cusps) and marks them with the proper polarity. This results in is a polarity-preserving feature map representing the edges with pairs of light and dark lines or curves on corresponding sides of the contour. The algorithm is implemented with parameters that are directly derived from visual models and measurements on human observers. Reference [125] takes into account the basic characteristics of the HVS such as masking the gradient image with luminance and also masking the activity in local image for edge labeling. An implementation of this method on a Canny detector is described as an example. The results show that the edge images obtained are more consistent with the perceptive edge images. In another HVS related approach the authors present a technique exploiting visibility of edges by human eyes [126]. The authors obtain threshold function according to the optical characteristics of the sensor and a contrast sensitivity function. The information is applied to edge detection using a binarization technique. In another complimentary method the authors compute the edge visibility for the HVS [127]. Two important processes in the HVS are taken into account: visual adaptation and contrast sensitivity. The primary contribution is a biologically inspired unified framework which mimics human vision and computes both edge localization and edge visibility.

In more recent works, information used in the edge-based methods combine different image cues from HVS to complete the segmentation. Examples in this category include the watershed algorithms [128]. These algorithms combine the image intensity with the edge information and use the mathematical morphology operations to obtain the segmentation. In the watershed algorithms, gray scale images are considered as reliefs and the edge magnitude is treated as elevation. Watershed lines are defined to be the pixels with local maximum edge magnitude. A region of the image in Watershed is defined as the pixels enclosed by the same line. The segmentation procedure is to construct watersheds during the successive flooding of the gray value relief. Watershed algorithms tend to present over-segmentation problems, especially when the images are noisy or the desired objects themselves have low signal-to-noise ratio. In Reference [129] the authors introduce a HVS-based algorithm which integrates image enhancement, edge detection and logarithmic ratio filtering techniques to develop an effective edge detection method. The algorithm performs well in tracking and segmenting dark gray levels in an image and preserves object's topology and shape.

Finally, clustering is collection of features that belong together. Currently, there is no broad theory available for clustering based segmentation. A broad family of approaches to segmentation involves integrating features such as brightness, color, or texture over local image patches as shown in Fig. 1. Clustering these features using different types of neural network such as SOM and other modeling techniques such as mixture fitting (e.g., EM), mode-finding, or graph partitioning yields segmentation [130]. Threshold-based algorithms generally assume that image regions have distinctive quantifiable features such as the image intensity, texture, color, reflectance, luminance or the gradient magnitude [131]. The procedure of segmentation is to search for the pixels whose values are within the ranges defined by the thresholds. Thresholds used in these algorithms can be selected manually or automatically. Both manual and automated selection of threshold values may need a priori knowledge and sometimes trial experiments. Automatic threshold selection often times combines the image information to obtain adaptive threshold values for edge extraction. Examples include different local and global edge extraction algorithms such as Canny, Otsu, Laplacian, Hough transform and object background models.

Due to noise and partial volume effect in the image, the edges and hence the segments may be incomplete or discontinuous. It is then necessary to apply post-processing techniques such as morphological operations to connect the breaks or eliminate the holes. Object background models, on the other hand, are based on histogram thresholding. These models assumes that there is a uniform background and objects are irregularly placed on this background [132]. Hence, finding an appropriate threshold between object and background obtains background-foreground segmentation. The simple background-foreground segmentation technique can be modified to account for pyramidal structure yielding multi-resolution segmentation [133]. There are many examples where image feature histograms may not have clear separation among foreground and background and hence, the simple thresholding methods may not be effective. Probabilistic methods are good candidates for these cases where image intensity is insufficient for foreground-background segmentation.

In [134], authors propose an automatic thresholding method following inspiration from the HVS which preserves edge structure in images. Edge thresholds based on human visual perception is obtained first, and then these edge thresholds are used to find several edge intervals. From these edge intervals, the threshold value at which most edge information is preserved in the thresholded image is obtained. Another novel thresholding method that uses human visual perception is presented in [135]. The method first utilizes statistical characteristics of an image to choose two gray levels as candidate thresholds by using the properties of human visual perception, and then determines the one having minimum standard deviation sum as the optimal threshold. Choice of candidate thresholds reduces search space of thresholds and accelerates threshold selection.

4.3. Cooperative and perceptual grouping based segmentation

Image segmentation based on spatially adaptive color and texture features following human perception grouping has been active area of research [136, 137]. The image features are first obtained independently, and then grouped to implement an overall segmentation as shown in Fig. 1. Texture feature estimation requires a finite neighborhood which limits the spatial resolution of texture segmentation. The color segmentation, on the other hand, provides accurate and precise edge localization. The authors use an adaptive clustering algorithm for color and texture features to obtain integrated image segmentation. The images are assumed to be of relatively low resolution and may be degraded or compressed.

Reference [138] presents another interesting image perceptual segmentation algorithm driven by HVS properties. Quality metrics for evaluating the segmentation result, from both region-based and boundary-based perspectives, are integrated into an objective function. The objective function encodes the HVS properties into a Markov random fields (MRF) framework, where the JND model is employed when calculating the difference between the image contents. The MRF is attractive for modeling texture and context of images [137]. A modified MRF model, also known as multi-scale random field (MSRF) model [139], uses unsupervised segmentation scheme. MSRF forms hybrid structure of quadtree and pyramid graph for scale representation. EM algorithm is used for solving sequential maximization of a posteriori whose solution calculates the required parameters of MSRF model. Supervised scheme for segmentation is used in [140] wherein the authors apply oriented Gabor filters, inspired by HSV, for extracting texture features. Texture feature vector is represented as Gaussian distribution. A posteriori probability scheme is formulated as Gibbs distribution for assigning a partition label to a pixel. The maximization of a posterior probability is obtained using Hopfield neural network with a deterministic relaxation modeling.

On the perceptual point of view, higher perceptual grouping levels are involved during object detection and recognition tasks. The authors in [141] present an image segmentation model based on visual attention mechanism. The model simulates the bottom-up human visual selective attention mechanism, extracts early vision features of the image and constructs the saliency map. The image is segmented by separating the salient regions and the background. The model builds on Itti-Koch saliency-based models [142]. Reference 35 discusses a model for image segmentation according to the early visual area in primate visual cortex, which combines multiple features to build the prediction of image segmentation for object recognition. The methodology consists of parallel and multiple feature fusion blocks and performs well in figure-ground segmentation.

The segmentation of moving objects is comparatively more challenging. Motion can provide an important clue for perceptual object grouping and hence segmentation. Optical flow is an important cue for moving object segmentation and detection. Without knowledge of the background positions, the background motion may not be computed effectively. Similarly, without knowing the background flow one may not determine which positions belong to the background region. Humans can effortlessly perceive objects in a scene using only kinetic boundaries, and can perform the perceptual grouping task even when other shape cues are not provided. The authors in [144] discusses a biologically inspired model derived from mechanisms found in visual areas in the brain such as V1 and others as suggested in Fig. 1 that achieves robust detection along motion boundaries. The model includes both the detection of motion discontinuities and occlusion regions based on how neurons in visual cortex respond to spatial and temporal contrast. In particular, they show that mutual interactions between the detection of motion discontinuities and temporal occlusions allow a considerable improvement of the kinetic boundary detection and hence segmentation.

The application of human visual attention is implemented in a model to improve the recognition accuracy of character recognition problems known as Completely Automated Public Turing Test to Tell Computers and Humans Apart (CAPTCHA) [145]. The technique focuses on segmenting different CAPTCHA characters to show the importance of visual preprocessing in recognition. Traditional character recognition systems show a low recognition rate for CAPTCHA characters due to their noisy backgrounds and distorted characters. The authors in Ref. 65 use the human visual attention system to let a recognition system know where to focus in presence of noise. The preprocessed characters are then recognized by an Optical Character Recognition (OCR) system.

5. Perceptual coding

The field of still image compression has been the focus of important research efforts for decades leading to the definition of several coding algorithms, where a few of them became international standards. The process started with the information theory introduced by *Shannon* in 1948 [146], the Huffman code in 1952 [147], the Discrete Cosine Transform (DCT) by *Ahmed* in 1974 [148], the arithmetic coding by *Rissanen* in 1979 [149] and finally leading to the widely used JPEG standard (ISO 10918) in 1992 [150] for lossy coding. Since then three other standards have emerged such as JPEG-LS (ISO 14495) in 1998 [151], JPEG 2000 (ISO 15444) in 2000 [152] and JPEG XR (ISO 29199) in 2009 [153]. In the meantime, numerous works have been performed either on defining optimized coding schemes, or introducing optimization processes in mathematical, informational and perceptual domains.

The process of the major part of lossy coding algorithms is performed in three main stages. First, a forward transform is applied on the input image; second, a quantization of the coefficients in the transform domain is performed and finally, an entropy coding is performed to reduce redundancy.

The performance of classical image coding algorithms for reduction of information redundancies and bit budgeting is undoubtedly attractive. Nevertheless, it is by far the only criterion used in benchmarking coding technologies. Furthermore, reduction of statistical redundancies is often not in line with perceptual aspects. It is now clearly established that the reduction of perceptually redundant information, for a given bit-budget, increases the performance while preserving the visual quality. For instance, the human contrast sensitivity indicates that the HVS is not able to perceive spatial frequencies beyond a given cut-off. Therefore, it may not be useful to preserve this information of very high spatial frequency for an image. Human perception has been and still is the focus of many image coding studies for understanding and exploiting some phenomena such as masking and spatial/temporal sensitivity. There are several ways to incorporate human perception into image coding schemes. Nonetheless, as illustrated on figure 2, the quantization is one of the most addressed stage in literature [154]-[176] .

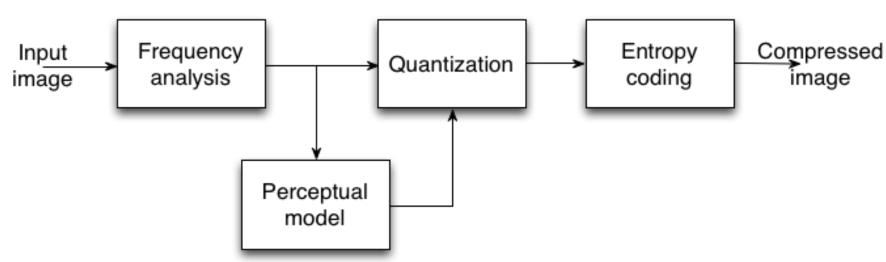

Figure 2: Generic perceptual coder - Quantization optimization.

Several perceptually uniform quantization strategies have been proposed.

For instance, *Ibrahim Sezan et al.* studied the visibility of quantization noise and proposed an efficient model based on their findings [154]. However, the various studies addressed only low dynamic range and specific luminance conditions. Other studies about perceptually optimized quantization have been targeted towards specific transforms. In the following, the exploration of the various perceptual coding approaches are addressed depending on their targeted scheme. For the sake of clarity and continuity, approaches have been grouped, when possible, according to the major image compression standards i.e. JPEG (DCT) and JPEG 2000 (DWT) and JPEG XR. Additional approaches have been addressed separately.

5.1. DCT-oriented approaches

Transform coding is able to achieve optimum statistical compression ratios. Several works have been performed in combining the DCT transform coding and visual perception resulting in a higher compression ratio and good reconstruction of the original image. Many of them addressed quantization of the DCT in order to improve related works (i.e. JPEG) from a perceptual point of view. The motivation came from the fact that the quantization matrix is not defined by the standard. [177] focused on the statistical nature of the coefficients where redundancy have been removed while keeping a good visual quality. *Ngan et al.* [156] relied on the HVS function, of the shape $H(f) = (a+bf)exp(-cf)$ defined by *Nill* in [178], where f is the frequency and a, b, c are coefficient allowing to tune the model, in order to transpose the cosine transform coefficients into the perceptual domain. Similarly, *Safranek* proposed a JPEG compliant encoder that removes perceptually irrelevant coefficients [160]. Supra-threshold image compression has been explored by *Pappas et al.* in [179] for minimizing perceptual image distortion measures that are matched to the HVS. More recently, *Sreelekha et al.* [180] used a CSF thresholding and a masking in the JPEG standard encoding process allowing to remove perceptually insignificant coefficients. These approaches provided some improvement to the JPEG-like compression schemes but the tradeoff between quality and bitrate is often difficult to reach.

An important approach known as *DCTune* has been introduced by *Watson* [157, 158] for visual optimization of DCT-based compression. It relies on luminance and contrast masking to generate quantization matrices adapted to individual images and their viewing conditions. This image dependent perceptual method defines the masked threshold $m_k = \max(t_k, |c_k|^w (t_k)^{1-w})$ as the maximum between the luminance threshold t_k and a non-linear combination of DCT coefficient t_k together with luminance and contrast masking where the exponent w controls the adaptive aspect of the proposed approach. An extension to color images has been given in [159] by using a YCC color space demonstrating thus a more severe compression of chromatic channels while having acceptable visual results. One negative aspect lies in the fact that the quantization matrices and the scalar value of each DCT block are embedded in the codestream resulting in an increase of the compressed image. *Tran* and *Safranek* [161] took into account local variations in masking based on an image segmentation scheme allowing for local adaptation. The drawback of this approach lies in the cost of the segmentation information needed at the decoding side.

The approach proposed in [181] aims at designing a JPEG perceptual quantization matrix based on the rate-distortion algorithm designed by Wu and Gersho and the integration of visual weightings. Macq [182] derived perceptual weighting factors depending on quantization noise introduced on transform coefficients. The extracted weighting factors present the advantage of varying as a function of the display and the viewing conditions while being independent of the image content. *Tong et al.* proposed a perceptual model based on texture and luminance masking properties used for scaling of the JPEG quantization matrix [183]. Therefore, masking is studied through a classification of blocks into plain, edge, and texture similarly to [161]. In [168], authors designed a perceptual quantization table of a DCT-based image coder by taking advantage of the Daly's perceptual model together with a uniform quantizer. To cope with the later, vector quantization has been used for perceptual coding as the approach introduced by *Macq et al.* [184] applying the LBG (Linde-Buzo-Gray) procedure in the DCT domain using an optimization of the perceptually-weighted signal-to-noise ratio. The performance of such an approach is dependent of the nature of the used perceptual metric.

In order to prevent high perceptual errors on individual images, *Malo et al.* proposed to bound the maximum perceptual error (MPE) for each frequency and amplitude in the coder [167]. They used a non-linear perceptual metric based on the contrast sensitivity function leading to the conclusion that bounding the perceptual distortion in each particular block of the image may be more important than minimizing the average perceptual distortion over a set of images. *Höntsch et al.* proposed a DCT-based, locally adaptive, perceptual-based image coder by fixing the objective of minimizing the bit-rate depending of the targeted perceptual distortion [165, 169]. Therefore, masking properties derived in a locally adaptive way based on local characteristics of images, are used. Hence, thresholds of local distortion sensitivity are extracted and used to adaptively control the quantization and dequantization stages of the coding process in order to comply with the initial target. In order to avoid sending side information that increases bit-budget, the estimation of the locally available amount of masking can be performed at the decoder side. The aforementioned approaches achieve an important improvement of compression ratio in comparison to [157] while keeping a similar complexity.

With the aim of optimizing the JPEG color image coding, *Westen et al.* proposed a new HVS model based on a set of oriented filters combining background luminance dependencies, luminance and chrominance frequency sensitivities, and, luminance and chrominance masking effects [185]. In order to cope with the orientation difference of the filters in the model domain and the DCT block transform, they proposed a general method to combine these domains by calculating a local sensitivity for each DCT (color) block. This leads to a perceptual weighting factor for each DCT coefficient in each block.

Different machine learning techniques have been successfully used in image coding. For instance, support vector machine (SVM) has been exploited by

Gómez et al. [186] where an extension of the work described in [187] using an adaptive ϵ-insensitivity has been proposed. The perceptual dimension lies in the fact that constant ϵ-insensitivity is perceptually valid in the spatial domain rather than in the DCT domain.

Recently, *Ma et al.* proposed a perceptual coding algorithm using DCT based on the idea that some macroblocks of the image can be coded at a lower resolution without impacting their visual quality [188]. In this method, more bits are available for the most prominent macroblocks. The downsampled blocks are obtained by minimizing the error between the original and the upsampled blocks in the DCT domain.

5.2. DWT-oriented approaches

DWT compression is often a lossy process and the invisibility of coding artifact is a real challenge. Many works have been devoted to perceptually optimize the wavelet-based coding. For example, the study performed by *Safranek and Johnston* can be considered as one of the early works [155]. It is based on a subband decomposition and quantization step sizes obtained from frequency and luminance sensitivity, and contrast masking. However, for a fixed display luminance, spatial variations in the local mean luminance of the image produce local variations in visual thresholds. An extension of this work is proposed in [189] by using an algorithm that locally adapts the quantizer step size at each pixel according to an estimate of the masking measure. Compared to [155], the methods in [189] offers better performance without requiring additional information. *Lai and Kuo* propose an unconventional wavelet-based compression method where instead of using the amplitude of wavelet coefficients, the contrasts of each resolution are coded [163]. Therefore, the visual error is uniformly distributed over the image and decreases with visual artifacts at low bit-rate.

CSF has been widely used in image coding schemes. For DWT, most of the implementations are based on a single invariant weighting factor per subband. Extensive experiments run by *Nadenau et al.* and described in [164, 190] allowed the introduction of four different ways of integrating the CSF in a JPEG 2000 scheme. Similarly, *Stoica et al.* proposed a weighting approach extracted from CSF that accounts for viewing distance when applying the perceptual optimization in the JPEG 2000 coder [172]. Both approaches improve the visual quality of JPEG 2000 compressed image while increasing the complexity created by the image-dependent optimization. In 2006, *Liu et al.* presented a standard compliant distortion-based JPEG 2000 encoding scheme using a locally adaptive HVS model [173]. This encoding scheme incorporates different masking effects and a perceptually weighted MSE taking into account spatial and spectral summation of individual quantization errors. The major drawback of this approach as well as most of them is that perceptual considerations are used for side tuning to obtain a given visual quality while the coder is not built following human vision properties.

Zeng et al. used self masking and neighborhood masking for the preservation of detailed edges in the framework of JPEG 2000 [191]. The masking function is applied before the quantization process with the aim of adjusting visual significance of individual coefficients. In the Embedded Block Coding with Optimal Truncation Points (EBCOT) coder described by *Taubman* in [192], the perceptual optimization lies in the distortion function used in the R-D (Rate-Distortion) process. Such perceptual optimization allows measurement of the sensitivity to quantization errors. However, the masking model used in EBCOT does not take into account the viewing conditions. In 2004, *Tan et al.* proposed a perceptual coder for monochrome images following the EBCOT structure and using a perceptual distortion measure taking advantage of an advanced vision model. The authors show a variant of the contrast gain control (CGC) model composed of three steps such as linear transform, masking response and detection. In [193], a monochromatic multichannel vision model has been extended to color and used to approximate perceived errors in the R-D optimization in the JPEG 2000 framework. In the same context, *Liu* proposed a new color JND estimator and used it within JPEG 2000 to improve the perceptual quality of compressed images[194, 195]. The approach does not require any side information and reduce the prediction error in DWT + DPCM compression.

Watson et al. proposed an interesting method on perceptually characterizing visual thresholds for wavelet quantization errors [162]. The authors measured visual detection thresholds for samples of DWT uniform quantization noise in Y, Cb, and Cr color channels. A mathematical model is derived for DWT noise detection thresholds with the level, orientation, and display visual resolution as parameters. The obtained model allows the definition of perceptually lossless quantization matrices. More recently, in a similar work performed by *Larabi et al.* [196], psychophysical experiments involving noise at various sub bands and in different channels, allowed the definition of visual detection thresholds for digital cinema applications. One important conclusion of this work was the insufficiency of the 250 Mbps limit, defined for JPEG 2000 digital cinema profile, to achieve visually-lossless compression. *Ramos and Hemami* conducted a psychophysical investigation about distortions visibility caused by wavelet coefficients quantization [166]. From these experiments, they propose a quantization strategy producing a minimum noticeable distortion leading to a perceptual improvement of wavelet-coded images. Based on the work of Watson [162], *Albanesi et al.* proposed a HSV-based quantization strategy for both lossy and lossless coding [170]. A related work introduced by *Liu et al.* [197] discusses an adaptive quantization using noise detection threshold associated with each coefficient in each subband of the color channels. Recently, *Sreelekha et al.* proposed a coding approach where contrast thresholds are applied at the quantization step. The novelty of this work is the facts that contrast thresholds are used on both luminance and chromatic channels, and are adapted to image content [198, 176].

A review of different approaches in literature suggests that perceptual optimization is often linked to the metric used to visually minimize the impact of quantization errors. Consequently, *Gershikov et al.* proposed a weighted mean square error (MSE) metric in order to achieve perceptually optimal coding [199]. They assume already obtaining a set of weighting factors corresponding to the perceptual impact of each subband of the transform. In the same fashion, *Wang et al.* considered the well known SSIM metric in order to generate maps to derive local perceptual quality indicator [174]. The extracted map is used in an iterative process where in each pass the remaining bits are allocated to visually important regions. This reallocation aims at decreasing the effect of spatial quality distribution within an image. However, even though using SSIM will certainly allow to preserve structural information, this metric is not always in accordance with human perception. A different perceptual optimization approach has been introduced by *Wang and Bovik* in [200]. This method takes advantage of the high spatial resolution of the HVS around a fixation point, also called foveation point, linked to the fovea. They then integrate this process in an image coding algorithm which re-order the bitstream to optimize foveated visual quality independently of the bit-rate. This re-ordering is achieved by using a specific quality metric exploiting the foveation phenomenon. This bio-inspired approach allows mimicking the foveal vision of the HVS. Nevertheless, it does not address jointly the problem of wavelet coefficient selection and quantization parameter definition.

A perceptual dithering approach has been used for image coding in [201]. They considered a hierarchical wavelet transform where the sibling subbands of the same level are decorrelated by applying a series of rotations. The change on the wavelet coefficients is made prior to quantization. The perceptual model used in this work relies on background luminance perceptibility and spatial masking effects [202].

5.3. Perceptually lossless or near-lossless

In addition to fully lossy and the lossless compression, a third approach has emerged and is known as near-lossless or perceptually lossless compression. It relies on the fact that some losses are not perceptible by a human observer. Although this notion is highlighted by all works dealing with perceptual optimization of image coding but it still requires further discussions. Instead of improving the visual quality of coding results, perpetually lossless approaches target the absence of visually difference between original and compressed images. The JPEG-LS standard [151] proposes such a feature even though the results are not always convincing for the near-lossless part. A perceptual optimization of the JPEG-LS standard has been introduced by *Chou et al.* [203] by making coding errors imperceptible or minimally noticeable. Hence, a JND model is used on the three color channels of each pixel allowing to perceptually tune the quantization step size in the predictive coding mode. A similar approach has been proposed in [204]. During the last decade, medical imaging has been the focus of the lossless coding efforts especially using a JPEG 2000-like compression. An approach dedicated to wavelet-based coding has been introduced by *Wu et al.* [205, 206]. It uses a contrast gain control model defined as a perceptual metric incorporating a CSF filtering and masking, in order to apply a visual pruning of visually insignificant information. In this work, it has been demonstrated that perceptually lossless coding achieves better results than lossless or nealy-lossless compression. However, medical images coding may be highly influenced by the nature of the diagnosis to be delivered as well as individual situation.

5.4. JPEG XR

JPEG XR [153, 207] is the latest compression standard of the JPEG family developed as a potential coder for extended range images. It uses a hierarchical two stages Lapped Bi-orthogonal Transform (LBT) which is based on a flexible concatenation of two operators such as the DCT-like Photo Core Transform (PCT) and the Photo Overlap Transform (POT). Due to its novelty and the lack of market adoption, a few studies have been devoted to perceptual optimization of JPEG XR. In the same fashion as the other JPEG standards, *Shonberg et al.* tackled the problem of spatial bit allocation in order to improve the perceived quality of a compressed image [175]. The idea is to use fewer bits for image features that are less crucial to visual quality. This is achieved by varying the step sizes used for quantization of the transform coefficients of each frequency band and color component of each macroblock in the image. The advantage of this approach is that no changes are required at the decoding side. However, the choice of the metric deciding whether a feature is visually important or not, is critical. Authors have chosen MS-SSIM which does not really belong to the perceptual metrics. Nevertheless, a subjective validation has been used to corroborate the objective quality decision.

5.5. Other approaches

Recently, *Masmoudi et al.* proposed in [208, 209, 210] an approach inspired by coding strategies of the mammalians visual system generating a compressed neural code for a visual stimulus. They rely on the bio-plausible Virtual Retina model developed by *Wohrer and Kornprobst* [211] that has been adapted for coding purposes. The proposed coder can be summarized by three processing steps each mimicking a layer of the retina. These are time-dependent edge detector (outer layers) followed by a non-linear contrast gain control (inner layers) and finally a conversion of the input stimulus into spikes (ganglionic layer). With this architecture, authors have demonstrated scalability and bit allocation efficiency by using the time-dependent behavior of the retina. At last, a dithering process is integrated in the proposed bio-inspired coder to account for the retinal noise occurring in the inner layer. This improvement allows for a faster recognition of the fine details of the image during decoding process.

In [212], *Niu et al.* described a perceptual coding strategy based on edges. It focuses on the preservation of scale-invariant second-order statistics of natural images to guarantee the perceptual quality. In this work, edge geometry is not explicitly coded. In order to describe optimal edge geometry, coding is performed in two stages such as a background layer of the image is coded first and is transmitted allowing to estimate trajectories of significant edges at the decoder side. The second stage is a refinement one using a residual coding technique based on edge dilation and sequential scanning in the edge direction. In [213], an interesting review is done for perception oriented video coding. Even though the purpose of this survey is focused on image, this papers provides very important opening that may apply on perception-based image coding.

There are various challenges for image coding, but often, not in the core coding itself. Indeed, it has been demonstrated that having a unique coder for every application is a utopian approach. Therefore, application-dependent coding scheme are preferred for many reasons. First because it implies to have a coding scheme adapted to the application with an appropriate domain transform, an adapted quantization and a set of embedded tools. For instance, security applications may need to have specific ROI-based coding, intra and inter super-resolution stage and metrics to characterizing the Detection, Recognition, Identification (DRI) indexes. On the other hand, new applications have emerged such as high dynamic range imaging requiring appropriate coding schemes with appropriate perceptual model. Most of the psychophysical models have been constructed on 8-bit displays and this raises the question of models' validity for such extended range data. Finally, a tradeoff has to be found between the fully bio-inspired schemes lacking in terms of real time application and simplistic perceptual models failing in capturing perceptual features fundamentally important for a human observer.

6. Visual information quality assessment

In any processing or transmission of visual information, the ultimate judge is the human observer. Generally, the performance evaluation of image processing tools is based on some objective and/or subjective criteria. Although, many objective performance evaluation measures have been developed for image processing and coding, the subjective evaluation remains the most reliable solution. Therefore, a large effort has been devoted to developing more robust objective measures that are consistent with *human visual system* (HVS) performance.

Indeed in many tasks where the final results are presented as images, observers are asked to judge the perceptual quality of the pictorial representation of the results. However, subjective evaluation of image processing methods is not practical for applications that involve automatic control and adjustment of machine parameters. It is, therefore, desirable to develop objective methods for evaluating image processing algorithms. However, in spite of the great number of objective measures developed for evaluating the quality of image processing techniques, such as noise filtering, segmentation, compression, etc., the most widely used assessment method is still based on subjective evaluation. Nevertheless, it is believed that by exploiting some perceptual criteria and computational models of the HVS one can derive efficient objective image quality measures. This field of research is growing rapidly and has now attained a high level of maturity. Since the work of Mannos and Sakrisson [214], numerous methods have been proposed for image distortion evaluation: some are inspired by perceptual mechanisms of the HVS, whereas others are based on more traditional signal processing techniques [215, 216, 217]. The choice of one metric over another is rather a hard task. There is no universal criteria on how to choose or to adapt a given image quality to a specific application. Depending on the available information from the original (undistorted) image, quality assessment techniques can be grouped into three categories: full-reference (FR), reduced reference (RR), and no-reference (NR), also called blind. FR methods require the original image to evaluate the quality of the distorted image, whereas RR methods require only a set of features extracted from both the original and the degraded image. When a priori knowledge on the distortion characteristics is available, NR methods can be used without referring to the original image. A brief review of image quality assessment (IQA) methods is provided herein; for a more comprehensive survey on Image Quality Metrics (IQM), the reader is refereed to [218, 219, 220, 221, 222]. Many FR objective measures have been proposed in the literature such as PSNR or weighted PSNR [217]. However, such metrics reflect the global properties of the image quality but are inefficient in predicting local structural degradations. Since image quality is subjective, the evaluation based on subjective experiments is the most accepted approach. Unfortunately, subjective image quality assessment necessitates the use of several procedures, which have been formalized by the ITU recommendation [223]. These procedures are complex, time consuming and non-deterministic. It should also be noted that perfect correlation with the HVS could never be achieved due to the natural variations in the subjective quality evaluation. These drawbacks led to the development of other practical and objective measures [224, 225, 235]. Basically, there are two approaches for objective Image Quality Assessment. The first and more practical are the distortion-oriented measures, e.g., the MSE, PSNR and other similar measures. However, for this class of IQA measures, the quality metric does not correlate with the subjective evaluation for many types of degradations. The second class corresponds to the HVS-model oriented measures. Unfortunately, there is no satisfactory visual perception model that can account for all the experimental findings on the HVS. All the proposed models have parameters that depend on many environmental factors and require delicate tuning in order to correlate with the subjective assessment [234]. The need for a reliable and consistent objective image quality measure has not been met yet.

In the following we provide a unified approach for objective image quality assessment of some image processing tasks.

6.1. performance evaluation of Visual information processing methods

There are many visual information processing methods which involve assessment of image quality of the outputs: image compression, image denoising, contrast enhancement, quantization and segmentation are among the methods where the performance evaluation is based on the perceptual quality of the results. It is worth noting that IQA involves higher level perceptual and cognitive factors that are not easy to model. Therefore, the efficiency depends strongly on the image characteristics used in the design of the IQA method. In some approaches, a set of image characteristics are used for evaluating the quality of the image processing results, some of which include gray-level histogram, entropy of the gray-level histogram, edge thickness, dynamic range, local variance of gray-level, mean edge gray-level, local contrast, and visibility map. A plethora of objective measures have been proposed for assessing the quality of image processing methods [226, 227, 228, 229, 230, 236, 237, 232, 233]. But at the end all the developed measures often have to be combined with subjective evaluation in order to evaluate the performance of the image processing tasks in terms of image quality and accuracy of the obtained results. Therefore, it is desirable to develop evaluation methods that incorporate some perceptual criteria in the design of objective measures [228, 229, 230, 236, 237, 231]. For example, in the case of image segmentation, such as edge detection, gray-level thresholding or region-based segmentation, the outputs are considered as simplified representations of the visual content of the image. Therefore, the objective of image segmentation evaluation is to quantify the visual quality of these representations as compared with the original image by using some perceptual criteria. However, at present time, there is no universal measure for evaluating image segmentation such as thresholding, edge detection or region segmentation. The most intuitive and popular approaches are based on the a priori knowledge of the segmentation results or the ground truth. Unfortunately, in many applications the ground truth is not available. The development of objective measures without ground truth is still an active field of research. There are some works in the area of psycho-visual image segmentation evaluation; however, the procedure is often very complex, time consuming and depends on many unpredictable factors [238, 239]. A new perceptual approach for image segmentation evaluation has been proposed in [240]. In this approach, it is argued that image segmentation could be considered as a perceptual process, which tends to transform the visual content of the image so as to provide a simplified representation of it. It becomes than possible to use IQM for performance evaluation of the segmented image output. In the case of image enhancement, namely contrast enhancement or denoising, the situation is quite different in the sense that the output is supposed to exhibit higher perceptual image quality. Some interesting HVS-based quantitative measures for evaluating image enhancement were presented in [241, 242, 243]. While many image quality metrics have been developed for image distortion estimation, there are only a few ad hoc objective measures for the image enhancement evaluation [242, 243, 244]. Very often we content ourselves by perceptual evaluation. To evaluate contrast enhancement methods, a measure based on the spectral energy analysis, introduced in [245], has been proposed [244]. The basic idea is to evaluate the amount of energy increase in the different bands and orientations, taking into account the directional and frequency selectivity of the HVS [246, 247, 29].

Through this brief overview it appears that image quality assessment is still an open problem; it is not possible to develop reliable image quality metrics for all known distortions. Image quality is a multidimensional problem and the best way is to proceed in two steps. First, one has to develop for each distortion an IQM, which correlates well with subjective evaluation. Then, a fusion strategy of the different IQMs could be used in order to derive global measure able to work for all the considered distortions as done in [248]. The problem of IQA could be also considered as a classification and identification problem. Indeed, to overcome the limitations of IQMs, in [249] the authors proposed a strategy where the degradation type contained in an image is first identified by using a classification scheme then the quality of that image is estimated using the most appropriate IQM for that specific degradation. This approach is not new and is used in many fields of research. For image processing performance evaluation we believe that the use of HVS-inspired approaches presents an interesting alternative to the classical evaluation metrics.

7. Conclusion

This paper considered perceptual aspects of human vision used in literature to improve the performance of few basic image processing techniques such as enhancement, segmentation, coding and quality assessment. The main purpose of this paper is to provide the reader with the most important works relying on perceptual modeling for the aforementioned research topics The Introduction section begins with discussions on information processing in human vision system tackling the most important characteristics of the human visual system: image contrast, visual masking, contrast sensitivity function and, orientation and frequency selectivity. Image enhancement has been the focus of many studies and perceptual enhancement has been tackled at three levels, i.e., image denoising, contrast enhancement, coding artifact reduction and tone mapping and enhancement of high dynamic range images. Perception is also used for segmentation purposes where the aim is to obtain a relatively small number of segmented regions, where each region can be seen as a main object or a meaningful part of an object. A review of the main image segmentation methods has been grouped into region-, edge- and perceptual grouping-based methods. Among these different segmentation techniques, perception-based image segmentation hold more promise due to its close resemblance of human vision processing. However, there is still a wide gap in meaningfully harnessing the limited understanding of human perception and effective high quality image segmentation. Another important field having benefited from the development of perceptual models is image coding. The latter, always seeks the right tradeoff between compression rate and artifact invisibility. Therefore, the coding literature has been explored depending on the transforms and standards of the state-of-the-art in order to provide a comprehensive description of the use of perceptual features in coding schemes. Finally, image quality is an important issue in image processing in its broad sense. Consequently, a section has been dedicated to this important topic with a special focus on its use for performance evaluation of some image processing tasks and lossy compression methods. Our review suggests that image quality assessment is still an open problem that concerns many issues related to visual information processing and communication.

An important issue when using perceptual approaches in image processing is to avoid applying available models without any consideration of the context, content or nature of the image. Very often, the used models are derived from some psycho-visual experiments conducted under limited and specific laboratory environments. For example, Weber-Fechner law is still used to estimate the visibility of a pixel in a small neighborhood, despite the real situation being far from the ideal configuration of Weber-Fechner experiments, where a target is seen over a uniform background. On the other hand, the JNC model by Moon and Spencer cannot be used in its original form, where there is a non-uniform background. The situation is even more complex when it concerns high dynamic images for which color models developed under the 8-bits assumptions may not be considered as valid. The color issue is also of great importance in image processing and analysis. Despite decades of intensive studies for understanding and modeling color vision it is not yet completely understood. However, the use of few common color models for image processing and coding is relatively satisfactory. Another important point that should be taken into account when using perceptual approaches is that the new commonly available image acquisition systems have spatial resolution and responses that go beyond the limitations of the HVS. Therefore, it may be useless to define some perceptual measures on the raw data. One way to circumvent these limitations is to derive an appropriate representation of the acquired images by using, for instance, pyramidal decomposition and define the local measures on the low level of this decomposition. Therefore, caution is required to make perceptual models relevant and useful for image processing tasks. Perceptual data fusion and decision making in the HVS is another issue that is not yet well understood. Substantial efforts are needed for developing effective models that may be used in the design of perceptual approaches for image processing. Finally, we believe that the best way to exploit our knowledge on visual perception mechanisms is to avoid the race of mimicking the entire properties and cognitive mechanisms of the HVS. Instead, one can develop HVS-inspired methods by combining some well-established computational models of perceptual vision using appropriate signal and image processing tools.

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