Beyond Pixel Count: A Perceptual Taxonomy and Review of Dominant Color Extraction Algorithms

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***Abstract*—Human vision tends to favor small but visually prominent colors, a 2% red patch in a green scene may dominate attention, but many algorithms ignore such areas. Dominant color extraction (DCE) has traditionally been based on pixel-frequency statistics, neglecting perceptually important details. This survey discusses algorithms aimed at bridging the gap between computational extraction and human vision. We offer a taxonomy of perception-aware DCE approaches: (1) perception-aware clustering, (2) fuzzy methods, and (3) deep learning methods. For each type, we examine strategies such as saliency weighting, perceptually uniform color spaces, and semantic context incorporation. Trade-offs, challenges, and future directions for robust, human-oriented DCE systems are discussed.**

***Keywords*—Dominant color extraction, perceptual metrics, clustering, fuzzy logic, deep learning, color spaces**

I. Introduction

A mere 2% patch of red in an otherwise green scene can dominate human attention, yet many algorithms fail to register it as important. This discrepancy arises because many algorithms rely on simple pixel-frequency statistics, failing to model the complexity of human color perception [1]. As the primary visual cue, color enables faster recognition and improved memorization of objects [2], enabling fields such as computer vision, digital imaging, multimedia, and human-computer interaction to integrate perceptual principles into their methodologies [3, 4]. Among these principles, the extraction of perceptually dominant colors, those that naturally attract human attention, remains a critical focus.

However, a large disparity exists between human and computational perception. Traditional algorithms often rely on pixel-frequency statistics, causing them to overlook small yet visually salient color regions that the human visual system effortlessly identifies. These perceptually salient colors, which can capture attention disproportionately regardless of size or frequency, often remain undetected by traditional pixel-based approaches, highlighting the core challenge in this field.

The capacity to extract these colors has wide-ranging applications in various fields. In content-based image retrieval, dominant colors are natural and salient features for expressing search queries [5]. In object detection, they augment features such as shape and texture to enhance recognition performance [6]. In graphic design and user interface (UI) development, successful color schemes balance dominant colors with infrequent but perceptually important accents [7]. Good choices improve emotional engagement, trust, and usability, while bad ones can drastically worsen the user experience [8].

Despite its importance, the field faces persistent challenges. Many existing approaches poorly detect smaller, visually salient regions, often due to a reliance on non-uniform color spaces like RGB, where Euclidean distance does not correspond to perceptual variation. While more perceptually uniform frameworks like CIELAB (L*a*b*) and HVC are more aligned with human visual perception [9], their use still remains inconsistent. To address these limitations and encourage progress, this paper presents a comprehensive survey of dominant color extraction approaches, with an emphasis on those driven by perceptual considerations. We consider traditional methods, clustering-based approaches, and modern deep learning models, highlighting their strategies for detecting both large and spatially limited but salient color areas, while discussing their strengths, weaknesses, and potential for perceptually aware applications.

II. Background on Color Perception and Representation

Human color vision is necessary to create DCE algorithms whose outputs correlate with human visual dominance judgments. Perceptual effects such as color constancy, contrast sensitivity, and visual saliency influence which colors are seen, remembered, and rated as ”dominant” in an image, often in manners not precisely serving pixel-based statistics. The following subsections describe these cognitive science and vision research basics of relevance to computational models of DCE.

A. Human Color Perception Principles Relevant to DCE

Color constancy enables color perception independent of illumination, e.g., a red apple still appearing red when seen in daylight and incandescent light [10]. In the case of DCE, such invariance is important to avoid misclassification under lighting variations. Contrast sensitivity is the lowest human-detectable chromatic or luminance difference [11], which reaches a peak at mid-spatial frequencies and diminishes at extremes [12]. Low-contrast regions can be undersampled unless contrast-aware processing is employed by algorithms. Visual salience is how distinctive regions capture attention

[13], i.e., even small but distinctive colors can dominate perception and should be assigned the respective importance in DCE [14].

B. Computational Representations & Challenges in DCE

Perceptually dominant color extraction is extracting the most visually salient colors from a given image those that naturally draw human attention [15].

Traditional methods, such as pixel-frequency counts and histogram-based quantization, are effective and simple for large uniform regions but typically miss small high-impact features like a flower stigma or a vivid insect [16]. Clustering techniques can improve grouping based on similarity of color, but under non-uniform color spaces, they still are unable to perceive high differences [9].

A main flaw in the literature is frequent use of RGB, which is a device-dependent, non-uniform color space. Equal Euclidean distances in RGB are not equal perceptual differences, reducing accuracy for small, visually distinct regions. In perceptually uniform spaces, however, equal distances are nearer equal perceptual differences, and therefore more suitable for DCE. Perceptually uniform (or approximately uniform) spaces such as CIELAB (L*a*b*), L*u*v*, LCH, and HVC better correspond to human perception since they separate lightness from chroma, as shown in most earlier studies [17].

Finally, color appearance is subjective, i.e., there is no single good dominant palette that suits all. What catches the attention of one observer may go unnoticed in another.

III. Taxonomy of Methods

A. In-depth Review of Taxonomy Categories

Dominant color extraction methods vary widely in both their computational strategies and the extent to which they consider principles of human visual perception. To provide a structured basis for their critique, we divide existing perceptual DCE methods along two main dimensions:

- **Algorithmic paradigm** – the core mechanism for grouping colors and generating palettes;
- **Perceptual integration level** – the extent to which the method models human vision (e.g., color constancy, contrast sensitivity, saliency).

Along these dimensions, three broad classes of perception-based dominant color extraction methods can be identified: perception-aware clustering, perception-aware fuzzy approaches, and perception-aware deep learning approaches. Table I classifies these categories, their characteristic features, exemplifying methods, and typical percep- tual features. The following subsection provides a detailed description of each category.

B. Taxonomy of Perceptual Approaches to DCE

The following subsections detail each of the categories in Table I, highlighting their algorithmic foundation, perceptual modeling strategy, example algorithms, strengths and limitations.

1) Perception-Aware Clustering: Historical dominant color extraction (DCE) relies significantly upon statistical clustering algorithms such as *k*-means, Mean Shift, or histogram-based quantization [18, 19]. These typically operate in RGB space, separating pixels by Euclidean distance. Though computationally inexpensive and sufficient for coarse matching, they lose perceptually important regions in complicated scenes. For instance, downsampling accelerates convergence but discards very small, high-saliency features. These constraints have led to the exploration of clustering techniques that directly integrate human-perception models.

Perception-aware clustering extends these classical approaches by incorporating perceptual models such that retrieved palettes are not only statistically frequent, but also perceptually important. Normal methods employ perceptually equivalent color spaces (CIELAB, LCH), saliency-weighted, or advanced perceptual distance measures (e.g., CIEDE2000) to align clustering output with human response [9, 20]. Optimization algorithms, such as Multidimensional Particle Swarm Optimization (MD-PSO) or fuzzy similarity modeling within HSV/HSL, subsequently enhance perceptual insensitivity and outperform standard MPEG-7 descriptors in most situations [21]. Recent works also include saliency detection [22], saturation–contrast balancing [23], or perceptual thresholding with ΔE_{00} to promote greater consistency [24].

In general, the literature consists of three broader methodological tendencies:

a) Color-Space–Based Methods: These techniques cluster pixels in perceptually uniform spaces such as CIELAB or LCH, where geometric distances better mimic human vision [19]. They are of greater perceptual fidelity but remain sensitive to illumination changes and more computationally expensive than their RGB-based counterparts.

b) Saliency-Enhanced Methods: These methods capture perceptual significance by visual saliency detection, prioritizing visually distinctive regions and preserving tiny high-contrast details [25]. Saliency-weighted clustering in L*a*b* space captures perceptual granularity well [26], but the outcome depends heavily on the quality of the underlying saliency model.

c) Perceptual Distance–Based Approaches: This class of methods incorporates perceptual measures of similarity, e.g., CIEDE2000 [20, 24], to replace standard Euclidean distance with human-centered measures. These approaches improve device and lighting invariance but require higher computational budgets and longer convergence times.

Comparative Insights:

- **Common ground:** There is a consensus that RGB-based clustering alone is not enough for perceptual correctness. Use of perceptually uniform color spaces, saliency weighting, and perceptual distance calculations is demonstrated repeatedly to be superior to traditional methods in maintaining human-relevant color data [9, 20, 25].
- **Methodological spectrum:** The region spans a continuum from color-space methods (interested in perceptual representation), through saliency methods (interested in

Table I: Taxonomy of Perceptual Approaches to Dominant Color Extraction

Category	Characteristic Approach	Example Techniques	Typical Perceptual Elements
Perception-Aware Clustering	Applies perceptual space clustering or visual weighting clustering to semantically extract color from a visual point of view.	K-means in CIELAB/LCH, saliency-weighted clustering, luminance/chroma sensitivity weighting	Perceptual uniformity, saliency maps, human contrast sensitivity
Perception-Aware Fuzzy Approaches	Combines perceptual clustering with segmentation or fuzzy logic to manage noisy pixels and mixed pixels.	Fuzzy C-means in CIELAB, hybrid histogram–clustering with saliency, segmentation + perceptual weighting	Spatial coherence, perceptual weighting, mixed-pixel adaptation
Perception-Aware Deep Learning Techniques	Uses neural models in an effort to learn master color extraction by employing saliency or attention as features.	CNN palette extraction in LAB, saliency-guided attention networks, transformer-based palette models	Learned perceptual features, context-aware color relevance

perceptual priority), to perceptual-distance techniques (imposing perceptual invariance).

- **Strengths:** Principal advantages consist of better retention of fine-grained information, more visual complexity resistance, and better agreement with human judgments.
- **Gaps:** There remain relevant issues, including computation inefficacy, reliance on other saliency models' accuracy, and sensitivity to illumination. Furthermore, the lack of standardized benchmarks for perceptual evaluation makes it difficult to make fair comparisons across studies.

Briefly, perception-aware clustering is a significant step beyond statistical clustering itself by incorporating perceptual models at the color space, region priority, or distance metric levels. The direction is towards hybrid approaches striking a balance between perceptual accuracy and computational costs, opening the door to human-centric DCE systems.

2) Fuzzy Approaches for Perceptual DCE: Fuzzy logic has been a successful approach to DCE by directly addressing the inherent uncertainty of actual images, such as mixed pixels, gradual transitions, and noise. These are not well modeled by crisp clustering methods (e.g., k-means or MPEG-7 DCD). Unlike crisp methods, fuzzy methods allow pixels to be partial members of several color clusters, in accordance with the gradual nature of human color perception, and furnish dominant colors that better correspond to human judgment [27].

Two major directions are distinguished in the literature:

a) Fuzzy-enhanced feature representation: These methods reformulate the color representation by directly incorporating fuzziness into the color model. Fuzzy histograms in HSV/YIQ offer soft pixel assignment between overlapping bins, with greater noisy or ambiguous pixel robustness [28]. The fuzzy HSI (FHSI) space defines color using fuzzy sets with linguistic variables, enabling perceptual harmony analysis in art, fashion, and design [29, 30]. These approaches introduce fuzziness at the representation level for perceptual alignment.

b) Fuzzy-driven clustering and optimization: The second is the use of fuzzy logic in clustering algorithms. Sophisticated variants of advanced fuzzy c-means (FCM) are in focus. CIQFCM pixelizes to CIELAB and synchronizes fuzzy memberships with perceptual similarity to the extent of 36$\times$ faster speed without perceptual overlaps lost [31]. Superpixel-based Fast FCM (SFFCM) superpixels and fuzzy memberships with minimal complexity maintained and perceptual boundaries preserved to improve noise robustness [32]. Other research complements FCM for specific applications, such as camouflage generation in RGB, where fuzzy membership ensures natural world similarity in perception and preserves local texture distributions [33].

Aside from FCM, optimization-based clustering merges fuzzy distance models with evolutionary methods. For example, Euclidean distance is replaced with a fuzzy measure in HSV/HSL so as to better model human perception of color class boundaries and categories [21]. Coupled with a particle swarm optimization paradigm, this method calculates the number of clusters dynamically optimally, evading MPEG-7's over-/under-clustering problem and k-means's loss of perceptual consistency.

Comparative Insights:

- **Common ground:** The majority of works concur that crisp clustering (e.g., k-means, MPEG-7 DCD) falls short based on fixed numbers of clusters, sensitivity to initialization, and poor performance under perceptual uncertainty. Fuzzy methods always excel over them in perceptual alignment, stability, and robustness [21, 31, 32].
- **Representation vs. clustering:** Some are aimed at fuzzy *representation* of color (e.g., fuzzy histograms, FHSI, fuzzy balls) [28, 29], and others are trying fuzzy *clustering/optimization* (e.g., CIQFCM, SFFCM, PSO with fuzzy metrics) [31, 32, 21]. **(author?)** [34]'s paper is a typical example of the latter. Representation-based algorithms are perceptually highly interpretable, whereas clustering-based algorithms aim for efficiency, scalability, and dynamic adaptability.
- **Color spaces:** HSV/HSL dominate for perceptually intuitive color modeling [21, 35], while CIELAB is opted where perceptual uniformity during clustering is required [31, 32]. HSI is also selected where its luminance and chrominance separation is deemed to be enough for

perceptual registration, as shown by **(author?)** [34]. Hybrid hybrids (HSV + YIQ) balance efficiency-perceptual accuracy [28].

- **Strengths:** Fuzzy logic improves boundary control, robustness to noise, and perception invariance. It bridges the gap between low-level extraction and high-level processing (emotion, aesthetics).
- **Gaps:** Computational cost remains an issue, especially in perceptually constant spaces like CIELAB. Most methods continue to employ *k*-means for initialization or combination and inherit some of its limitations. Research targeted at application (e.g., art, camouflage) shows versatility but systematic paradigms applicable to a broad range of real-world tasks remains in infancy.

In short, fuzzy techniques are an important step toward dominant color extraction: from rigid, fixed-color models towards perception-sensitive, dynamic clustering and representation. The field is converging toward hybrid models attaining perceptual accuracy vs. computational expense, often combining fuzzy logic with high-level optimization or application-specific perceptual rules.

3) Perception-Aware Deep Learning Techniques: Deep learning has revolutionized dominant color extraction (DCE) through direct modeling of high-level semantic context and human perceptual mechanisms from data. This transition abandons statistical clustering to acquire colors not just common but also semantically and perceptually relevant, and it captures subtle associations between color, saliency, and object identity [36, 16].

Three large architectural paradigms can be found in the literature:

a) Semantic Segmentation-Guided Extraction: This approach uses deep networks like DeepLabv3 to first identify and isolate semantically significant regions (e.g., the body of a car, hair), ignoring distracting background elements. The dominant color is then captured by clustering only from such sanitized pixels [37, 38]. This approach mimics straightforward human attention to objects so that the final palette is derived from perceptually salient content rather than the entire image, greatly improving relevance.

b) Integrated End-to-End Deep Learning Models: This revolution is constructing models that naturally anticipate color palettes, integrating saliency and semantic guidance within the model. One such example is CD-Attention, which combines CNNs and Vision Transformers using a dual-branch framework to directly model human color difference perception [36]. Other methods employ generative models; one specific system utilizes a GAN to generate an initial palette, followed by perceptual improvement with a reinforcement learning agent that fine-tunes color elements [39]. These are a break from the use of deep learning as a pre-processing step towards integrating it into the center extraction engine.

c) Hybrid and Specialized Algorithmic Pipelines: This trajectory emulates effective application-level systems that pair deep learning with optimized algorithms. For instance, object detection is achieved by Mask R-CNN and its output is treated by novel, efficient clustering algorithms in perceptually-aligned color spaces like HSV for real-time robotics performance [40]. Another scientific visualization pipeline uses a CNN to estimate colormaps from Lab histograms and then enforces the resulting colormaps with perceptual rules [15]. These hybrid methods prioritize pragmatic efficiency for a specific domain.

Comparative Insights:

- **Common ground:** All methods employ high-level guidance (semantic or saliency-guided) to align output with human perception, beyond simple pixel clustering [36, 37, 16].
- **Architectural spectrum:** Methods range from modular (deep learning for pre-processing followed by clustering) [37, 38, 16] to completely integrated (end-to-end palette prediction) [36, 39]. Modular architectures are more transparent, whereas integrated models perform better.
- **Perceptual strategies:** Perceptual consistency is achieved either *explicitly* by performing computations in perceptual color spaces (CIELAB, HSV) [16, 40, 38] or through perceptually-grounded loss functions [39], or *implicitly* by training networks on human-labeled data to learn perceptual relationships directly [41, 42].
- **Strengths:** Deep learning is highly effective at learning semantic context and subtle visual patterns for useful, context-sensitive palettes. It is highly robust to cluttered backgrounds.
- **Gaps:** A key challenge is the lack of standardized test sets for perceptual DCE [36]. Performance is often domain-data-dependent, and high-complexity models are computationally expensive and not easily interpretable.

Overall, deep learning provides semantic and perceptual awareness to DCE, advancing the field from adjunct tools to end-to-end systems simulating human vision. But it is not clear whether models are truly 'perception-aware' or only perception-aligned based on large datasets. Deep networks vary from fuzzy or clustering methods that represent perceptual rules explicitly because they rely on perceptual alignment that results from training data.

IV. Evaluation Strategies

Evaluating dominant color extraction (DCE) remains as challenging as designing algorithms themselves, since both perceptual fidelity and computational feasibility must be considered. Across the literature, strategies can be grouped into three dimensions: ground truth creation, evaluation metrics, and benchmarking protocols.

Ground truth. Robust evaluation depends on reliable reference palettes, yet there is no universal gold standard. Some works construct annotated datasets with pixel-level masks and voting among multiple annotators to mitigate subjectivity [38]. Others adopt human-curated palettes from artworks or films [43], while fuzzy approaches propose "soft" ground truths using perceptual membership functions rather than crisp assignments [44]. These strategies underscore the need for reproducible and perceptually valid benchmarks.

Metrics. Classical methods rely on statistical image similarity, e.g., Mean Squared Error, L2 distance, or average color difference in perceptual spaces such as CIE94 or CIEDE2000 [20]. More recent studies integrate structure- and perception-oriented measures: SSIM and PSNR for visual fidelity, Weighted SSIM for texture preservation, Dynamic Time Warping for ordered palettes [15], and confusion matrices or F1-scores for categorical evaluation [37]. A common thread is that frequency-based metrics alone are inadequate; perceptually grounded distances or human-in-the-loop scoring provide more reliable assessment. Some deep learning works complement quantitative scores with qualitative comparisons against designer-curated or expert-selected palettes [41, 39].

Benchmarking protocols. Evaluation frameworks vary widely. Classical descriptors often report retrieval precision and recall on standard datasets (e.g., Corel, Wang) [22], whereas fuzzy and clustering methods emphasize efficiency–accuracy trade-offs by reporting runtime reduction alongside perceptual error [31]. Deep models increasingly adopt large-scale synthetic or domain-specific datasets (e.g., interior design, vehicle color recognition, movie analysis) [41, 37], often augmented to address imbalance and improve generalization. Comparative baselines typically include k-means, MPEG-7 DCD, and fuzzy c-means, providing continuity across studies.

Open issues. Despite progress, evaluation remains fragmented. There is no shared benchmark unifying classical, fuzzy, and deep methods, nor consensus on the balance between human subjectivity and objective metrics. Future work should pursue standardized datasets, incorporate perceptual user studies, and report both accuracy and efficiency, enabling fairer comparisons and more human-centered benchmarks.

V. Conclusion

This survey has spanned the development of dominant color extraction (DCE) from simple statistical techniques to perception-aware algorithms. We introduced a taxonomy that encompasses three main paradigms: clustering with perceptual spaces and metrics, fuzzy logic addressing perceptual uncertainty, and deep learning casting semantic context. Discussion is given that while these approaches considerably enhance compliance with human vision by introducing saliency, uniform color spaces, and learned features, there are inevitable difficulties. There are no public benchmarks within the research community, and sophisticated models sacrifice interpretability for performance. Future work needs to be directed towards building public datasets, designing efficient but lightweight models, and incorporating color vision deficiency as a variable to enable truly robust and human-centric DCE systems.

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