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

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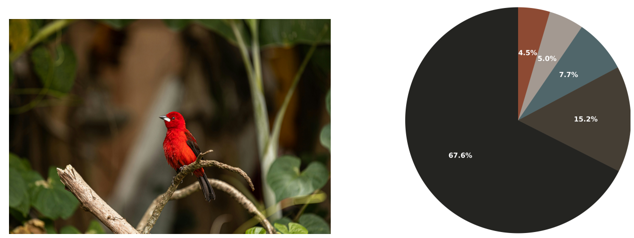
***Abstract*—Human vision prioritizes small but visually prominent colors, a tiny red patch in a green scene can dominate attention, yet many algorithms overlook such areas. This survey presents a comprehensive taxonomy of perception-aware dominant color extraction (DCE) methods. It examines techniques like clustering in perceptually uniform color spaces, fuzzy logic for handling uncertainty, and deep learning incorporating semantics and saliency. We provide a comparative analysis of the principles, strengths, and limitations of these approaches, highlighting key trade-offs between efficiency, interpretability, and perceptual fidelity. This work guides the development of robust, human-aligned DCE systems for computer vision and design applications.**

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



(a) A red cardinal on a branch (b) Color frequency analysis

Figure 1. An example of perceptual dominance defying pixel frequency. a The vivid red cardinal is the immediate focus of human attention [4]. b A frequency-based algorithm would overlook the red due to its small area, highlighting the core challenge.

I. Introduction

A cardinal flaw in many computational vision systems is their blindness to a key perceptual reality: a minuscule yet vivid color, like a red bird in a green bush, can command human attention instantly. This discrepancy arises because many algorithms rely on simple pixel-frequency statistics, failing to model the complexity of human color perception [1] and its computational foundations [2]. As the primary visual cue, color enables faster recognition and improved memorization of objects [1], enabling fields such as computer vision, digital imaging, multimedia, and human-computer interaction to integrate perceptual principles into their methodologies [2, 3]. 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, color features are a fundamental low-level cue that augment other information such as shape and texture to enhance the recognition performance of computational models [6]. Dominant color extraction has also been adapted for efficient computer vision preprocessing, where methods such as ISDCC compress images by encoding dominant channels while preserving key structures [7]. Furthermore the dominant colors in an image can be used for image retrieval, color editing, palette generation, and several other applications [8].

Despite its importance, the field faces persistent challenges. Many existing approaches poorly detect smaller, visually salient regions, often due to a reliance on standard RGB-based color spaces like sRGB, 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.

The contribution of this paper is two-fold. First, we propose a taxonomy of dominant color extraction (DCE) methods, structured by both algorithmic paradigm and level of perceptual integration. This framework goes beyond simple categorization, showing how the field has progressed from pixel-frequency statistics to perceptually grounded deep models. Second, we outline key challenges and emerging trends, providing guidance for future research toward closer alignment with human perception.

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, which reaches a peak at mid-spatial frequencies and diminishes at extremes [11]. Low-contrast regions can be undersampled unless contrast-aware processing is employed by algorithms. Visual salience is how distinctive regions capture attention, i.e., even small but distinctive colors can dominate perception and should be assigned the respective importance in DCE [12].

B. Computational Representations & Challenges in DCE

As defined in prior work, perceptually dominant color extraction (DCE) aims to identify a scene's most visually salient colors, which command attention regardless of their spatial frequency.

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 [13]. Clustering algorithms can improve color similarity-based grouping, but their effectiveness depends largely on the color space that supports them. When performed in non-uniform spaces based on the RGB model, clustering results can be misaligned with perceived differences, underscoring the necessity for perceptually uniform spaces such as CIELAB and similar models [9].

A main flaw in the literature is the frequent use of standard RGB-based color spaces like sRGB. These spaces are device-dependent and non-uniform; their geometry does not align with human vision. Equal Euclidean distances in these RGB-based spaces 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 [14].

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. Overview of the Taxonomy

Dominant color extraction methods vary significantly both in their computational methodology and their level of perceptual consideration. We categorize these methods into three basic paradigms based on their algorithmic strategy and level of perceptual integration:

1) **Perception-Aware Clustering**, which complements statistical methods with perception principles;
2) **Fuzzy Approaches**, which model the inherent uncertainty in human color naming;
3) **Deep Learning Techniques**, which learn to detect semantically useful colors from data.

Each class is detailed in the next subsections, and a side-by-side comparison of their strengths, weaknesses, and best application contexts is given in table I.

B. Taxonomy of Perceptual Approaches to DCE

1) Perception-Aware Clustering: Conventional dominant color extraction (DCE) relies primarily on computationally efficient statistical clustering techniques like *k*-means or histogram quantization in color spaces based on the RGB model [15, 16]. While low in computational cost, such a strategy is prone to losing semantically important areas for complex scenes, as it is based on Euclidean distance rather than the human visual system. This limitation has motivated the development of clustering techniques with explicitly built-in perceptual models, so that extracted palettes are not just statistically frequent but also perceptually salient.

Perception-aware clustering extends these conventional techniques by incorporating perceptual models so that palettes retrieved are not only statistically frequent, but also perceptually relevant. Conventional methods make use of perceptually uniform color spaces (CIELAB, LCH), saliency-weighted, or high-level perceptual distance measures (e.g., CIEDE2000) to adjust clustering results to the human response [9, 17]. Optimization algorithms, such as Multidimensional Particle Swarm Optimization (MD-PSO) or fuzzy similarity modeling in HSV/HSL, then enhance perceptual insensitivity and outperform standard MPEG-7 descriptors in the majority of scenarios [18]. Recent studies also include saliency detection [19], saturation–contrast balancing [8], or perceptual thresholding with ΔE_{00} for developing greater consistency [12].

In general, the literature includes three broader methodological trends:

a) Color-Space–Based Methods: These techniques cluster pixels in perceptually uniform color spaces like CIELAB or LCH, in which geometric distances better approximate human vision [16]. They are more perceptually accurate than

RGB-based color spaces like sRGB but more computationally demanding and sensitive to illumination changes.

b) Saliency-Enhanced Methods: These techniques utilize visual saliency detection to emphasize the visually distinctive regions, thereby preserving small high-contrast details that statistical approaches miss [20]. Performed in a space like L*a*b*, saliency-weighted clustering nicely captures perceptual granularity [21], but the outcome is heavily coupled with the quality of the underlying saliency model.

c) Perceptual Distance–Based Approaches: This class replaces simple Euclidean distance with more complex, human-centered measures like CIEDE2000 [12, 17]. This improves device and lighting invariance and leads to improved consistency at the expense of a significantly higher computational budget and longer convergence times.

Synthesis and Outlook: It is clear from the literature that a move beyond RGB-based clustering towards perceptual correctness is necessary. The methodological approaches span a continuum of emphasis: from enhancing color representation itself (color-space methods), to prioritizing percepts of saliency (saliency-enhanced methods), to enforcing a higher degree of perceptual invariance (distance-based methods). Collectively, the perception-aware methods provide enhanced performance over traditional methods, such as greater retention of fine-grained detail [20], better robustness to visual clutter [17, 20], and closer alignment with human judgment [9, 17].

However, fundamental challenges still exist. These include the computational inefficiency of operating in complex color spaces or with sophisticated distance metrics, reliance on the performance of auxiliary models (particularly for saliency detection), and ongoing sensitivity to changing imaging conditions. The lack of standard perceptual benchmarks also makes direct and fair comparison between studies less straightforward. Thus, the recent trend in research is towards hybrid approaches that carefully combine these methods to balance the improved perceptual quality with achievable computational complexity.

2) Fuzzy Approaches: Fuzzy logic addresses a basic limitation of hard clustering algorithms (e.g., k-means, MPEG-7 DCD): their inability to express the natural uncertainty in images, e.g., mixed pixels, gradual transitions, and noise. By allowing pixels to possess partial membership in multiple color clusters, fuzzy methods equal the gradual nature of human color perception and furnish dominant colors that better align with human judgment [22]. The consensus across the literature is that hard clustering always lags due to fixed cluster numbers, initialization sensitivity, and poor treatment of perceptual uncertainty. Fuzzy methods, by contrast, are shown consistently to outperform them in perceptual alignment, robustness, and stability [18, 23].

The literature can be broadly categorized into two strategic directions:

a) Fuzzy-Enhanced Feature Representation: These methods embed fuzziness within the color model itself. Techniques like fuzzy histograms in HSV or YIQ space apply soft assignment to overlapping bins for greater noise and ambiguous pixel robustness [24]. The fuzzy HSI (FHSI) space represents color through linguistic variables and fuzzy sets to facilitate perceptual harmony analysis for art and design applications [25]. These approaches prioritize perceptual interpretability by operating on a fuzzified color representation.

b) Fuzzy-Driven Clustering and Optimization: This direction employs fuzzy logic in clustering. Advanced forms of Fuzzy C-Means (FCM) are prominent. For example, the CIQFCM algorithm maps image pixels to a quantized CIELAB color space, drastically reducing the data required for clustering. This allows it to achieve a 36× speedup on large 1024×1024 images while accurately extracting perceptually dominant colors [23]. Superpixel-based Fast FCM (SFFCM) reduces computational complexity by preprocessing pixels into superpixels before applying FCM, effectively preserving perceptual boundaries and improving noise immunity [26].

Apart from FCM, other optimization paradigms include fuzzy distance measures. For example, replacing Euclidean distance by a fuzzy metric in HSV/HSL better models human perception of color classes. When coupled with evolutionary algorithms like Particle Swarm Optimization (PSO), this can automatically determine the number of clusters and hence avoid the over-/under-clustering problems of MPEG-7 DCD and k-means [18].

Synthesis and Outlook: Fuzzy logic has proved to be superior to hard clustering for perceptual DCE in its improved boundary handling, robustness, and perceptual invariance. Representation-based methods (e.g., fuzzy histograms, FHSI) are perceptually interpretable and harmony, or aesthetics, oriented, whereas clustering-based methods (e.g., CIQFCM, SFFCM, PSO) are efficiency, scalability, and applicability oriented to different image data. A shared thread between both approaches is the selection of color space: HSV/HSL for perceptual intuitiveness are preferred [18, 27], CIELAB for perceptual uniformity in clustering [23, 26], and HSI for luminance-chrominance decoupling [28]. Hybrid couplings (e.g., HSV+YIQ) are also attempted to trade off between computational efficiency and perceptual faithfulness [24].

Beyond low-level extraction, fuzzy models have also been applied to reach into higher-level perceptual domains such as emotion and aesthetics, proving their versatility between technical and artistic applications. Despite these strengths, the computational cost of fuzzy clustering, especially in perceptually uniform spaces, remains an issue. In addition, most methods still employ k-means for initialization or hybridization, and therefore inherit some of its shortcomings. While application-driven work (e.g., in art or camouflage) demonstrates flexibility, systematic approaches with general applicability to real-world applications are lacking. Future research is trending towards hybrid methods that attempt a trade-off between perceptual accuracy and computational feasibility, most commonly involving the integration of fuzzy logic with evolutionary optimization or application-driven perceptual heuristics.

3) Deep Learning Techniques: Deep learning has revolutionized dominant color extraction (DCE) by directly encoding high-level semantic context and human perceptual processes from data. This paradigm shift goes beyond statistical clustering for extracting colors that are not only frequent but also semantically and perceptually prominent, encoding fine-grained relationships between color, saliency, and object identity [13, 29].

There have been three prevailing architectural paradigms:

a) Semantic Segmentation-Guided Extraction: Deep networks such as DeepLabv3 can first segment semantically meaningful regions of interest, e.g., object parts or salient objects, suppressing irrelevant background [30]. Representative colors are then selected from these segmented regions through clustering methods such as k-means [31], obtaining palettes that capture perceptually meaningful content.

b) Integrated End-to-End Deep Learning Models: In this case, models explicitly predict color palettes by embedding saliency and semantic guidance within the network. CD-Attention, for instance, combines CNNs and Vision Transformers for human color difference perception modeling [29], while other work employs GANs to generate palettes with reinforcement learning refinement [32]. These models move beyond pre-processing roles, putting deep learning at the extraction core.

c) Hybrid and Specialized Algorithmic Pipelines: Pragmatic pipelines combine deep learning with traditional methods for domain-specific effectiveness. For instance, the system using Mask R-CNN with the proposed AVW/PXS algorithms was compared against Mask R-CNN integrated with traditional clustering techniques like K-means [33]. Similarly, in a different domain, CNN-predicted lab colormaps were derived in perceptually uniform color spaces [34], demonstrating how hybrid approaches can enhance performance beyond standalone deep learning or heuristic methods

Synthesis and Outlook: Deep learning has been an enabling paradigm for the integration of semantic and perceptual awareness in DCE, advancing the state of the art from adjunct tools to end-to-end systems that approximate human vision. Methods can be placed on a spectrum: modular pipelines (deep learning as clustering pre-processing) yield interpretability and control, but end-to-end integrated architectures offer superior performance at the cost of interpretability. Perceptual consistency is either enforced explicitly (using perceptual color spaces or perceptual loss functions) [32, 33], or implicitly, by learning perceptual relationships from labeled data [35].

Despite their strengths, robustness to cluttered backgrounds and capability for encoding context-sensitive patterns, deep models have fundamental challenges. Performance is often data-domain dependent, models are computationally demanding, and interpretability is limited. One fundamental open question is if such systems are actually 'perception-aware' or merely perception-aligned through training statistics, in contrast to fuzzy or clustering methods in which perceptual rules are analytically defined. This task of relatively and equally judging perceptual tasks, including segmentation, is a long-standing problem in the field [16]. Future work will likely focus on efficient, interpretable, and generalizable architectures that trade off between perceptual fidelity and computational tractability.

C. Comparative Analysis

The three paradigms represent a fundamental trade-off between computational complexity, interpretability, and the ability to model high-level perception. Clustering methods offer efficient and interpretable baselines. Fuzzy logic provides an effective way of dealing with perceptual uncertainty and noise. Deep learning models are effective but computationally expensive and are "black boxes," though unbeatable at semantic context capture. The choice of algorithm is therefore heavily application-dependent on the specific requirements of the application for accuracy, efficiency, and explainability, as presented in table I.

IV. Evaluation Strategies

Dominant color extraction (DCE) assessment is as challenging as algorithm design itself, in that both computational efficiency and perceptual accuracy need to be considered. Across the literature, methodologies may be organized in terms of three axes: ground truth generation, evaluation metrics, and benchmarking procedures.

Ground truth. Gunduz et al. [31] address the issue of ground truth incompleteness in dominant color extraction by using semantic segmentation to determine salient objects, thus reducing the process subjectivity. Others employ human-curated palettes from paintings or films [36], while others adopt survey based approach to collect ground-truth data [37]. Such approaches promote the use of reproducible and perceptually good benchmarks.

Metrics. Historical 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 [17]. More recent approaches incorporate structure- and perception-based metrics: SSIM and PSNR for visual fidelity, Weighted SSIM for texture, Dynamic Time Warping for ordered palettes [34], and confusion matrices or F1-scores for categorical evaluation [30]. They share a commonality that frequency-based measures in isolation are not sufficient; perceptually rooted distances or human-in-the-loop scoring are more stable evaluation. A number of deep learning papers supplement quantitative scores with qualitative comparisons against designer-curated [32] or expert-selected palettes [35].

Benchmarking protocols. Evaluation protocols differ greatly. Classical reports more often detail retrieval precision and recall on standard corpora (e.g., Corel, Wang) [38], whereas fuzzy and clustering techniques emphasize efficiency–accuracy balances reporting run-time reduction with perceptual error [23]. Deep models increasingly often draw on vast synthetic or special domain datasets (e.g., interior design, vehicle color recognition, film analysis) [30, 35], typically augmented to handle skewness and improve generalization. Comparative baselines typically include k-means, MPEG-7 DCD, and fuzzy c-means, to facilitate continuity across studies.

Open issues. Despite advances, evaluation remains fragmented. There is no consensus benchmark that might unify classical, fuzzy, and deep approaches, nor agreement on the trade-off between human subjectivity and objective metrics.

Table I. Comprehensive Comparative Analysis of Perceptual DCE Methodologies

Aspect	Perception-Aware Clustering	Fuzzy Approaches	Deep Learning Approaches
Core Principle	Modifies clustering by moving from non-uniform spaces (sRGB) to perceptual spaces (CIELAB) and incorporating saliency maps	Uses soft membership (e.g., FCM) to handle mixed pixels and gradients.	Uses neural networks (CNNs, Transformers) to learn color relevance from data.
Characteristic Approach	Groups pixels in perceptual color spaces or applies visual weighting to emphasize perceptual importance.	Combines fuzzy logic with perceptual models to smoothly handle uncertainty, gradients, and noisy boundaries.	Learns color saliency and contextual importance directly from data using neural architectures.
Typical Perceptual Elements	Perceptual uniformity, saliency maps, human contrast sensitivity.	Spatial coherence, perceptual weighting, mixed-pixel adaptation.	Learned perceptual features, context-aware color relevance.
Perceptual Modeling Level	**Low-Level:** Color uniformity, preattentive saliency.	**Mid-Level:** Uncertainty, categorization, granularity.	**High-Level:** Semantic context, object-based saliency.
Key Strength	Computationally efficient; intuitive and interpretable.	Robust to noise/ambiguity; aligns well with human color categorization.	Captures complex context; superior performance on semantic tasks.
Key Limitation	Struggles with semantic context; sensitive to initial parameters.	Higher computational cost than clustering; complex parameter tuning.	Black-box; requires large datasets; very high computational cost.
Interpretability	**High.** Cluster centers are directly explainable.	**Medium.** Membership degrees provide soft interpretation.	**Low.** Decisions are not easily traceable.
Ideal Use Case	General-purpose applications, processing large datasets, extracting global color themes.	Applications requiring human-like reasoning (e.g., art analysis, design), noisy images.	Domain-specific tasks with ample data (e.g., product color identification, film style analysis).

Standardized datasets must be the target of future work, together with perceptual user studies and both accuracy and efficiency reported, to enable more sane comparisons and more human-centric 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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