IDS-CMP-2025: Computational Image Analysis Standard

November 25, 2025

Ideamorphic Studies Documentation Standards

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1. Scope and Purpose

This standard defines the computational methods employed by the Ideamorphic Studies for objective image characterization. MMIDS-CMP-2025 establishes reproducible, deterministic analysis protocols for extracting quantitative visual metrics from artwork documentation images.

1.1 Applicability

This standard applies to all computational image analyses performed on artwork documentation within the Ideamorphic Studies's publication system. Results generated under this standard are suitable for:

- Academic citation and scholarly reference
- Comparative analysis across artwork corpora
- Machine-readable metadata generation
- Objective visual characterization

1.2 Design Principles

- **Determinism:** Identical inputs produce identical outputs
- **Reproducibility:** Methods are fully specified and replicable
- **Objectivity:** No subjective interpretation in measurement
- **Transparency:** All algorithms and parameters documented

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2. Analysis Architecture

MMIDS-CMP-2025 comprises four independent analysis modules executed sequentially on each source image:

Module	Function	Primary Output
Color Extraction	Dominant color identification	Color palette with percentages
Texture Analysis	Surface pattern characterization	Roughness and pattern metrics
Brightness & Contrast	Luminance distribution analysis	Dynamic range and contrast values
Spatial Distribution	Color relationship mapping	Clustering and harmony metrics

2.1 Input Requirements

- **Format:** RGB image array (8-bit per channel)

- **Minimum Resolution:** 500 × 500 pixels
- **Maximum Resolution:** Auto-downsampled to 1000 × 1000 for performance
- **Color Space:** sRGB (converted internally as needed)

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3. Module 1: Color Extraction

3.1 Method Overview

Color extraction employs K-means clustering to identify statistically dominant colors within the image. The algorithm partitions pixel color values into K clusters, with cluster centroids representing the extracted colors.

3.2 Algorithm Specification

Primary Method: K-means clustering (scikit-learn implementation)

`Parameters: - n_clusters: 10 (default, configurable) - random_state: 42 (deterministic seeding) - n_init: 10 (initialization attempts) - max_iter: 300 (convergence iterations)`

Alternative Methods: - Histogram analysis (16^3 bin quantization) - OpenCV K-means quantization (cv2.KMEANS_RANDOM_CENTERS)

3.3 Color Space Transformations

Each extracted color undergoes conversion to multiple color spaces:

HSL (Hue-Saturation-Lightness): - Hue: 0–360° angular position on color wheel - Saturation: 0.0–1.0 color intensity - Lightness: 0.0–1.0 brightness value

LAB (CIELAB): - L: 0–255 lightness channel - a: 0–255 green-red axis (centered at 128) - b: 0–255 blue-yellow axis (centered at 128) - Chroma: $\sqrt{(a-128)^2 + (b-128)^2}$ - Hue: arctan2(b-128, a-128) in degrees

3.4 Color Family Classification

Colors are assigned to a 12-band color wheel based on LAB hue angle:

LAB Hue Range	Color Family
345°–15°	Red
15°–45°	Red-Orange
45°–75°	Orange
75°–95°	Yellow-Orange
95°–110°	Yellow
110°–165°	Yellow-Green
165°–195°	Green
195°–225°	Blue-Green
225°–255°	Blue

LAB Hue Range	Color Family
255°–285°	Blue-Violet
285°–315°	Violet
315°–345°	Red-Violet

Achromatic Detection: Colors with chroma < 5 and |a-128| < 10 and |b-128| < 10 are classified as: - Black (L < 20) - White (L > 200) - Gray (20 ≤ L ≤ 200)

3.5 Accent Color Detection

Spatially coherent accent colors are detected through region-based analysis:

1. Create mask of pixels dissimilar to dominant colors (threshold: RGB distance > 40)
2. Label connected regions using scipy.ndimage.label
3. Filter regions by minimum size (20 pixels)
4. Calculate region importance score:
5. Size score: min(region_size / 1000, 1.0) × 0.3
6. Saturation score: HSL saturation × 0.3
7. Contrast score: border color distance × 0.4
8. Accept regions with importance > 0.08

3.6 Output Format

json { "method": "k-means", "colors": [{ "rank": 1, "hex": "C4D0B0", "percentage": 23.5, "family": "yellow-green", "name": "pale olive" }], "families": { "yellow-green": 45.2, "green": 30.1 }, "accent_colors": [{ "hex": "8B4A6B", "family": "red-violet", "name": "dusty mauve [Accent]", "chroma": 32.5 }] }

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4. Module 2: Texture Analysis

4.1 Method Overview

Texture analysis quantifies surface characteristics through multiple complementary techniques: roughness measurement, gradient analysis, pattern detection, and spatial variation mapping.

4.2 Roughness Metrics

Global Roughness: - Standard deviation of grayscale pixel intensities - Normalized to 0.0–1.0 range (÷ 255)

Local Roughness: - 5×5 kernel local standard deviation - Mean and variance of local roughness values

Edge Density: - Canny edge detection (thresholds: 50, 150) - Ratio of edge pixels to total pixels

4.3 Gradient Analysis

Sobel Gradient Computation: `grad_x = cv2.Sobel(gray, CV_64F, 1, 0, ksize=3) grad_y = cv2.Sobel(gray, CV_64F, 0, 1, ksize=3)` magnitude = $\sqrt{(grad\_x^2 + grad\_y^2)}$ `direction = arctan2(grad_y, grad_x)`

Derived Metrics: - Mean gradient magnitude (normalized) - Gradient variance - Gradient smoothness: $1 - (\sigma\_gradient / \mu\_gradient)$ - Directional coherence: $\sqrt{(mean(\cos(\theta))^2 + mean(\sin(\theta))^2)}$

4.4 Pattern Analysis

Local Binary Pattern (LBP): - 8-point neighborhood comparison - Binary encoding of intensity relationships - Pattern complexity = variance(LBP) / 255^2

Autocorrelation: - FFT-based 2D autocorrelation - Detection of repetitive patterns via off-center peaks

Frequency Domain: - FFT magnitude spectrum analysis - Detail frequency ratio: high_freq_energy / total_energy

4.5 Spatial Variation

Image divided into 4×4 grid (16 regions): - Inter-region variation: σ(region_means) / 255 - Texture consistency: 1 - (σ(region_stds) / μ(region_stds))

4.6 Output Format

`json { "global_roughness": 0.135, "mean_local_roughness": 0.089, "edge_density": 0.042, "mean_gradient_magnitude": 0.067, "directional_coherence": 0.234, "pattern_complexity": 0.156, "spatial_variation": 0.078, "texture_consistency": 0.823 }`

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5. Module 3: Brightness & Contrast Analysis

5.1 Method Overview

Brightness and contrast analysis quantifies luminance distribution, dynamic range, and local contrast patterns using established photometric measurements.

5.2 Luminance Metrics

Grayscale Conversion: - cv2.COLOR_RGB2GRAY (luminance-weighted)

Basic Statistics: - Mean brightness: μ(gray) / 255 - Brightness variance: σ(gray) / 255 - Brightness uniformity: 1 - (σ / μ) - Brightness skewness: $E[(x - \mu)^3] / \sigma^3$

Entropy: - Histogram-based information content - $H = -\Sigma(p\_i \times \log_2(p\_i))$

5.3 Contrast Measurements

RMS Contrast: - Root mean square of intensity deviations - C_rms = σ(gray) / 255

Michelson Contrast: - C_m = (I_max - I_min) / (I_max + I_min) - Suitable for periodic patterns

Weber Contrast: - C_w = |I_object - I_background| / I_background - Object: 10th percentile, Background: 90th percentile

Local Contrast: - 7×7 kernel local mean subtraction - Mean and uniformity of local contrast

5.4 Dynamic Range Analysis

Basic Range: - (max - min) / 255

Effective Range: - (P95 - P05) / 255 (excludes outliers)

Tonal Distribution: - Shadows: histogram[0:85] percentage - Midtones: histogram[85:170] percentage - Highlights: histogram[170:255] percentage

Clipping Assessment: - Shadow clipping: histogram[0] percentage - Highlight clipping: histogram[255] percentage

5.5 Multi-Scale Local Contrast

Analysis at three scales (3×3, 7×7, 15×15 kernels): - Fine contrast (detail) - Medium contrast - Coarse contrast (large-scale variation) - Multi-scale ratio: fine / coarse

5.6 Output Format

`json { "mean_brightness": 0.672, "brightness_variance": 0.145, "rms_contrast": 0.234, "michelson_contrast": 0.756, "dynamic_range": 0.892, "shadow_percentage": 12.3, "midtone_percentage": 65.4, "highlight_percentage": 22.3, "fine_contrast": 0.089, "coarse_contrast": 0.156 }`

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6. Module 4: Spatial Distribution Analysis

6.1 Method Overview

Spatial distribution analysis examines how colors are arranged across the image, measuring clustering, transitions, saturation patterns, and color harmony relationships.

6.2 Spatial Clustering

Method: 1. Sample pixels at regular intervals (√1000 step size) 2. K-means clustering on sampled RGB values (K=8) 3. For each cluster, calculate average distance between member pixels 4. Normalize by image diagonal

Metrics: - Spatial coherence: 1 - (normalized_avg_distance) - Color clustering coefficient: 1 - (within_cluster_var / total_var)

6.3 Color Transition Analysis

LAB-based Gradient: - Sobel gradients computed per LAB channel - Combined gradient: $\sqrt{\Sigma \text{ channel\_gradients}^2}$

Transition Metrics: - Smoothness: 1 - min(1, mean_gradient / 100) - Uniformity: 1 - min(1, gradient_variance / 10000) - Sharp transition ratio: pixels > P90(gradient) / total - Directionality: coherence of gradient angles

6.4 Saturation Distribution

HSV Saturation Analysis: - Mean saturation (0.0–1.0) - Saturation variance - Distribution categories: - Low: $S < 0.3$ - Medium: $0.3 \leq S < 0.7$ - High: $S \geq 0.7$ - Saturation clustering: spatial coherence of saturation levels

6.5 Color Harmony Analysis

Hue Concentration: - Circular variance of saturated pixel hues - Concentration = 1 - circular_variance

Complementary Balance: - Detection of opposite hue pairs (180° apart) - Balance = complementary_pairs / total_saturated

Analogous Dominance: - 12 groups at 30° intervals, 45° tolerance - Dominance = max_group / total_saturated

Temperature Bias: - Warm hues: 0°–60° and 300°–360° - Cool hues: 120°–240° - Bias = warm_ratio - cool_ratio (-1 to +1)

6.6 Output Format

`json { "spatial_coherence": 0.456, "color_clustering": 0.678, "color_transition_smoothness": 0.789, "sharp_transition_ratio": 0.034, "mean_saturation": 0.263, "saturation_variance": 0.089, "hue_concentration": 0.567, "complementary_balance": 0.123, "analogous_dominance": 0.678, "temperature_bias": -0.234 }`

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7. Quality Assurance

7.1 Determinism Verification

All random operations use fixed seeds: - K-means: random_state=42 - All results reproducible given identical input

7.2 Performance Optimization

- Images > 1,000,000 pixels automatically downsampled
- Sampling strategies for computationally intensive operations
- Target processing time: < 30 seconds per image

7.3 Error Handling

- Graceful fallback values for edge cases
- Empty/corrupt image detection
- Numeric overflow prevention (uint8 → int conversion)

7.4 Validation

Each metric includes defined ranges: - Normalized values: 0.0–1.0 - Percentages: 0–100 - Angles: 0–360° - Temperature bias: -1.0 to +1.0

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8. Implementation Reference

8.1 Software Dependencies

Library	Version	Purpose
NumPy	≥1.20	Array operations

Library	Version	Purpose
OpenCV	≥4.5	Image processing, color conversion
scikit-learn	≥1.0	K-means clustering
SciPy	≥1.7	ndimage, spatial distance
webcolors	≥1.11	CSS3 color name matching

8.2 Color Space Standards

- RGB: sRGB IEC 61966-2-1
- LAB: CIELAB D65 illuminant
- HSL: Standard cylindrical representation

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9. Citation

When referencing analyses performed under this standard:

> *Quercy, A. (2025). Computational Image Analysis Standard - MMIDS-CMP-2025. Ideamorphic Studies. https://ideamorphism.org/en/publications/2025/11/mmids2025cmp-computational-image-analysis-standard.html*

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10. Version History

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1.0	November 2025	Initial release

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REFERENCES

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