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DEVELOPMENT OF NEW APPROACHES TO COLOR INTERPRETATION IN IMAGES USING COMPUTATIONAL EXPERIMENTATION

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Abstract

Color plays a fundamental role in how we perceive and analyze images, yet traditional approaches, like the RGB model, often struggle to capture the nuances needed for precise feature recognition. In this study, we explore new ways to interpret color in images through computational experimentation. Two innovative methods, named “Separate” and “Max,” were developed and tested on a small set of synthetic images, created by shifting a base image diagonally. Using Fourier and wavelet-based analysis, we evaluated how these approaches support feature recognition. The results suggest that the Separate method can reveal details more effectively than the conventional Luminosity RGB model, offering clearer insights into image content. This work demonstrates that thoughtfully designed computational experiments can inspire more flexible and accurate strategies for interpreting color, providing a fresh perspective on image analysis and feature extraction.

Keywords: *color interpretation, image recognition, Fourier transform, wavelet transform, RGB Model*
Mathematics Subject Classification *(2020): 68U10*

1. Introduction

Color plays a fundamental role in both human perception and machine

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vision, helping humans recognize, understand, and interact with the environment, while allowing computers to process visual information numerically. Unlike humans, machines interpret colors as data, translating shades into numerical values for further analysis. Digital images are composed of pixels, each containing color information. In the widely used RGB (Red, Green, Blue) model, colors are formed by mixing varying intensities of the three primary channels, with each component ranging from 0 to 255. For example, pure red is represented as (255, 0, 0), while white is (255, 255, 255).

At the initial stage of image processing, which involves feature extraction, various approaches are applied for interpreting RGB images. Commonly used methods include the Lightness method, the Average method, and the Luminosity method. The Lightness method averages the most and least pronounced color components [max{R, G, B}+min{R, G, B}]/2, the Average method uses a simple mean (R+G+B)/3, and the Luminosity method applies a weighted mean 0.21·R+0.72·G+0.07·B to account for human color perception, giving more weight to green. While these methods are widely used, no single approach perfectly converts color images to grayscale, as each model reflects a different interpretation of color and brightness.

This study aims to develop new approaches to color interpretation in images and evaluate them empirically. Two experimental methods, referred to as "Separate" and "Max" are proposed to improve feature recognition and image analysis. For comparison, the Average method is selected as a baseline, which calculates grayscale values as a simple mean of the three equally weighted RGB components. By combining these approaches with recognition techniques, this work explores more effective strategies for color-based feature extraction and expands the potential applications of computer vision technologies.

2. Problem definition

The recognition of any image requires adapting the corresponding recognition method to the selected approach for color interpretation. This involves identifying the key features for recognition and choosing an appropriate evaluation criterion to ensure the highest possible accuracy. To explore an alternative approach to color interpretation, a new RGB model is proposed that provides grayscale values derived from color components. For the computational experiment, an artificial image set (AIS) Z0={ξ01, ξ02, …, ξ06} was created (see Fig. 1). The set was generated by uniformly shifting a base image – the State Emblem of the Republic of Azerbaijan – diagonally to the right in equal steps. This controlled setup allows a systematic assessment of the proposed methods for color interpretation and their impact on feature recognition.

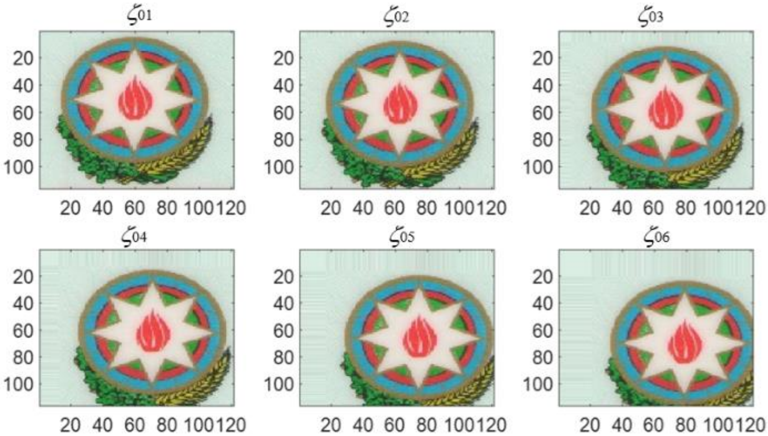

Fig. 1. The AIS Z0 constructed by uniformly shifting images

The image set Z0 is used as a test family for applying criteria to evaluate the accuracy of recognition methods. These criteria have been described in detail and empirically validated on similar families of one-dimensional signals in previous studies [2-4]. The focus of this study is on recognition techniques based on the Fourier transform (FT) [4] and the continuous wavelet transform (CWT) [5, 6]. These methods are applied to RGB-based color interpretations in grayscale, including the conventional Luminosity method and the two newly proposed approaches, referred to as “Separate” and “Max

3. Criteria for Assessing the Accuracy of Recognition Techniques

The numerical evaluation of the adequacy of recognition methods is based on three key criteria, which were originally proposed by A.B. Kerimov [1] and experimentally validated in [2, 3] using artificial families of one-dimensional signals. $F=\{\lambda_1, \lambda_1, \ldots, \lambda_n\}$ denote the set of signals, generated by uniformly shifting a base signal λ_1 to the right by a step δ. The following criteria are applied to assess the performance of recognition methods:

Criterion C_1 (uniformity): the distance from the base signal λ_1 to a signal λ_i (i=2÷n) should increase uniformly as the signal is shifted to the right along the diagonal. The numerical interpretation of this criterion is given by the formula:

$$MCV1_r^\delta = \max\{[MV(CV1_r^\delta) - CV1_r^\delta(j)]\} \quad (j=2\div n), \tag{1}$$

where $CV1_r^\delta(j) = \left[D_r^\delta(\lambda_1, \lambda_{j+1}) - D_r^\delta(\lambda_1, \lambda_j)\right] / \Delta t$ (j=2÷n).

Criterion C_2 (symmetry): the distances from a signal $\lambda_i \in F$ (i=2÷n-1) to its immediately preceding and succeeding signals should be approximately equal, ensuring relative symmetry of the signals within the set F. In other words, the ratio of these distances should be close to one. This criterion is numerically expressed as:

$$MCV2_r^\delta = \max\{[MV(CV2_r^\delta) - CV2_r^\delta(i)]\} \quad (i=2\div n-1), \tag{2}$$

where $CV2_r^\delta(j) = D_r^\delta(\lambda_1, \lambda_{i+1}) / D_r^\delta(\lambda_{i-1}, \lambda_i)$ (i=2÷n-1).

Criterion C_3 (convergence rate): as the signals $\lambda_i \in F$ (i=2÷n) approach the base signal λ_1, the rate of convergence of the corresponding distance values should increase. Here, the rate of convergence of distance values is defined as $CV3_r^\delta(i) = \left|D_r^\delta(\lambda_1, \lambda_i) - D_r^\delta(\lambda_1, \lambda_{i+1})\right| / D_r^\delta(\lambda_1, \lambda_{i+1})$ (i=1÷n), and the criterion is numerically formulated as:

$$MCV3_r^\delta = \min\{CV3_r^\delta(i)\} \quad (i=1\div n). \tag{3}$$

These criteria provide a systematic framework for quantitatively assessing the performance of recognition methods when applied to RGB-based grayscale interpretations, including conventional methods such as Luminosity and the newly proposed “Separate” and “Max” approaches.

4. The Separate method for converting color images in the context of their recognition

The transformation of images from the set Z_0 using the classical “Average” color conversion method generates a new set, which, after linearization, is represented as the family of one-dimensional signals $Z_2=\{\xi_{21}, \xi_{22}, \ldots, \xi_{26,}\}$, shown in Fig. 2.

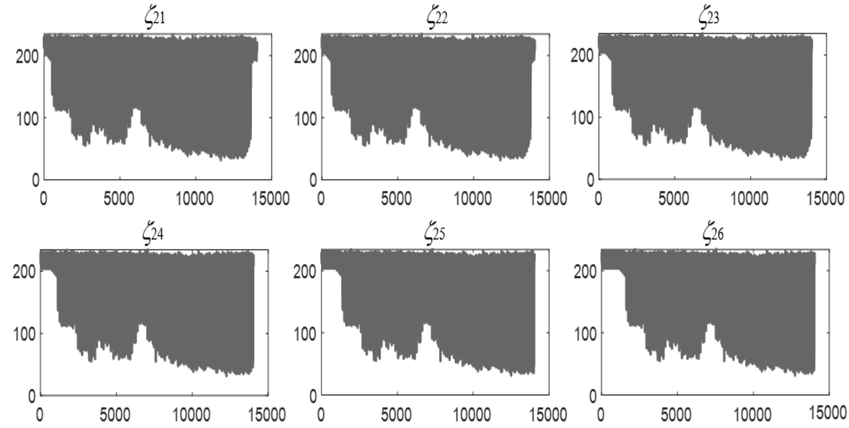

Fig. 2. The family of one-dimensional signals Z_2

The proposed **Separate** method converts the color components of an image to extract grayscale values for each channel (R, G, and B) independently. This approach is applied to a set of 18 signals $F_1=\{R_1, R_2, \ldots, R_6; G_1, G_2, \ldots, G_6; B_1, B_2, \ldots, B_6\}$, which, after linearization, are represented as a family of one-dimensional signals $F_2=\{r_1, r_2, \ldots, r_6; g_1, g_2, \ldots, g_6; b_1, b_2, \ldots, b_6\}$, as illustrated in Fig. 3.

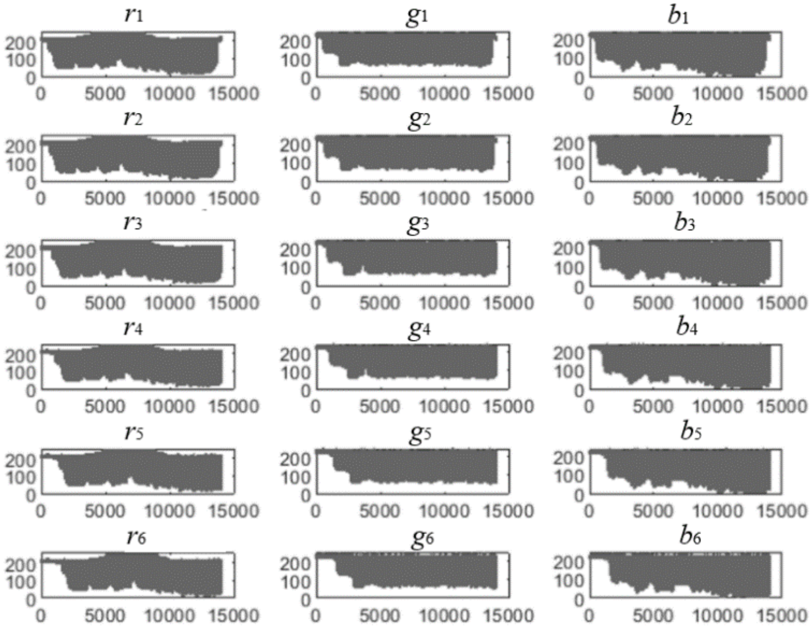

Fig. 3. The family of one-dimensional signals F_2

Further, an empirical analysis of different approaches to interpreting the RGB color model (**Average,** Luminosity, **Separate** and Max**)** is conducted based on the signal sets Z_2 and F_2. The recognition methods evaluated include the FT and CWT.

Tables 1, 2, 3 and 4 present the results of pairwise comparisons of signals from the sets Z_2 and F_2 using the FT and CWT and above approaches to interpretation of color. For the signals in F_2, the Euclidean metric is used as the comparison criterion, i.e., the distance between signals rgb_i and rgb_j (i, j=1÷6) at the sampling points is defined as:

$$d = \sqrt{(r_i - r_j)^2 + (g_i - g_j)^2 + (b_i - b_j)^2}\ . \quad (4)$$

Table 1. Results of pairwise comparison of signals from Z_2 using FP (**Average** approach**)**

	ξ_{21}	ξ_{22}	ξ_{23}	ξ_{24}	ξ_{25}	ξ_{26}
ξ_{21}	0	5.944	10.265	16.620	23.3854	29.9768
ξ_{22}	5.944	0	8.369	15.521	22.6175	29.3816
ξ_{23}	10.265	8.369	0	13.071	21.0123	28.1646

ξ_{24}	16.620	15.521	13.071	0	16.4518	24.947791
ξ_{25}	23.3854	22.6175	21.0123	16.4518	0	18.7545
ξ_{26}	29.9768	29.3816	28.1646	24.9478	18.7545	0

Table 2. Results of pairwise comparison of signals from Z_2 using FP (Luminosity approach**)**

	ξ_{21}	ξ_{22}	ξ_{23}	ξ_{24}	ξ_{25}	ξ_{26}
ξ_{21}	0	6.9718	11.5736	17.7172	24.2685	30.6708
ξ_{22}	6.9718	0	9.2381	16.2879	23.2455	29.8679
ξ_{23}	11.5736	9.2381	0	13.4146	21.3311	28.4033
ξ_{24}	17.7172	16.2879	13.4146	0	16.5850	25.0359
ξ_{25}	24.2685	23.2455	21.3311	16.5850	0	18.7546
ξ_{26}	30.6708	29.8679	28.4033	25.0359	18.7546	0

Table 3. Results of pairwise comparison of signals from F_2 using FP (**Separate** approach**)**

	rgb_1	rgb_2	rgb_3	rgb_4	rgb_5	rgb_6
rgb_1	0	11.5087	18.4591	28.8115	40.4654	51.7948
rgb_2	11.5087	0	14.5397	26.8995	39.1271	50.7562
rgb_3	18.4591	14.5397	0	22.6315	36.3253	48.6291
rgb_4	28.8115	26.8995	22.6315	0	28.4138	43.0419
rgb_5	40.4654	39.1271	36.3253	28.4138	0	32.3304
rgb_6	51.7948	50.7562	48.6291	43.0419	32.3304	0

Table 4. Results of pairwise comparison of signals from Z_2 using FP (Max approach**)**

	ξ_{21}	ξ_{22}	ξ_{23}	ξ_{24}	ξ_{25}	ξ_{26}
ξ_{21}	0	7.0554	12.4477	18.7301	25.2060	31.4567
ξ_{22}	7.0554	0	10.2551	17.3504	24.1984	30.6552
ξ_{23}	12.4477	10.2551	0	13.9954	21.9179	28.8890
ξ_{24}	18.7301	17.3504	13.9954	0	16.8678	25.2727
ξ_{25}	25.2060	24.1984	21.9179	16.8678	0	18.8197
ξ_{26}	31.4567	30.6552	28.8890	25.2727	18.8197	0

Tables 5, 6, and 7 present the numerical evaluations of the method using the FT (r=1) with respect to its compliance with criteria C_1, C_2 and C_3 for the considered color interpretation approaches.

Table 5. Numerical evaluation of the RGB-model using the FT with respect to its compliance with criterion C_1.

RGB model	$CV1_1^{\delta}(2)$	$CV1_1^{\delta}(3)$	$CV1_1^{\delta}(4)$	$CV1_1^{\delta}(5)$	$MCV1_1^{\delta}$
Average	0.7269	0.6191	0.4071	0.2819	0.2013
Luminosity	0.6601	0.5308	0.3698	0.2638	0.6601
Separate	0.6039	0.5608	0.4045	0.2800	0.6039
Max	0.7643	0.5047	0.3457	0.2480	0.7643

Table 6. Numerical evaluation of the RGB-model using the FT with respect to its compliance with criterion C_2.

RGB-model	$CV2_1^{\delta}(2)$	$CV2_1^{\delta}(3)$	$CV2_1^{\delta}(4)$	$CV2_1^{\delta}(5)$	$MCV2_1^{\delta}$
Average	0.4079	0.5619	0.2586	0.1400	0.1400
Luminosity	0.3251	0.4521	0.2363	0.1308	0.4521
Separate	0.2634	0.5565	0.2555	0.1378	0.1378
Max	0.4535	0.3647	0.2052	0.1157	0.4535

Table 7. Numerical evaluation of the RGB-model using the FT with respect to its compliance with criterion C_3.

RGB model	$CV3_1^{\delta}(2)$	$CV3_1^{\delta}(3)$	$CV3_1^{\delta}(4)$	$CV3_1^{\delta}(5)$	$MCV3_1^{\delta}$
Average	0.7801	0.7107	0.6176	0.5791	0.5791
Luminosity	0.7913	0.7300	0.6532	0.6024	0.6024
Separate	0.7813	0.7120	0.6407	0.6235	0.6235
Max	0.8013	0.7431	0.6646	0.5668	0.5668

The aggregated evaluations of the RGB-models using the FT with respect to Criteria C_1, C_2 and C_3 for the considered color interpretation approaches are summarized in Table 8.

Table 8. The aggregated evaluations of the RGB-models using the FT.

RGB-model	Criterion C_1	Criterion C_2	Criterion C_3	Aggregated evaluation
Average	0.2013	0.1400	0.5791	2.0682
Luminosity	0.6601	0.4521	0.6024	2.0682
Separate	0.6039	0.5565	0.6235	1.8905
Max	0.7643	0.4535	0.5668	2.9821

In addition to the FT, the CWT is applied to both sets Z_2 and F_2 to evaluate the performance of the recognition methods under a multi-scale analysis. The CWT provides a detailed representation of signal features at different scales, allowing a more nuanced comparison of the signals derived from the Average and Separate approaches. Pairwise distances between the wavelet-transformed signals are calculated using the Euclidean metric, providing a quantitative measure of similarity and enabling the assessment of the effectiveness of each color interpretation method.

The empirical results indicate that the Separate method produces a more distinct separation between individual color channels, which leads to improved feature recognition compared with the classical Average method. Tables 9, 10, 11 and 12 summarize the pairwise distances and highlight the comparative performance of the recognition methods across the signal sets. Overall, this analysis demonstrates that the Separate approach, combined with FT or CWT-based recognition techniques, offers a robust framework for evaluating RGB-to-grayscale conversion methods in the context of image recognition.

Table 9. Results of pairwise comparison of signals from Z_2 using CWT (**Average** approach**)**

	ξ_{21}	ξ_{22}	ξ_{23}	ξ_{24}	ξ_{25}	ξ_{26}
ξ_{21}	0	0.0969	0.1972	0.6134	0.8016	0.8390
ξ_{22}	0.0969	0	0.1879	0.6117	0.8003	0.8375
ξ_{23}	0.1972	0.1879	0	0.5863	0.7807	0.8183
ξ_{24}	0.6134	0.6117	0.5863	0	0.5204	0.5882
ξ_{25}	0.8016	0.8003	0.7807	0.5204	0	0.3396
ξ_{26}	0.8390	0.8375	0.8183	0.5882	0.3396	0

Table 10. Results of pairwise comparison of signals from F_2 using CWT (Luminosity approach**)**

	ζ_{21}	ζ_{22}	ζ_{23}	ζ_{24}	ζ_{25}	ζ_{26}
ζ_{21}	0	6.2887	26.8595	28.9293	70.3629	109.0500
ζ_{22}	6.2887	0	26.1776	28.8449	70.6051	109.2131
ζ_{23}	26.8595	26.1776	0	30.5769	74.9702	112.1486
ζ_{24}	28.9293	28.8449	30.5769	0	70.2556	109.0850
ζ_{25}	70.3629	70.6051	74.9702	70.2556	0	83.5467
ζ_{26}	109.0500	109.2131	112.1486	109.0850	83.5467	0

Table 11. Results of pairwise comparison of signals from F_2 using CWT (Separate approach**)**

	rgb_1	rgb_2	rgb_3	rgb_4	rgb_5	rgb_6
rgb_1	0	15.1913	49.3815	54.2531	132.2202	203.8762
rgb_2	15.1913	0	47.2942	53.7081	132.8808	204.3273
rgb_3	49.3815	47.2942	0	58.1975	140.3541	209.3781
rgb_4	54.2531	53.7081	58.1975	0	130.3035	202.8278
rgb_5	132.2202	132.8808	140.3541	130.3035	0	155.5640
rgb_6	203.8762	204.3273	209.3781	202.8278	155.5640	0

Table 12. Results of pairwise comparison of signals from F_2 using CWT (Max approach**)**

	ζ_{21}	ζ_{22}	ζ_{23}	ζ_{24}	ζ_{25}	ζ_{26}
ζ_{21}	0	7.9745	26.1788	27.9194	68.1061	105.3575
ζ_{22}	7.9745	0	25.2026	28.0667	68.4728	105.6047
ζ_{23}	26.1788	25.2026	0	29.9439	72.6822	108.4430
ζ_{24}	27.9194	28.0667	29.9439	0	68.1358	105.4748
ζ_{25}	68.1061	68.4728	72.6822	68.1358	0	80.6324
ζ_{26}	105.3575	105.6047	108.4430	105.4748	80.6324	0

Tables 13, 14, and 15 present the numerical evaluations of the method using the CWT (r=2) with respect to its compliance with criteria C_1, C_2 and C_3 for the considered color interpretation approaches.

Table 13. Numerical evaluation of the RGB-model using the CWT with respect to its compliance with criterion C_1.

RGB model	$CV1_1^{\delta}(2)$	$CV1_1^{\delta}(3)$	$CV1_1^{\delta}(4)$	$CV1_1^{\delta}(5)$	$MCV1_1^{\delta}$
Average	1.0344	2.1104	0.3070	0.0466	0.9238
Luminosity	3.2711	0.0771	1.4322	0.5498	3.2711
Separate	0.9982	2.0002	0.3336	0.0824	0.8565
Max	2.2828	0.0665	1.4394	0.5470	2.2828

Table 14. Numerical evaluation of the RGB-model using the CWT with respect to its compliance with criterion C_2.

RGB model	$CV2_1^{\delta}(2)$	$CV2_1^{\delta}(3)$	$CV2_1^{\delta}(4)$	$CV2_1^{\delta}(5)$	$MCV2_1^{\delta}$
Average	0.9385	2.1202	0.1266	0.5324	0.1266
Luminosity	3.1627	0.1681	1.2977	0.1892	3.1627

Separate	2.1132	0.2305	1.2390	0.1939	2.1132
Max	2.1604	0.1881	1.2754	0.1834	2.1604

Table 15. Numerical evaluation of the RGB-model using the CWT with respect to its compliance with criterion C_3.

RGB model	$CV3_1^{\delta}(2)$	$CV3_1^{\delta}(3)$	$CV3_1^{\delta}(4)$	$CV3_1^{\delta}(5)$	$MCV3_1^{\delta}$
Average	0.9555	0.7651	0.3215	0.4916	0.4916
Luminosity	0.6452	0.4111	0.9285	0.2341	0.2341
Separate	0.6485	0.4103	0.9102	0.3076	0.3076
Max	0.6464	0.4099	0.9377	0.3046	0.3046

The aggregated evaluations of the RGB-models using the CWT with respect to Criteria C_1, C_2 and C_3 for the considered color interpretation approaches are summarized in Table 16.

Table 16. The aggregated evaluations of the RGB-model using the CWT.

RGB-model	Criterion C_1	Criterion C_2	Criterion C_3	Aggregated evaluation
Average	0.9238	0.1266	0.4916	3.0848
Luminosity	3.2711	3.1627	0.2341	6.6679
Separate	2.2506	2.1132	0.3076	4.6714
Max	2.2828	2.1604	0.3046	7.7260

5.Discussion

The results of pairwise comparisons of signals from the set F_2, constructed using the **Separate** RGB model, show a monotonic increase in the distances according to the ascending indices of the signals rgb_i (i=2÷6). This pattern is observed for both recognition methods, using the FT and CWT. Such a consistent increase is expected and is further supported by similar results obtained using the traditional **Average** RGB model. This observation serves as an indirect validation of the proposed approach to color interpretation, here referred to experimentally as **Separate**, confirming its reliability and applicability in the context of image recognition.

A more robust validation of the proposed approach is provided by the results of the empirical analysis of the recognition methods' adequacy with respect to Criteria C_1, C_2 and C_3. This analysis was conducted using the artificial sets of one-dimensional signals Z_2 and F_2, generated by extracting recognition features via the two RGB color models applied to the selected images. As shown in Tables 8 and 16, the aggregated evaluations across Criteria C_1, C_2 and C_3 for recognition methods using the **Separate** RGB model are significantly lower than the corresponding evaluations obtained with the **Average** RGB model. This finding serves as an objective argument in favor of the **Separate** color interpretation approach, confirming its effectiveness and validity in the context of image recognition.

The Max method represents an alternative approach to RGB color interpretation, focusing on identifying the maximum contribution among the R, G, and B components for each pixel. Pairwise comparisons of signals derived from the set F_2 using the Max method demonstrate a monotonic trend similar to that observed with the Separate method, both for the FT and CWT recognition techniques. This consistent behavior indicates the method's ability to preserve feature distinctions across signal indices.

6.Conclusion

In this work, we examined how alternative ways of interpreting color can influence the broader process of understanding images. The two proposed approaches (Separate and Max) allowed us to look at grayscale conversion not as a routine preprocessing step, but as a meaningful stage where valuable information about the structure of an image may either be preserved or inadvertently lost.

Through a computational experiment based on a controlled family of shifted images, it became clear that the way color is transformed into grayscale strongly affects the behavior of recognition methods. The Separate approach demonstrated the most stable and predictable results: distances between signals evolved more naturally, symmetry was better preserved, and convergence patterns were more consistent with the underlying geometry of the image set. The Max method also showed improvements compared to the familiar Average model, confirming that the conventional approach is not always the most informative for recognition tasks.

These observations suggest that revisiting the early stages of image processing–even such familiar steps as grayscale conversion – can noticeably enhance the performance of traditional analytical tools such as Fourier and wavelet transforms. In a broader sense, the results highlight the importance of being attentive to the initial assumptions built into our models: sometimes a small conceptual shift opens a new perspective on well-established techniques.

Looking ahead, the proposed methods could be tested on more complex or naturally varied image families, integrated into modern machine-learning workflows, or explored in applied domains where subtle tonal differences are crucial – such as remote sensing, cultural heritage preservation, or medical imaging. The study shows that even simple changes in color interpretation can enrich the analytical toolkit used to understand images and the patterns they contain.

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