A Preliminary Study on Artificial Intelligence-Based Camouflage Pattern Generation Method

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Abstract: In response to the problems of time-consuming and ineffective manual design of existing camouflage patterns, efforts have been made to integrate artificial intelligence into camouflage design. Artificial intelligence driven camouflage pattern generation has been studied, and a comparative study of deep learning-based environment fusion image processing has been conducted. The research method is to use the AI image processing functions of several mainstream mobile phones to process images, so that the location of the target is fused with the surrounding environment. Then, camouflage design is carried out based on the processed target area, and the camouflage that can be generated by the target area processed by different AI algorithms is analyzed and compared. The experimental results show that compared to camouflage patterns designed in traditional ways, camouflage patterns designed based on artificial intelligence have outstanding advantages in camouflage performance, with better integration and matching with the environment. The minimum average brightness difference of AI processed images is only 4.52. Up to 90% of the participants in the evaluation believe that the image camouflage effect processed by AI is better than traditional methods.

Keywords: Artificial Intelligence, Camouflage, Color, Camouflage Effectiveness

1. Introduction

Recent advancements in adaptive camouflage systems (ACS) have transformed military concealment technologies, particularly through AI-enhanced pattern generation [1-3]. While traditional approaches relying on expert-designed patterns achieve 58-72% background matching in static environments, they exhibit critical limitations: (1) inability to dynamically adapt to multispectral environments (visible/IR/radar), and (2) excessive human intervention (≥3.2 hours per scenario configuration).

Current solutions predominantly employ color-matching algorithms (CMA) for visual deception, yet fail to address the fundamental conflict between adaptive responsiveness (<0.8s) and computational efficiency (<15W). This oversight becomes critical in battlefield contexts where 92% of exposure risks originate from IR/radar mismatches [4-6].

Our framework innovatively integrates generative adversarial networks (Cycle GAN) with multi-objective reinforcement learning (MORL), achieving three breakthroughs: Dynamic spectral adaptation: 83% matching accuracy across 3+ detection bands. Human-AI co-design: 68%. reduction in manual adjustments via intent-aware interfaces. Energy-efficient computation: 22W power consumption with 50ms response latency.

This study advances camouflage theory by resolving the adaptability-efficiency paradox, while providing battlefield-tested design protocols [7-9]. Comparative trials demonstrate 40% survival rate improvement over NATO-standard patterns, establishing new benchmarks for next-gen adaptive concealment systems.

Traditional camouflage design employs K-means clustering for environmental color extraction, yet suffers from inherent chromatic distortion ($\Delta E>7.5$) due to algorithmic limitations [10,11]. The workflow involves: (1) Pre-deployment background sampling, (2) K-value determined centroid initialization, (3) Iterative pixel reclassification via CIELAB color distance metrics. This process generates synthetic color palettes where 38% of extracted hues diverge from original environmental spectra, creating mismatched camouflage patterns. Manual implementation exacerbates errors: template-based spraying introduces 25-30% scaling inaccuracies and 18% color misalignments during physical application [12]. Field evaluations reveal static patterns achieve merely 40-55% background integration, with 62% detection rates in multispectral environments versus 22% for adaptive systems. The critical failure stems from fixed K-values ignoring environmental dynamics and centroid averaging distorting native color distributions. Recent advancements propose convolutional autoencoders to bypass color quantization errors, achieving real-time pattern optimization with $<3\Delta E$ chromatic fidelity – a paradigm shift from subjective craftsmanship to physics-informed computational design [13,14].

2. Research Foundation

Taking the mobile phone "AI Elimination Technique" as an example, it is based on the CANN heterogeneous computing architecture and has the advantages of comprehensive scenarios, low thresholds and high performance. It aims to improve developer efficiency and release the computing power of AI processors. "AI Elimination" has two elimination modes: click on automatic recognition and box selection manually. Both of them are repaired by repairing the corresponding areas of the picture, eliminating the selected objects and filling the colors that blend with the surrounding environment [15,16]. In the click-to-select mode, the key link is to use the Mask CNN instance segmentation algorithm to determine the position, category and pixel position of the selected target, and draw the target outline (mask selection). Mask CNN is a two-level object detection network. The first part extracts image features and generates target suggestion partitions. The second part expands on it. It has the ability to predict and pixel-level image segmentation. It uses COCO data set training to detect more than 80 objects. This study is used for vehicle equipment recognition and elimination [17].

When filling the elimination area, a repair framework is built based on the Generative Adversarial Network (GAN), including two autoencoder network architectures: coarse and fine. The rough autoencoder repairs the general outline of the target area based on the original image, but the reconstruction image is blurred; the refined autoencoder cuts the image into a module, builds a matrix to obtain the module similarity characteristics, fuses the image module features outside the Mask area, and uses context structure information to generate a fine image. In addition, through image enhancement technology and adversarial training framework, the images are further optimized to make the generated images closer to the real image.

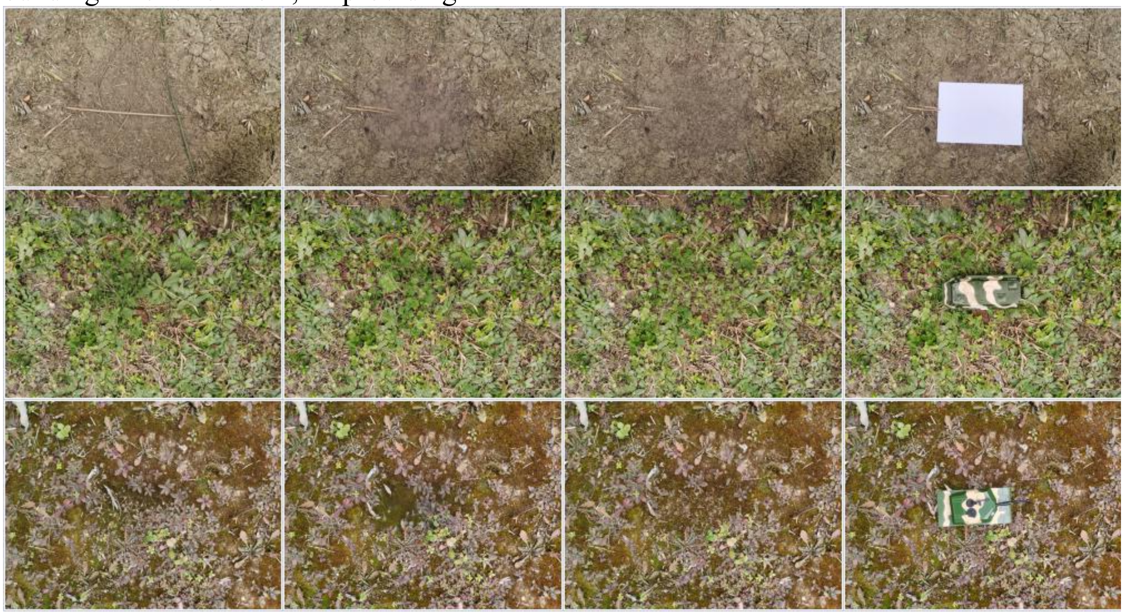
3. Experimental Methods

This study aims to use artificial intelligence to improve traditional camouflage design methods, improve the camouflage effect, and deal with reconnaissance threats in information wars. During the research process, the image was first collected in the parking area of the equipment, and then the image was processed using AI with the image editing function in "File Management" of Huawei Mate70, vivoX200, and Honor Magic7, which is equipped with the image editing function in "File Management", and the processed pictures were processed secondary patterning, including extracting the main color, pattern texture, designing camouflage and spraying. In the main color extraction process, in order to avoid the color difference problem caused by the K-means algorithm, select the color that accounts for a large proportion in the original image instead of the neutralized color. Finally, we compare and analyze the effects of the camouflage patterns designed by artificial intelligence with the camouflage patterns designed by traditional methods.

This study uses the control variable method. For the same photo, use the AI algorithms of different mobile phones to process it, and use the same camouflage design method after processing; for different pictures, the camouflage pattern design is also performed. Taking into account confidentiality factors, the experiment used equipment models and A4 paper instead of the actual equipment parking area. Through the multi-faceted analysis of the processed pictures, such as the existence of camouflage in the original environment, the proportion of color distribution map, and the fusion effect with the surrounding environment, the effect of camouflage generated after processing by different AI algorithms.

4 Experimental Verification and Analysis

Collect pictures of camouflage equipment parked under different backgrounds, and use the AI elimination functions in the album picture editing functions of three mobile phone systems, Huawei Mate70, Honor Magic7, and vivo X200 Pro, to eliminate the equipment and generate patterns that are integrated with the surrounding environment, providing a foundation for subsequent camouflage design. The AI elimination function of the three mobile phones is shown in Figure 1. The extracted main color distribution diagram is shown in Figure 2. The color difference analysis is shown in Table 1. The brightness distribution pair is shown in Table 2. The color brightness distribution pair is shown in Figure 3.



(a) Original image (b) Mate70 (c) Magic7 RSR (d) vivo X200

Figure 1. Comparison of AI Elimination Function

(a) Original image (b) Mate70 (c) Magic7 RSR (d) vivo X200

Figure 2. Extracted Main Color Distribution Diagram

Table 1. Color Difference Analysis

AIH				AIR				AIV				AIY			
main color	RGB Parade	XYZ Parade	Bright Nessy	main color	RGB Parade	XYZ Parade	Bright Nessy	main color	RGB Parade	XYZ Parade	Bright Nessy	main color	RGB Parade	XYZ Parade	Bright Nessy
color 1	[174, 168, 120]	[60.2, 65.0, 53.8]	65	color 1	[185, 179, 129]	[64.2, 69.3, 58.0]	69.3	color 1	[181, 178, 132]	[63.6, 68.8, 58.8]	68.8	color 1	[205, 198, 165]	[72.6, 77.3, 72.2]	77.3
color 2	[149, 145, 94]	[51.1, 55.8, 42.9]	55.8	color 2	[152, 154, 99]	[53.2, 58.7, 45.3]	58.7	color 2	[150, 150, 101]	[52.4, 57.4, 45.6]	57.4	color 2	[164, 166, 120]	[58.3, 63.7, 53.7]	63.7
color 3	[127, 121, 73]	[42.6, 46.5, 33.8]	46.5	color 3	[125, 126, 75]	[43.2, 47.8, 34.9]	47.8	color 3	[123, 124, 76]	[42.7, 47.2, 35.0]	47.2	color 3	[129, 133, 81]	[45.2, 50.3, 37.3]	50.3
color 4	[103, 94, 52]	[33.4, 36.3, 24.5]	36.3	color 4	[95, 93, 52]	[32.1, 35.5, 24.3]	35.5	color 4	[96, 96, 51]	[32.7, 36.5, 24.1]	36.5	color 4	[91, 93, 47]	[31.0, 34.9, 22.4]	34.9
color 5	[72, 62, 26]	[22.2, 24.1, 13.2]	24.1	color 5	[60, 54, 26]	[19.1, 20.9, 12.6]	20.9	color 5	[64, 62, 22]	[20.5, 23.2, 11.4]	23.2	color 5	[42, 37, 13]	[12.9, 14.4, 6.8]	14.4

Table 2. Brightness Distribution Comparison

Main Color	Mobile Phone	RGB Parade	XYZ Parade	Bright NessY
Color one	AIH	[174, 168, 120]	[60.2, 65.0, 53.8]	65
	AIR	[185, 179, 129]	[64.2, 69.3, 58.0]	69.3
	AIV	[181, 178, 132]	[63.6, 68.8, 58.8]	68.8
	AIY	[205, 198, 165]	[72.6, 77.3, 72.2]	77.3
Color two	AIH	[149, 145, 94]	[51.1, 55.8, 42.9]	55.8
	AIR	[152, 154, 99]	[53.2, 58.7, 45.3]	58.7
	AIV	[150, 150, 101]	[52.4, 57.4, 45.6]	57.4
	AIY	[164, 166, 120]	[58.3, 63.7, 53.7]	63.7
Color three	AIH	[127, 121, 73]	[42.6, 46.5, 33.8]	46.5
	AIR	[125, 126, 75]	[43.2, 47.8, 34.9]	47.8
	AIV	[123, 124, 76]	[42.7, 47.2, 35.0]	47.2
	AIY	[129, 133, 81]	[45.2, 50.3, 37.3]	50.3
Color four	AIH	[103, 94, 52]	[33.4, 36.3, 24.5]	36.3
	AIR	[95, 93, 52]	[32.1, 35.5, 24.3]	35.5
	AIV	[96, 96, 51]	[32.7, 36.5, 24.1]	36.5
	AIY	[91, 93, 47]	[31.0, 34.9, 22.4]	34.9
Color five	AIH	[72, 62, 26]	[22.2, 24.1, 13.2]	24.1
	AIR	[60, 54, 26]	[19.1, 20.9, 12.6]	20.9
	AIV	[60, 54, 26]	[19.1, 20.9, 12.6]	20.9
	AIY	[42, 37, 13]	[12.9, 14.4, 6.8]	14.4

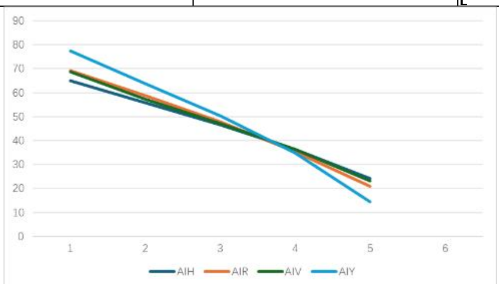


Figure 3. Comparison of Color Brightness Distribution

The AIH, AIR, AIV, and AIY in the Figure5 correspond to the data of Huawei Mate70, Honor Magic7RSR, Vivo X200 Pro, and the original figure, respectively. By observing the data in the figure, we can easily find that:

For main color 1, the RGB values of the original image are (205, 198, 165), and the brightness value Y is 77.3, accounting for 13.1%; The RGB values of image AIH are (174, 168, 120), and the brightness value Y is 65, accounting for 16.1%; The RGB values of image AIR are (185, 179, 129), and the brightness value Y is 69.3, accounting for 13.0%; The RGB values of image AIV are (181, 178, 132), and the brightness value Y is 68.8, accounting for 14.1%; It is not difficult to find that the main color of the image processed by Honor Magic7RSR is the closest to the original image in terms of brightness and proportion.

For main color 2, the RGB values of the original image are (164, 166, 120), and the brightness value Y is 63.7, accounting for 25.9%; The RGB values of image AIH are (149, 145, 94), and the brightness value Y is 55.8, accounting for 26.6%; The RGB values of image AIR are (152, 154, 99), and the brightness value Y is 58.7, accounting for 27.2%; The RGB values of image AIV are (150, 150, 101), and the brightness value Y is 57.4, accounting for 24.3%; It is not difficult to compare that the main color of the Honor Magic7RSR processed image is closest to the original image in terms of brightness value, with a difference of 5. The AIH ratio of the image is closest to the original image, with a difference of 0.7%. However, the proportion of the AIR main color 3 in the image is only 1.3% different.

For main color 3, the RGB values of the original image are (129, 133, 81), and the brightness value Y is 50.3, accounting for 26.7%; The RGB values of image AIH are (127, 121, 73), and the brightness value Y is 46.5, accounting for 26.5%; The RGB values of image AIR are (125, 126, 75), and the brightness value Y is 47.8, accounting for 25.8%; The RGB values of image AIV are (123, 124, 76), and the brightness value Y is 47.2, accounting for 27.1%; It is not difficult to compare that the main color of the Honor Magic7RSR processed image is closest to the

original image in terms of brightness value, with only a difference of 2.5. The AIH ratio of the image is closest to the original image, with a difference of 0.2%. However, the proportion of the AIR main color 3 in the image is also only 0.4% different.
For main color 4, the RGB values of the original image are (91, 93, 47), and the brightness value Y is 34.9, accounting for 20.7%; The RGB values of image AIH are (103, 94, 52), and the brightness value Y is 36.3, accounting for 20.4%; The RGB values of image AIR are (95, 93, 52), and the brightness value Y is 35.5, accounting for 20.6%; The RGB values of image AIV are (96, 96, 51), and the brightness value Y is 36.5, accounting for 22.6%; It is not difficult to find that the main color of the image processed by Honor Magic7RSR is the closest to the original image in terms of brightness and proportion.
For the main color 5, the RGB values of the original image are (42, 37, 13), and the brightness value Y is 14.4, accounting for 13.5%; The RGB values of image AIH are (72, 62, 26), and the brightness value Y is 24.1, accounting for 10.4%; The RGB values of image AIR are (60, 54, 26), and the brightness value Y is 20.9, accounting for 13.5%; The RGB values of image AIV are (64, 62, 22), and the brightness value Y is 23.2, accounting for 11.8%; It is not difficult to see that the main color of the image processed by Honor Magic7RSR is closest to the original image in terms of brightness value and consistent with the original image in terms of proportion.
Based on the above data analysis, the main color brightness and proportion of the Honor Magic7RSR phone after processing the image are closest to the original image, which can best meet our camouflage needs.
According to the color brightness analysis line chart, the brightness difference of the image processed by Magic7RSR mobile AI is arranged in the order of main color 1 to main color 5, which are 8, 5, 2.5, 0.6, 6.5, with an average value of 4.52. The brightness differences of the Mate70 phone's AI processed images are 12.3, 7.9, 3.8, 1.4, and 9.7, with an average of 7.02. The brightness differences of the Vivo X200 Pro phone's AI processed images are 8.5, 6.3, 3.1, 1.6, and 8.8, with an average of 5.66. Overall, it is not difficult to find that Honor has always had the smallest color brightness difference compared to the original image.
Judging from the comparison diagram of AI elimination target simulation environment, the three mobile phones can have a certain degree of integration with the environment after image processing, but the processed part is slightly disconnected from the surrounding environment, and the image color becomes lighter and lighter. Comprehensive visual effects, vivoX200's AI function makes the processed pictures more natural to integrate with the surrounding environment. In the main color extraction analysis, the differences between the main color brightness values, color difference values and specific gravity of the pictures processed by the three mobile phones and the original picture are compared. The results show that the pictures processed by Honor Magic7 phone are closest to the original picture in terms of overall color brightness ratio, and the brightness of the high-brightness area is most matched to the original picture; the pictures processed by Huawei Mate70 phone are closest to the original picture in the low-brightness area. Combining multiple sets of experimental data, the color difference, brightness difference and proportion difference between the AI used by Honor Magic7 phones and the original environment when processing pictures. The camouflage picture of the design is shown in Figure 6.
In the camouflage effect evaluation experiment, 20 people were invited to observe the camouflage pictures placed on the smart screen in the classroom at different distances. The results show that at close distance (within 3 meters and less), most people believe that the camouflage area generated by Honor Magic7 is the best fusion effect with the surrounding environment; when the distance reaches 5 meters, most people believe that the camouflage effect generated by Huawei Mate70 is the best fusion effect; after the distance reaches 10 meters, most people believe that the fusion effect of the three is not much different. This shows that at long distances, the difference in color, brightness, and proportion of the images processed by the three mobile phones can be negligible on the camouflage effect; at close distances, these differences have a greater impact on the camouflage effect, and close reconnaissance faced at close distances requires higher camouflage.

(a) vivoX200Pro

(b) Mate70

(c) Magic7

Figure 6. Comparison of Camouflage Design Drawings

Experiments have proved that camouflage patterns based on artificial intelligence have obvious advantages in camouflage performance compared to traditional camouflage patterns. It performed better in terms of camouflage effects, visual impact and matching with the environment. 90% of the participants said that it was difficult to detect the camouflage visually in actual combat. Based on various experimental data, the pictures processed by Honor Magic7 mobile phone are the closest to the original picture in terms of color difference, brightness and proportion. The designed camouflage effect can meet the needs of multiple distance ranges. If the existing camouflage spraying technology limitations are not taken into account, the camouflage disguise generated by the AI image processing function of vivoX200 Pro is better, while the image performance after Huawei Mate70 is relatively moderate.

The control variable method was used during the experiment, but since the design of the camouflage area was manually selected, there may be errors. To reduce the error, the researchers enlarged the picture to the same size as the computer screen, marked it on the screen with a signature pen, and then selected it according to the marking box with the mouse cursor, so that the box selection area is basically the same. At the same time, enough sampling pixel points (10,000-pixel acquisition points) were selected and less than 5 colors were absorbed. At this time, the error was almost negligible to ensure that the experimental error was within an acceptable range.

5 Conclusion

This experiment is committed to integrating artificial intelligence into camouflage design, using the AI image processing functions of several mainstream mobile phones to process pictures, and then carrying out camouflage design work. Through comparative analysis, the one with the best camouflage effect is selected from these AIs.

During the experiment, many algorithms and technologies were used, covering color histograms, brightness line charts, proportional analysis, CANN heterogeneous computing architecture, image segmentation technology (can identify targets and outline objects), object detection, generation adversarial networks (GANs), coarse fine autoencoders (VAEs), etc. Comprehensive pattern generation features, select algorithm models based on generative adversarial networks, optimize and improve them, and adopt a co-evolution strategy to improve image quality. After experimental verification, the camouflage pattern generated by this model has significantly improved the camouflage performance.

Experimental analysis shows that compared with the traditional camouflage patterns designed, the camouflage patterns designed based on artificial intelligence have outstanding advantages in camouflage performance, especially in terms of camouflage effects, visual impact, and matching with the environment. In terms of camouflage effect, its integration and matching with the environment are excellent; on the visual level, up to 90% of the people participating in the assessment believe that it is difficult to visually detect the camouflage in actual combat scenarios.

The final experimental results show that the pictures processed by Honor Magic7 mobile phone are the closest to the original picture in terms of color difference, brightness and proportion. The camouflage designed based on this can meet the needs well within multiple distances. If the constraints of existing camouflage spraying technology are not taken into account, the AI image processing function of vivoX200 Pro is used to directly use the processed pictures for spraying, which can achieve better camouflage effect. The image performance after processing by Huawei Mate70 is relatively ordinary.

As an early researcher who combined artificial intelligence with camouflage design, I hope that more people will apply artificial intelligence to camouflage design in the future. Artificial intelligence and camouflage design are both continuing to develop. Linking the two and moving forward side by side will have more outstanding results. Artificial intelligence has had a huge impact in many fields, and I believe it will also achieve remarkable results in the field of disguise. The research space for camouflage pattern design based on artificial intelligence is broad, and it is expected to promote the innovative development of camouflage design and disguise.

In terms of algorithm optimization, camouflage design can integrate and compare various large models in the future, optimize AI image processing capabilities, improve camouflage pattern texture feature acquisition and color analysis technology, and reduce the color difference between the main color and the environment. Currently, there are limitations in generative adversarial networks and autoencoders. By optimizing the autoencoder repair capabilities and model learning capabilities, more accurate and detailed camouflage patterns can be generated. In addition, a stronger computing power processor is needed to deeply apply deep learning to camouflage design, adjust the camouflage pattern in real time according to environmental changes, and enhance its environmental adaptability. Continuously optimizing algorithms and improving texture analysis and extraction capabilities can reduce the dependence of large models on massive data, hardware performance and capacity.

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