

Supplementary Information for

Digital camouflage encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands

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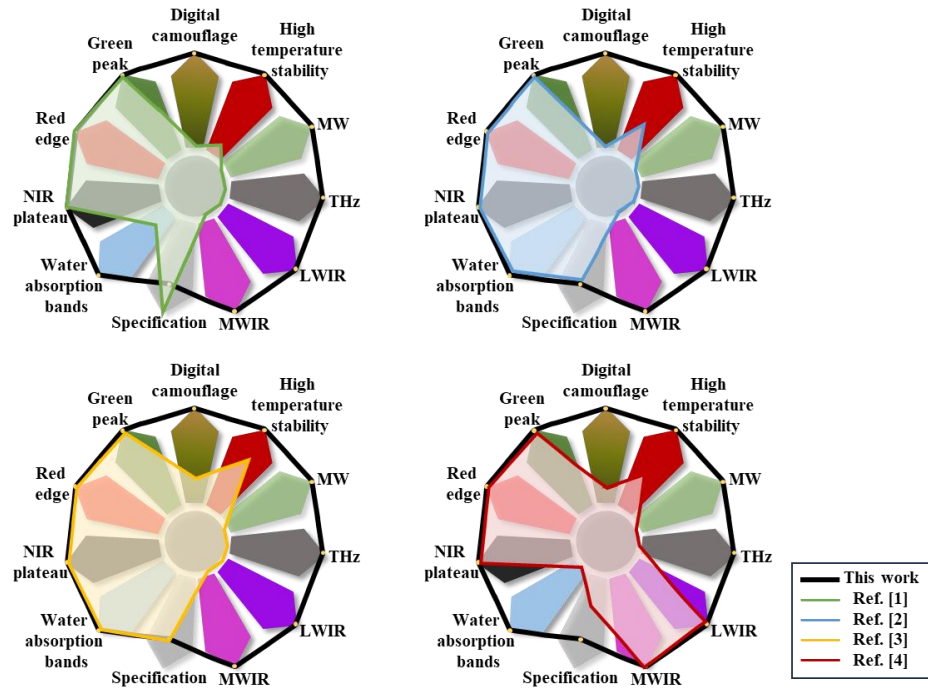
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Supplementary References

Supplementary Notes

Supplementary Note 1. Comparison with other work

Other works, including a few notable examples, fail to address the challenges presented in the main text. As shown in Supplementary Fig. 1¹⁻⁴, this camouflage strategy builds upon digital camouflage and significantly addresses the following issues: (i) the fulfillment of all optical spectral characteristics of vegetation while closely adhering to military specifications; (ii) coverage across multiple typical detection wavelengths; and (iii) outstanding high-temperature stability (see Supplementary Note 15).

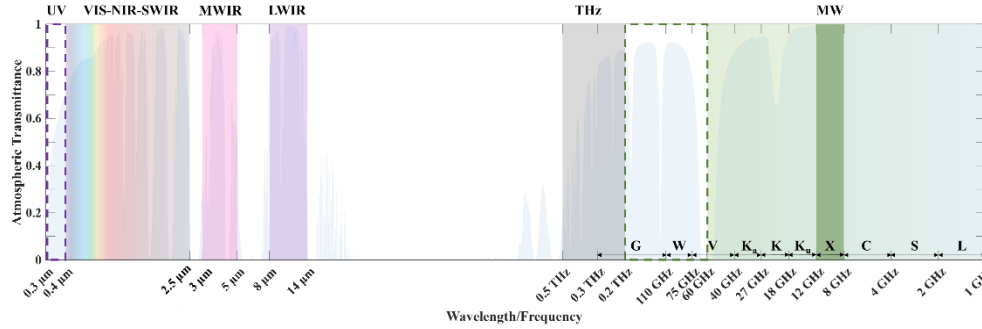


Supplementary Fig. 1 | Comparison with other work.

Supplementary Note 2. Calculation of the proportion of camouflage bands relative to atmospheric windows

The logarithms of typical atmospheric windows (0.3-2.5 μm , 3-5 μm , 8-14 μm , 600-4500 μm (0.066-0.5 THz), 5000-300000 μm (1-60 GHz)) and the bands studied in this research (0.4-2.5 μm , 3-5 μm , 8-14 μm , 600-1500 μm (0.2-0.5 THz), 5000-300000 μm (1-60 GHz)) were taken, and the calculations reveal that the bands investigated in this study account for 80.19% of the typical atmospheric windows.

In this manuscript, the bands with significant atmospheric transmission that have not been considered include (dashed boxes in Supplementary Fig. 2): (i) 0.3-0.4 μm (ultraviolet, UV), which is rarely considered due to the limitations of detectors⁵; (ii) below 0.2 THz, 60-75 GHz (part of the V-band), 75-110 GHz (W-band), and 110-200 GHz⁶ (part of the G-band). These bands from 60-200 GHz cannot be incorporated into the scheme as it requires simultaneous consideration of THz and 1-60 GHz MW camouflage.



Supplementary Fig. 2 | The overview of atmospheric windows.

Supplementary Note 3. Maximum object distance calculation

The angular resolution of human vision is approximately 57.3". The threshold increases to 60.3" when the brightness contrast exceeds 0.4. In outdoor environments, this threshold is further enlarged by a factor of ~ 2.5 ⁷. The dimension of a single pixel in digital camouflage, P , is 2 cm. The maximum object distance at which the human eye can distinguish the device is given by⁸:

$$l_{max} = \frac{P}{\theta} \quad (\text{S1})$$

The calculated l_{max} is 27.40 m, which means that the human eye cannot distinguish the device at a distance of about 28 m.

Supplementary Note 4. Lock-on range calculation

The lock-on range is determined by the sensitivity of the IR detector and the irradiance on the IR detector⁹. As an example, the lock-on range in the MWIR band, $R_{LO, 3-5 \mu\text{m}}$, is calculated as follows:

$$R_{LO, 3-5 \mu\text{m}} = \sqrt{A_{obj} \cdot H_{3-5 \mu\text{m}} / (\Omega_{obj} \cdot NEI \cdot \xi_{min})} \quad (\text{S2})$$

where A_{obj} is the effective area of object, $H_{3-5\mu m}$ is MWIR band integrated irradiance on the detector, Ω_{obj} is the effective solid angle of object, $NEI \cdot \xi_{min}$ is the minimum threshold value of the IR detector. $H_{3-5\mu m}$ depends on the radiation intensity of object and the reflected earthshine radiation:

$$H_{3-5\mu m} = \Omega_{obj} \cdot \int_{3\mu m}^{5\mu m} \varepsilon(\lambda) M_{bb}(\lambda, T_{obj}) \tau_{atm}(\lambda) - \varepsilon(\lambda) M_{bb}(\lambda, T_{background}) \tau_{atm}(\lambda) d\lambda, \quad (S3)$$

where $\varepsilon(\lambda)$ is the object's surface emittance, M_{bb} is blackbody spectral radiant exitance, T_{obj} is object's surface temperature, $T_{background}$ is background temperature, τ_{atm} is the atmospheric transmission.

Supplementary Note 5. Theoretical supplement for hyperspectral digital camouflage

In hyperspectral field, the absolute value differences are described using spectral distance^{10,11} (SD), which can be calculated as:

$$SD(I_a, I_b) = \sqrt{\sum_{i=1}^n [I_a(\lambda_i) - I_b(\lambda_i)]^2} \quad (S4)$$

The shape differences of 2 spectra are commonly described using spectral angle mapping^{12,13} (SAM), which can be calculated as:

$$SAM(I_a, I_b) = \cos^{-1} \left(\frac{\sum_{i=1}^n [I_a(\lambda_i) \cdot I_b(\lambda_i)]}{\sqrt{\sum_{i=1}^n [I_a(\lambda_i)]^2 \cdot \sum_{i=1}^n [I_b(\lambda_i)]^2}} \right) \quad (S5)$$

Additionally, the information entropy from commonly used probability and statistical theory is used to establish the spectral information divergence¹⁴ (SID) for analyzing the similarity between two vectors, which can be calculated as Eq. (S6). In Eq. (S6), $D(I_a||I_b) = \sum_{i=1}^n a_i \cdot \lg(a_i/b_i)$, $D(I_b||I_a) = \sum_{i=1}^n b_i \cdot \lg(b_i/a_i)$. While $a_i = I_a(\lambda_i) / \sum_{i=1}^n I_a(\lambda_i)$ and $b_i = I_b(\lambda_i) / \sum_{i=1}^n I_b(\lambda_i)$ represent the probabilities of I_a and I_b .

$$SID(I_a, I_b) = D(I_a||I_b) + D(I_b||I_a) \quad (S6)$$

In this work, we define a new spectral parameter, spectral weight distance (SWD), as given in Eq. (S7). The parameter SWD is based on the principles of spectral distance (SD) and spatial color mixing in digital camouflage, describing the differences between two spectral vectors. It can also be applied to degenerate low-dimensional spaces (e.g., the VIS color space). Different weight coefficient vectors, α_i , are assigned to I_a and I_b in Eq. (S7). Additionally, an extra cross term is introduced, weighted by the coefficient matrix, $\beta_{i,j}$, where $\alpha_i, \beta_{i,j} \in R$, with $\alpha_i = 0.5$ and $\beta_{i,j} = 0$ in this study.

$$SWD(I_a, I_b) = \sqrt{\sum_{i=1}^n \alpha_i \cdot [I_a(\lambda_i) - I_b(\lambda_i)]^2 + \sum_{i=1}^n \sum_{j=i}^n \beta_{i,j} \cdot I_a(\lambda_i) \cdot I_b(\lambda_j)} \quad (S7)$$

In general, the spectra of vegetation are diverse, the absolute intensity information of the spectrum is uncertain, but the relative position information is definite. Therefore, it is important to give different weights to different wavelengths. In Eq. (S8), k and b linearly change SID to increase the universality of GCD ($k = 50, b = 0$ in this study).

$$SID'(I_a, I_b) = k \cdot SID(I_a, I_b) + b \quad (S8)$$

Moreover, in this work, a more widely applicable mathematical metric, deviation rate¹⁵, which is not specific to spectroscopy, is also used to evaluate the spectra:

$$DR(I_a, I_b) = \left| \frac{\sqrt{\sum_{i=1}^n [I_a(\lambda_i) - I_b(\lambda_i)]^2}}{\sqrt{\sum_{i=1}^n I_b(\lambda_i)^2}} \right| \quad (S9)$$

To evaluate the hyperspectral camouflage performance represented by the deviation rate, the deviation rate between two points on the same leaf was calculated to be 0.1954 (~ 0.2 , Supplementary Fig. 3).

In digital camouflage, color and pattern serve as the two fundamental pillars. Traditionally, the primary color of digital camouflage is a crucial visual attribute that indicates the varying reflectance of a target across the VIS RGB channels. In the case of IR digital camouflage, intensity can be mapped to color bars and subsequently to the VIS HSV color space, converting a single intensity channel into RGB channels. The digital camouflage color difference⁸, denoted as D , between two pixels, a and b , can be expressed in terms of their spectra I_a and I_b as

$$D(I_a, I_b) = \sqrt{(R_a - R_b)^2 + (G_a - G_b)^2 + (B_a - B_b)^2}, \quad (S10)$$

where R , G , and B correspond to the RGB values of the pixels. For optical hyperspectral digital camouflage, under the definition of this work, the difference between two hyperspectral digital camouflage pixels, a and b , can be quantified using the generalized color difference (GCD), expressed as

$$GCD(I_a, I_b) = \sqrt{SWD(I_a, I_b)^2 + \{SID'(I_a, I_b) \cdot \sin[SAM(I_a, I_b)]\}^2}. \quad (S11)$$

Additionally, the method for determining the undetermined parameters ($\alpha_i, \beta_{i,j}, k, b$) in the above equations follows the principle that GCD should balance both digital camouflage and hyperspectral classification, ensuring that GCD values among the three ROIs are as equal as possible. Based on this principle, we optimized the undetermined parameters in this study. The computed exact values of $\alpha_i, \beta_{i,j}$ are provided in the Supplementary

data 1 and 2 respectively, with $k = 48.657$, $b = -2.375$. For the convenience of readers in performing quick calculations, the parameters can be approximated as $\alpha_i = 0.5$, $\beta_{i,j} = 0$, $k = 50$, and $b = 0$.

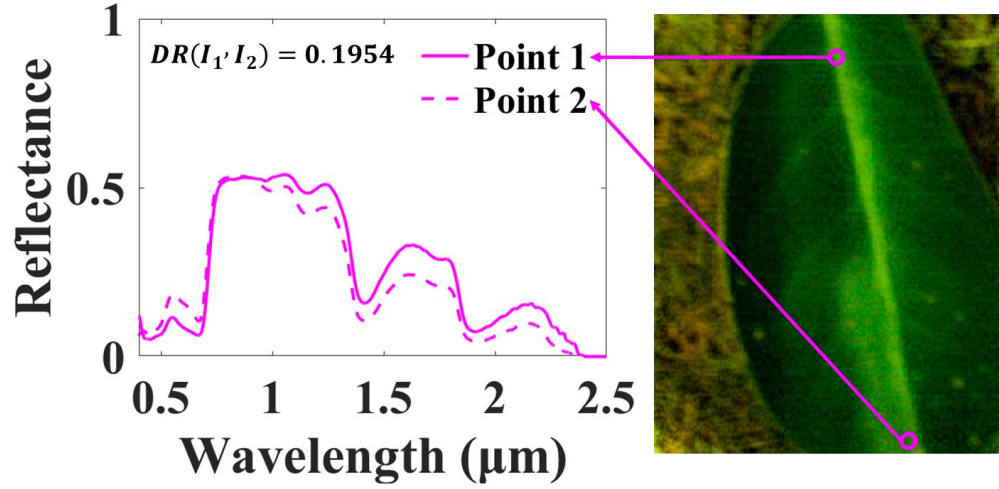
To efficiently calculate the relevant parameters (SD , SAM , SID , SWD , GCD) and classify them efficiently, a deep neural network (DNN) is used to approximate the above formulas: (i) A dataset of hyperspectral images of vegetation backgrounds is selected, containing 1,421,558 spectral data points, each with 128 wavelength channels. (ii) A simple neural network architecture with three hidden layers, each containing 5 neurons, is trained using PyTorch on an Intel Core i9 14900KF CPU and an NVIDIA GeForce RTX 4080 SUPER GPU to accelerate computation. (iii) The training dataset (1,350,530 spectral data points) is processed in 122.97209 seconds. (iv) The test set (71,028 spectral data points) achieves a Test Loss of 0.02771 in just 0.00047 seconds. In contrast, direct formula-based calculations take 36.06872 seconds, demonstrating a $\sim 70,000$ times efficiency improvement.

To choose an appropriate classification method, histograms (Supplementary Fig. 4) are generated to establish the relationship between the dataset and the three ROIs for the parameters. Selecting an appropriate threshold can classify the data or image. An optimal classification method should spread the data across the three ROIs and show distinct feature peaks. In this regard, SWD and GCD perform best for classification, as they exhibit three peaks in the histograms of all three ROIs. However, considering interpretability, SID classification is used in this study.

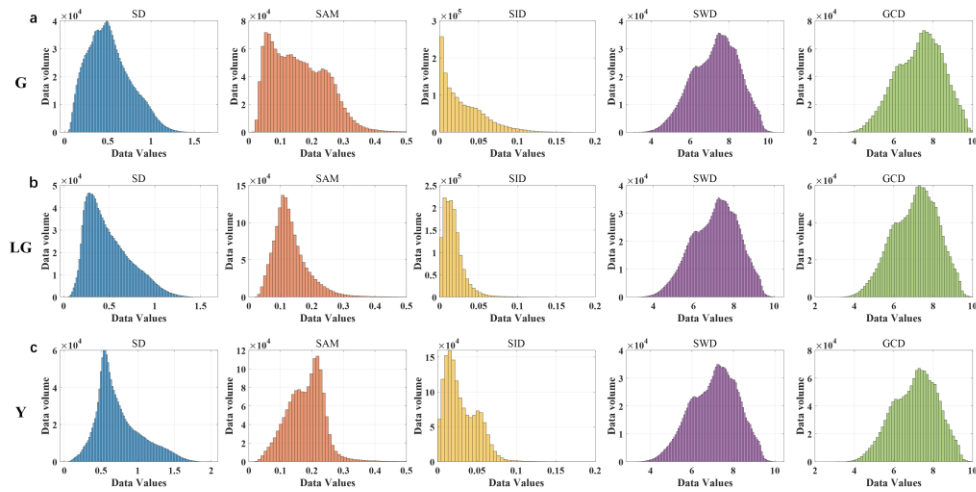
The pattern of digital camouflage within a band is composed of primary colors specific to that band (Supplementary Table 1). Multispectral digital camouflage patterns should be designed to simulate different textures of the background, given the varying response characteristics in each band. However, for a specific pixel, there is coupling between the spectral characteristics of different bands, which complicates the simultaneous design of multiple patterns. Therefore, this coupling should be minimized to facilitate the design of patterns across multiple bands for effective camouflage. The degree of coupling among multispectral digital camouflage patterns can be characterized by structural similarity ($SSIM$), which is used to evaluate image similarity¹⁶. The average $SSIM$, representing the degree of coupling among N digital patterns, can be calculated as

$$\overline{SSIM} = \sum_{i=1}^{N-1} \sum_{j=i+1}^N SSIM(P_i, P_j) / C_N^2. \quad (S12)$$

P represents the pattern of a specific band, C_N^2 refers to the number of combinations where 2 patterns are selected out of N bands. The $SSIM$ is calculated by $ssim$ function in MATLAB, and the pattern images used in the calculation are obtained from the experimental figures in the article.



Supplementary Fig. 3 | Spectral comparison between two points on the same leaf.



Supplementary Fig. 4 | Histograms of dataset parameters for different ROIs: a. Green plant, b. Light-green plant, and c. Yellow plant.

Supplementary Table 1 | Multiband level-pixel coupling table.

Multilayer structure	δ of sub-pixel (μm)	Optical	MWIR	LWIR	THz	X-band
GS	10			LL1	LT2	LX1,
	77	LH1	LM4	LL2	LT1	LX2,
	150			LL3	LT4	and LX3
LGS	10			LL1	LT2	LX1,
	77	LH2	LM4	LL2	LT1	LX2,
	150			LL3	LT4	and LX3
YS	10		LM1	LL1	LT4	LX1,
	77	LH3	LM2	LL2	LT4	LX2,
	150		LM3	LL3	LT3	and LX3

Supplementary Note 6. Digital camouflage pattern design method and camouflage effect

Here, the design process of the 400-1000 nm optical hyperspectral digital camouflage pattern is selected as a representative example. The patterns for other bands can also be designed using this method. This paper mainly highlights the pattern decoupling performance between multiple bands.

As shown in Supplementary Fig. 5:

- (i) Background image selection and hyperspectral imaging: Determine the background image and perform hyperspectral imaging, using the regions of interest (ROIs) of three types of vegetation for classification. The hyperspectral classification process here is equivalent to determining the primary colors (for ordinary primary color extraction, the k-means algorithm is used).
- (ii) Camouflage area definition: Determine the camouflage area size as $16 \times 16 \text{ cm}^2$, with a single pixel size of $2 \times 2 \text{ cm}^2$. Pixelate the corresponding plant background of the camouflage area directly to obtain the initial camouflage pattern.

(iii) Pattern refinement: Apply a random small template and a random single point to the initial camouflage pattern to generate a pattern sample, which is used to decorate large spots to improve the hierarchy of the camouflage pattern¹⁷.

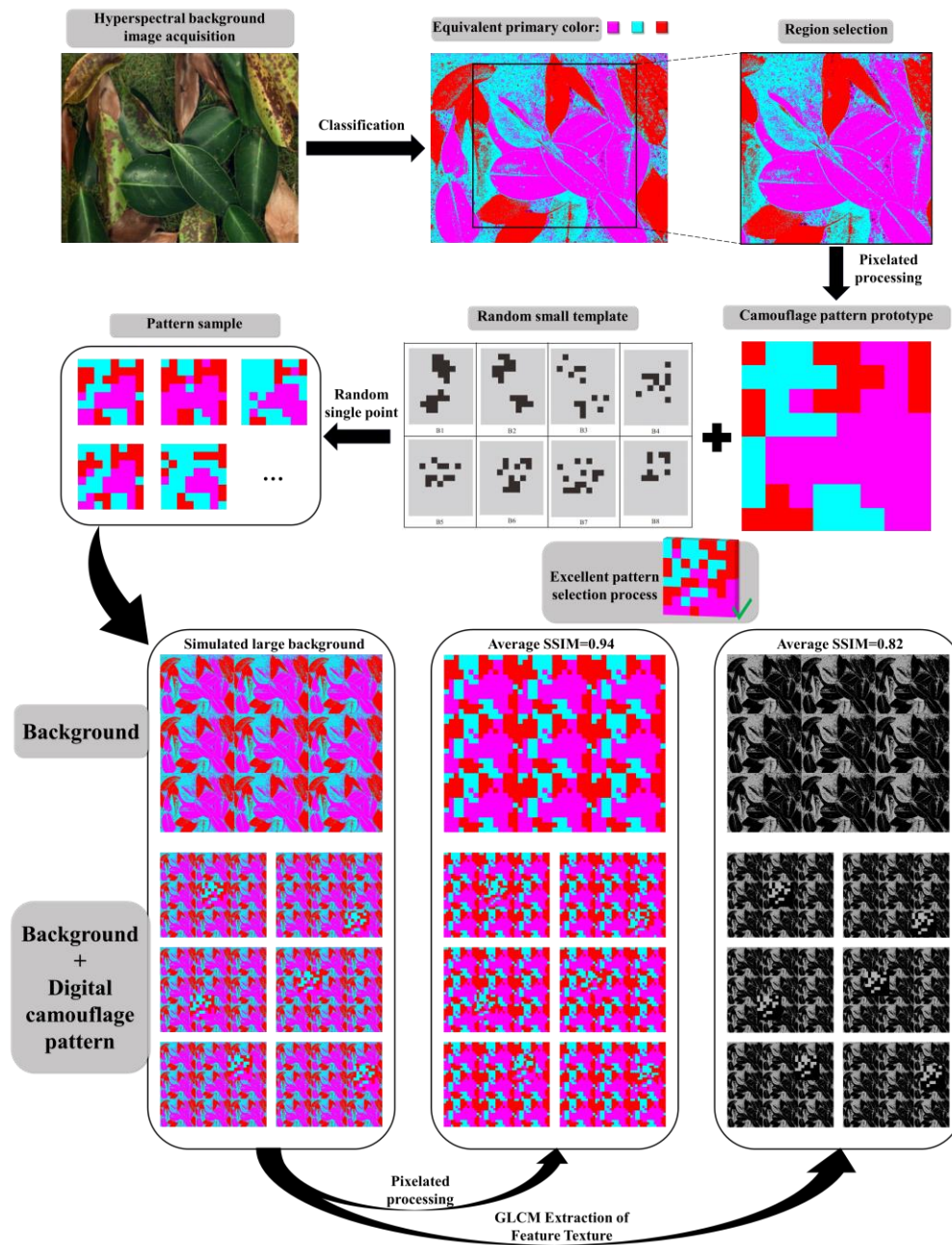
(iv) Background expansion and simulation: Expand the original background nine times to simulate a large area scene. Randomly add the generated pattern sample to the simulated large area background to create a simulated experimental camouflage image. This verifies the texture matching degree of the pattern at various positions.

(v) Pixelation-based evaluation: Compare the simulated experimental camouflage image with the large area background, and apply pixelation to simulate the image during long-distance spatial color mixing. The average SSIM value of the pattern selected in this work is 0.94.

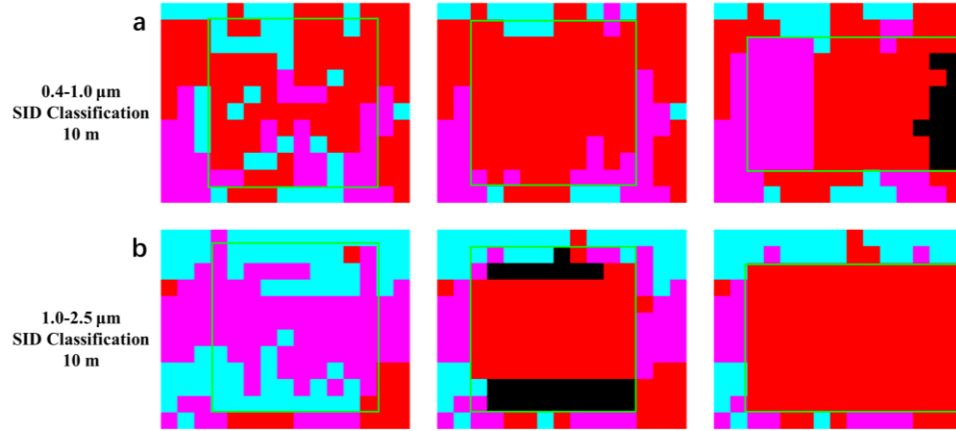
(vi) Texture feature analysis: Compare the simulated experimental camouflage image with the large area background, and use the gray-level co-occurrence matrix (GLCM) to calculate the characteristic texture features. The average SSIM value of the pattern selected in this work is 0.82.

In addition, human psychology experiments are conducted on the selected camouflage patterns in steps (iv) and (vi) (Supplementary Table 2). In Supplementary Fig. 5, the final Background Simulation, Pixelation-Based Evaluation, and Texture Feature Analysis include twelve images, which are enlarged to a size of $11.6 \times 9.3 \text{ cm}^2$, with each camouflage pixel having a side length of 1 cm. Additionally, twelve uncamoouflaged images (with the target set in black) at the same positions are generated as controls. Ten participants with normal corrected vision observe the images from a 15 m line, point out the target using a laser pointer, and measure the time with a stopwatch. As shown in Supplementary Table 2, participants take about 4 to 13 times longer to identify the camouflaged targets compared to the uncamoouflaged ones, which to some extent reflects the effectiveness of the camouflage patterns.

Additionally, based on the optical hyperspectral classification images in Fig. 4b and 4c, simulated images at a distance of approximately 10 m are provided (Supplementary Fig. 6). The digital camouflage device is already visually blended with the background texture, while the fabric and paint references remain exposed under hyperspectral classification and show poor integration with the background texture.



Supplementary Fig. 5 | Digital camouflage pattern design process.



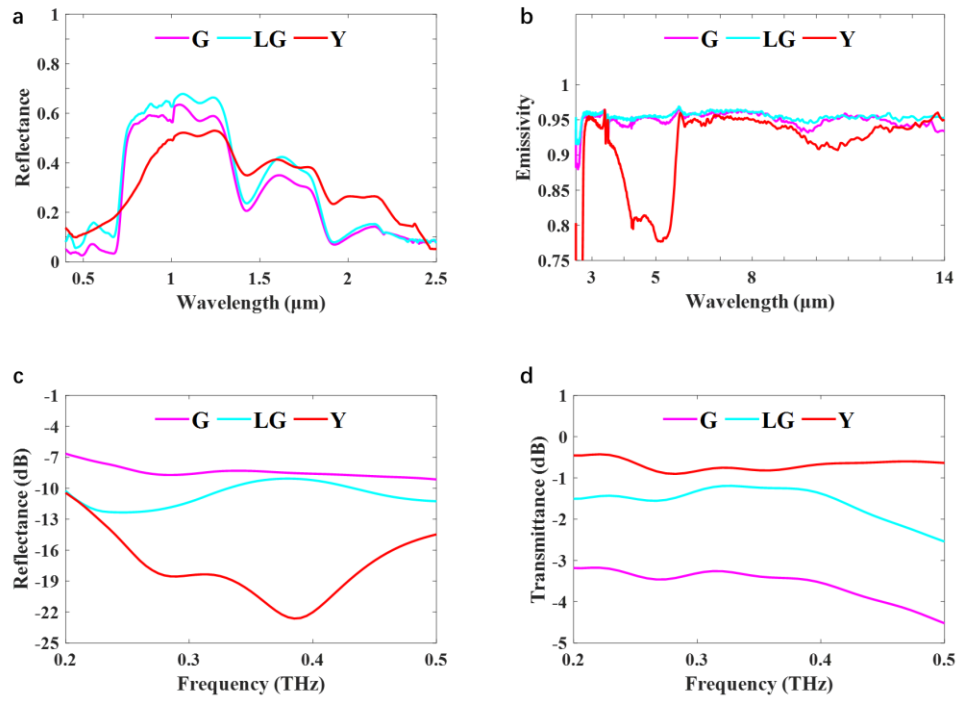
Supplementary Fig. 6 | Simulated optical hyperspectral classification images at 10 m, in the a. 0.4–1.0 μm range and b. 1.0–2.5 μm range.

Supplementary Table 2 | Time taken to find targets in simulated scenes.

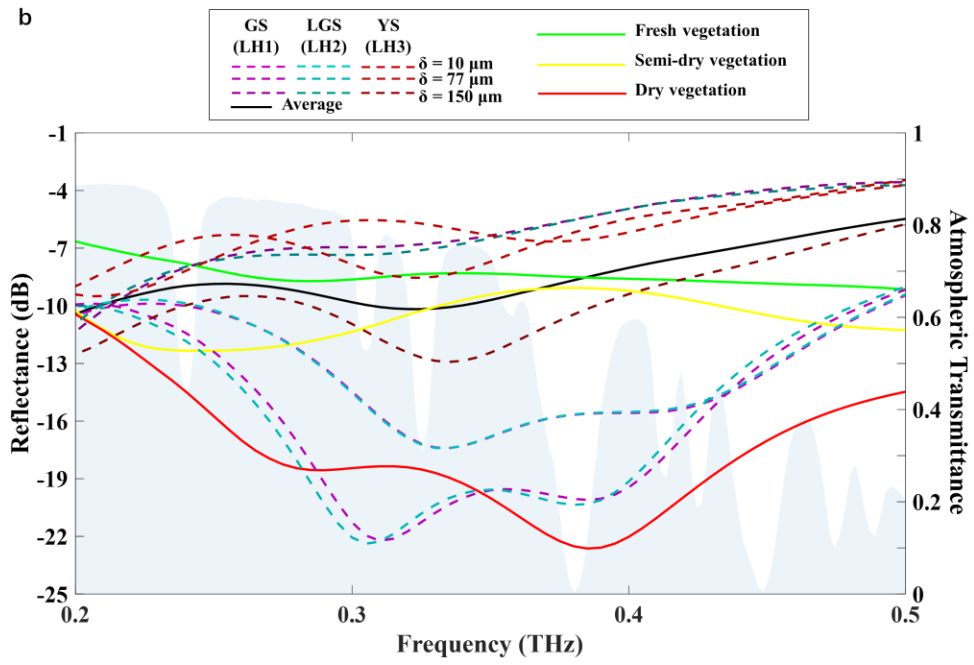
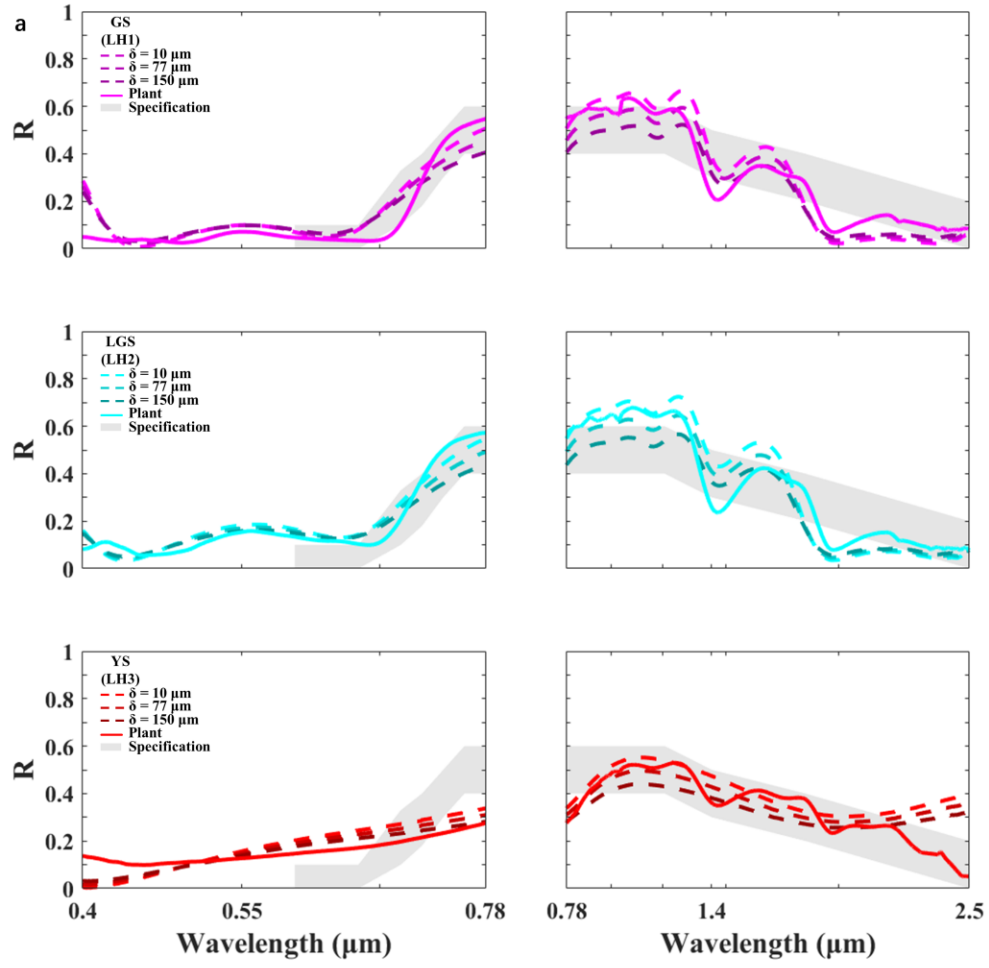
	Average detection time for uncamouflaged images (s)	Average detection time for camouflaged images (s)
Simulated images (iv)	0.10	1.44
Texture images (vi)	0.23	1.35

Supplementary Note 7. Reference spectra

In the optical band (Supplementary Fig. 7a and 8a), the three types of ROIs, fresh green vegetation (G), fresh light-green vegetation (LG), and withered yellow vegetation (Y), exhibit different distinct characteristic responses in the green peak, red edge, NIR plateau, and water absorption bands. In the thermal IR band (Supplementary Fig. 7b), the emissivity of Y in the MWIR is about 0.85, differing from that of G and LG, thus leading to a 4-level pattern in the MWIR (while the temperature is set to 3-levels in this study). In the THz band, Y and LG exhibit significant transmission (Supplementary Fig. 7d and 8b). Combined with the reflection spectra in Supplementary Fig. 7c, the actual environmental reflection spectra will become more complex, resulting in a 4-level pattern in the THz band.



Supplementary Fig. 7 | Reference spectra of vegetations. **a.** Optical reflectance. **b.** Thermal infrared emissivity. **c.** Terahertz reflectance and **d.** transmittance.



Supplementary Fig. 8 | Spectral comparison between vegetation and pixel of a. optical hyperspectra and b. THz band.

Supplementary Note 8. Multilayer structure design method

The multilayer structures are designed using the QUBO model and employing the factorization machine (FM) model¹⁸. As shown in Supplementary Fig. 9, taking the GS design as an example, the specific steps are as follows:

(i) Select an initial material library and assign numerical identifiers, then determine the appropriate quantized thickness based on the refractive index. In binary encoding, there are 7 materials and 1 empty material (as shown in Supplementary Table 3, the encoding for the empty material is 111, with a thickness of 0). Each material is represented using a 3-bit encoding scheme.

(ii) Given the total number of bits for the sample, n , as 30, i.e., 10 layers, the initial sample includes 1 all-zero array, 30 arrays with a single 1 in different positions, 435 arrays with two 1s in different positions, and 1000 random samples. Based on the standard spectrum, the transfer matrix method (TMM) is used to calculate the initial sample's *FOM* as

$$FOM = SD_{0.4-2.5 \mu m} + 10 \times (SAM_{0.4-0.78 \mu m} + SAM_{0.78-1.35 \mu m} + SAM_{1.45-1.78 \mu m} + SAM_{2.0-2.35 \mu m}). \quad (S12)$$

Use the FOM as the value of the Hamiltonian function and apply the alternating least squares (ALS) method to iterate 300 times to solve the Hamiltonian function's coefficients.

(iii) Simulated annealing and machine learning iterate with each other n^2 times, producing the 'Result 1' from the iterative loop.

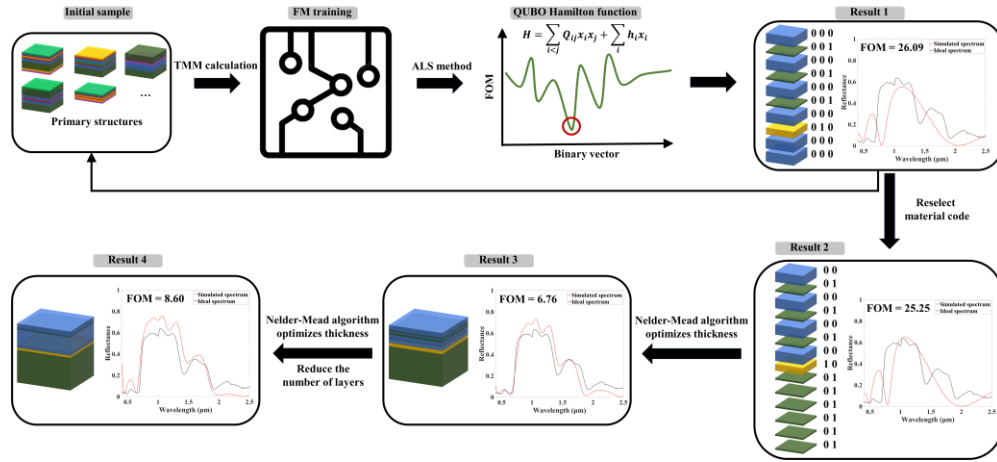
(iv) Re-encode ZnS, Ge, Ti, and empty material (as shown in Supplementary Table 4, the empty material's encoding is 11, with a thickness of 0). Each material now occupies 2 bits. Given the total number of bits as 30, i.e., 15 layers, this provides greater freedom for optimization. Repeat the previous three steps to obtain 'Result 2' from the iterative loop.

(v) Based on 'Result 2', the Nelder-Mead algorithm is used to further optimize the thickness to achieve the best performance, resulting in 'Result 3'.

(vi) Considering the complexity of the preparation process, reduce the number of layers of the multilayer structure based on ‘Result 3’. Use the Nelder-Mead algorithm again to optimize the thickness and obtain the final result, ‘Result 4’.

(vii) Repeat the above six steps based on different standard curves to obtain the multilayer structures for LGS and YS.

Here, only the optical band spectrum design is considered, and the decoupling control methods for other bands are described in other supplementary information.



Supplementary Fig. 9 | Multilayer structure design method

Supplementary Table 3 | Material code 1

Material	Binary code	Thickness (nm)
ZnS	0 0 0	50
Ge	0 0 1	5
Ti	0 1 0	30
Au	0 1 1	5
Ag	1 0 0	10

SiO ₂	1 0 1	50
MgF ₂	1 1 0	50
<i>None</i>	1 1 1	0

Supplementary Table 4 | Material code 2

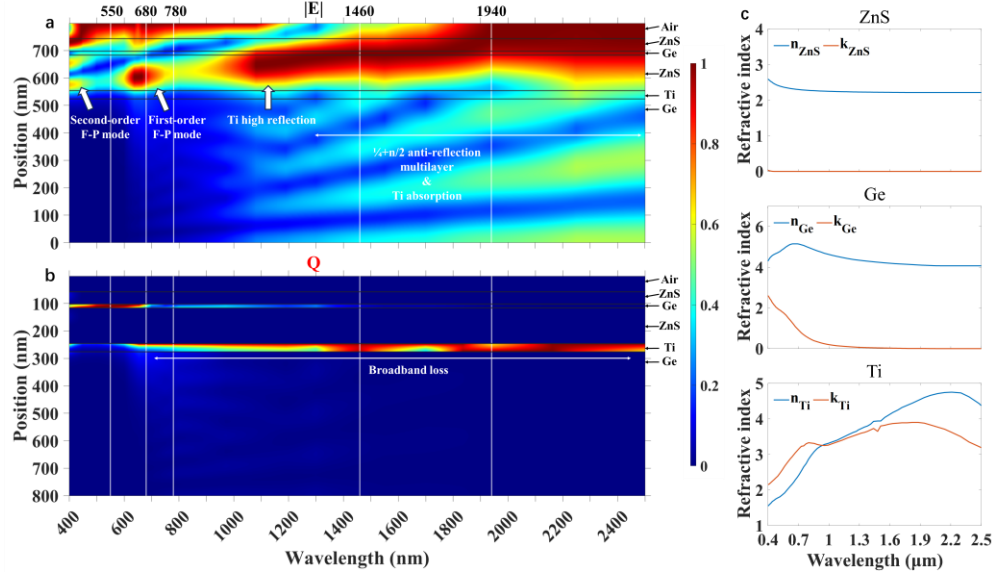
Material	Binary code	Thickness (nm)
ZnS	0 0	50
Ge	0 1	5
Ti	1 0	30
<i>None</i>	1 1	0

Supplementary Note 9. Simulations of optical hyperspectra, thermal IR, and THz bands

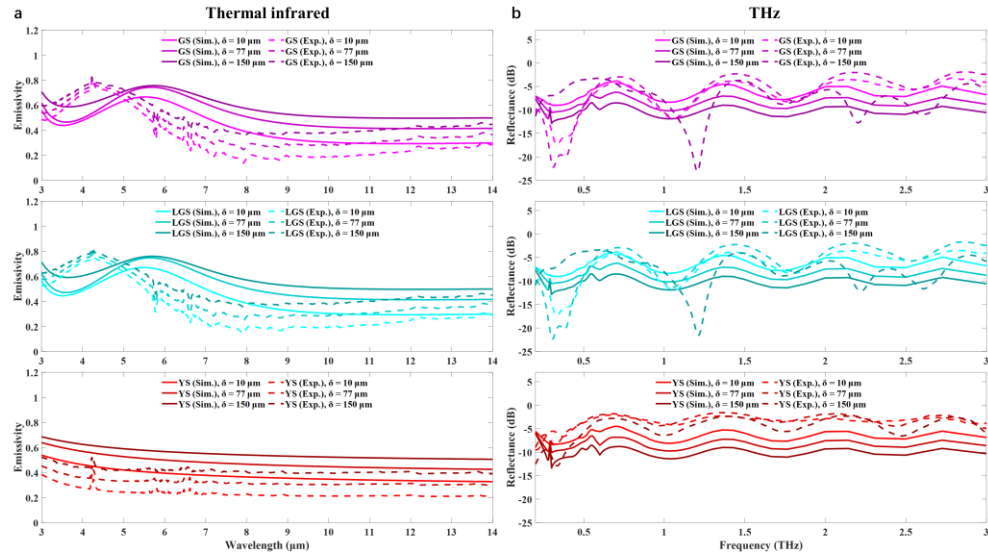
Using GS as an example (similar for LGS, LYS, RS, and BGS), its electric field (Supplementary Fig. 10a) and loss (Supplementary Fig. 10b) from short to long wavelengths are analyzed as follows: (i) For the upper ZnS/Ge/ZnS/Ti layers, an F-P cavity is formed in the VIS band, where the second-order resonance occurs before 550 nm, and the first-order resonance occurs after 550 nm, resulting in the relative high reflection green peak at 550 nm. (ii) At longer wavelengths, the F-P mode is no longer dominant. As the loss of Ge decreases (Supplementary Fig. 10c), the high reflectivity of Ti governs the ZnS/Ge/ZnS/Ti stack, leading to a rapid increase in reflectance and forming the red edge and NIR reflection plateau. (iii) Beyond 1300 nm, the electric field begins to transmit through the thin Ti layer. At this point, the water absorption bands are regulated synergistically by the 1/4+n anti-reflection effect of all layers and the absorption of the Ti layer.

We simulate the sub-pixels in GS, LGS, and YS and compare the results with the experimental data (Supplementary Fig. 11). As shown in Supplementary Fig. 11a, in the thermal IR band, the spectral characteristics of the pixels are determined by the multilayer structure, while the sub-pixel only adjusts the duty cycle. A larger sub-pixel line width results in higher thermal infrared emissivity. In the THz band

(Supplementary Fig. 11b), the sub-pixel behaves like a THz metasurface, modulating the THz spectrum together with PI. The reflectance is jointly controlled by the sub-pixel line width and the metal thickness in GS, LGS, and YS.



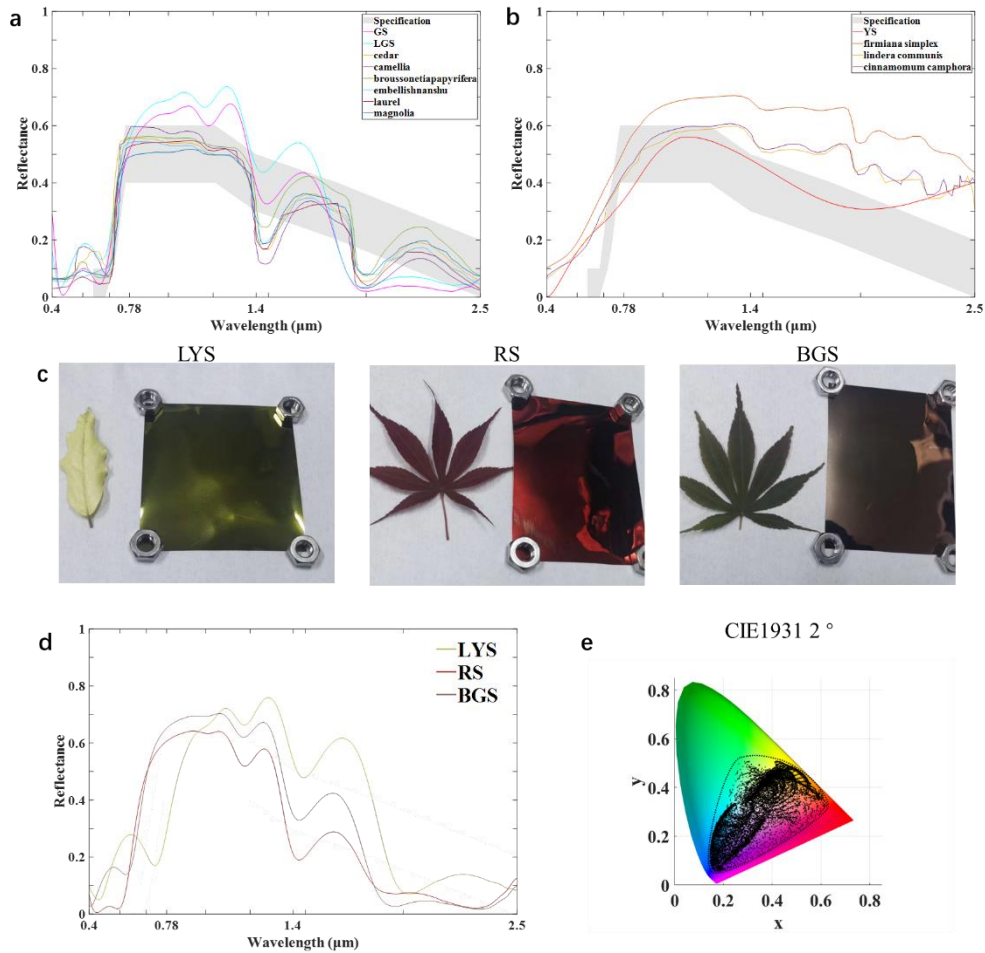
Supplementary Fig. 10 | Simulated optical hyperspectral properties of GS. a. Electric field distribution ($|E|$). **b.** Resistive loss (Q). **c.** Refractive indices of the materials.



Supplementary Fig. 11 | Comparison between simulation and experimental results for a. the thermal IR band and **b.** the THz band.

Supplementary Note 10. Various color of multilayer structure

In natural environment, the vegetational VIS spectral features are shifted due to differences in pigment types and growth stages, resulting in distinct VIS colors¹⁹. The NIR plateau and water absorption bands remain intact (Supplementary Fig. 12a and 12b). Based on structures similar to GS/LGS, fresh light-yellow vegetation simulation (LYS), fresh red vegetation simulation (RS), and fresh brown-green vegetation simulation (BGS) were investigated (Supplementary Fig. 12c and 12d). Supplementary Fig. 12e shows the approximate color gamut under CIE 1931 2° (D50 illuminant) for structures with unchanged NIR and SWIR characteristics, demonstrating that the design can adapt to various types of vegetation backgrounds²⁰.

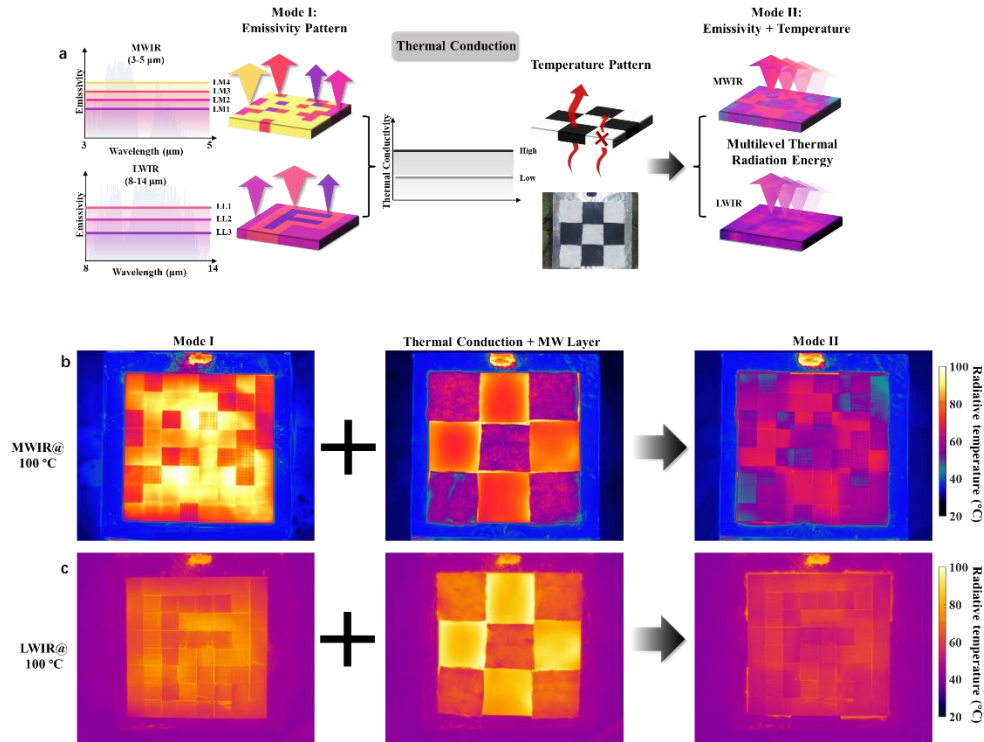


Supplementary Fig. 12 | Various color demonstration. **a.** Comparison of the optical spectra among GS/LGS and various fresh leaves. **b.** Comparison of the optical spectra among YS and various withered leaves. **c.** VIS

images of other three multilayer structures. **d.** Spectra of other three multilayer structures. **e.** CIE chart of multiple multilayer structures.

Supplementary Note 11. Thermal IR decoupled method

The energy signals received by the thermal IR camera depend on the surface emissivity and temperature of the target. In Supplementary Fig. 13a, the temperature distribution is controlled by adding a thermal conduction layer, resulting in an effect where the emissivity pattern and temperature pattern jointly modulate the thermal radiation energy pattern. In Supplementary Fig. 13b and 13c, after the addition of the thermal conduction layer, the surface pattern of the sample transforms into a composite multilevel pattern, which decouples the thermal IR pattern from other spectral patterns. Additionally, the thermal conduction layer reduces the average radiative energy on the device surface.

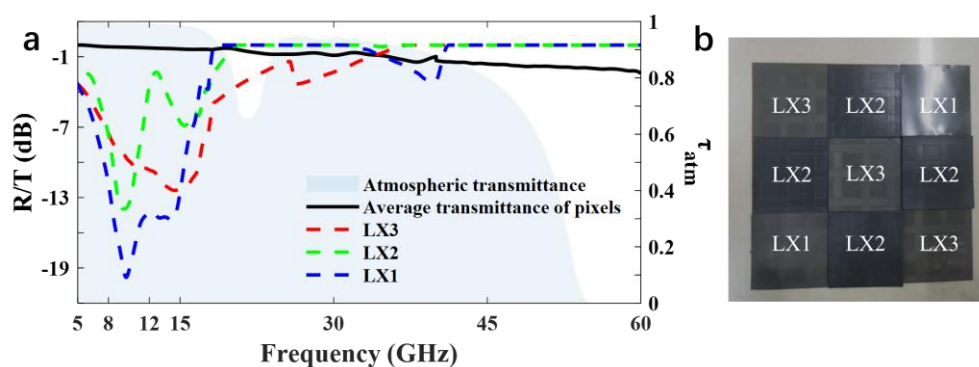


Supplementary Fig. 13 | Thermal IR dual-mode of the device. a. The principle of the thermal IR dual-mode.

b. MWIR demonstration. **c.** LWIR demonstration.

Supplementary Note 12. X-band absorbing materials

In Supplementary Fig. 14a, the average transmittance spectrum of the pixels exhibits broadband high transparency (black bold solid line), indicating that the MW pattern is completely decoupled from other bands (measured using the free-space vector network method). The colored dashed lines show the MW reflectance of LX1-3 (measured using the arch method with a vector network analyzer). In Supplementary Fig. 14b, three different types of MW absorbing material, X-S-070, X-S-130, X-NF-200, form LX1–3 MW pattern, respectively. The MW absorbing materials can withstand up to 200 °C.

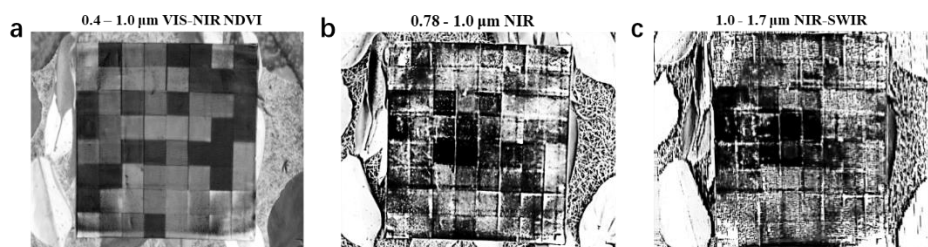


Supplementary Fig. 14 | MW performance. a. MW spectra. **b.** X-band absorbing material image.

Supplementary Note 13. Optical hyperspectral experimental supplement

The normalized difference vegetation index (NDVI) image of the data within the 400-1000 nm range was calculated (Supplementary Fig. 15a), device mimics different growth conditions of plants. The grayscale in the image reflects the condition of the vegetation. Additionally, by weighted averaging the hyperspectral channels, it simulated the IR images of common NIR/SWIR cameras (Supplementary Fig. 15b and 15c).

The visible colors (CIE 1931 2° with D50 illuminant) of green, light-green, and yellow plants and samples (digital camouflage device, fabric reference, and paint reference) are calculated and presented in Supplementary Table 5. The color of fabrics and paints is customized according to the device, but some color differences exist due to the surface morphology. The detailed spectral parameter comparison among the digital camouflage device, fabric reference, and paint reference is listed in Supplementary Tables 6-8 (the data is interpolated to intervals of 1 nm).



Supplementary Fig. 15 | The optical images of the device. a. VIS-NIR NDVI image. b. NIR image. c. NIR-SWIR image.

Supplementary Table 5 | Visible color of plant and samples.

	Green	Light-green	Yellow
	(60.88, 68.62, 50.08)	(103.21, 103.79, 70.98)	(113.62, 98.65, 89.74)
Plant			
Digital	(71.82, 86.25, 72.08)	(112.24, 117.57, 59.79)	(137.66, 117.40, 88.68)
camouflage			
device			
	(79.03, 88.98, 71.17)	(115.99, 117.61, 82.46)	(126.75, 99.65, 70.48)
Fabric			
	(79.35, 83.33, 78.20)	(88.23, 90.58, 71.40)	(173.77, 134.57, 95.51)
Paint on Al			
plate			

Supplementary Table 6 | Detailed spectral parameter comparison among green samples.

Device	Fabric	Paint
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$SD(I_a, I_b)$	2.4789	17.4043	15.3712
$\cos[SAM(I_a, I_b)]$	99.04%	90.79%	88.03%
$SID(I_a, I_b)$	0.0370	0.4223	0.4324
$SID_{0.4-1\ \mu m}(I_a, I_b)$	0.0172	0.1684	0.1856
$SID_{1-2.5\ \mu m}(I_a, I_b)$	0.0198	0.2539	0.2469
$SWD(I_a, I_b)$	1.2395	8.7022	7.6856
$GCD(I_a, I_b)$	1.2655	12.4133	12.8170
$DR(I_a, I_b)$	0.1825	1.0994	0.9681

Supplementary Table 7 | Detailed spectral parameter comparison among light-green samples.

	Device	Fabric	Paint
$SD(I_a, I_b)$	2.2183	16.6483	15.2274
$\cos[SAM(I_a, I_b)]$	99.31%	91.49%	79.78%
$SID(I_a, I_b)$	0.0202	0.3409	0.5403
$SID_{0.4-1\ \mu m}(I_a, I_b)$	0.0056	0.1278	0.1543
$SID_{1-2.5\ \mu m}(I_a, I_b)$	0.0146	0.2131	0.3860
$SWD(I_a, I_b)$	1.1062	8.3242	7.6137
$GCD(I_a, I_b)$	1.1155	10.8004	17.9933
$DR(I_a, I_b)$	0.1343	0.9425	0.8488

Supplementary Table 8 | Detailed spectral parameter comparison among yellow samples.

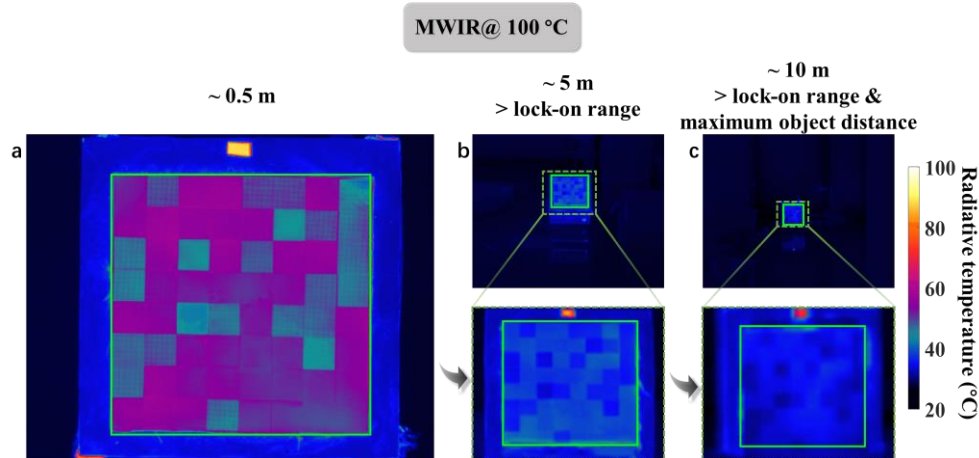
	Device	Fabric	Paint
$SD(I_a, I_b)$	2.1990	15.6074	18.3661
$\cos[SAM(I_a, I_b)]$	99.25%	97.93%	91.05%

$SID(I_a, I_b)$	0.0301	0.4265	0.5673
$SID_{0.4-1\ \mu\text{m}}(I_a, I_b)$	0.0064	0.1229	0.1707
$SID_{1-2.5\ \mu\text{m}}(I_a, I_b)$	0.0237	0.3035	0.3966
$SWD(I_a, I_b)$	1.100	7.8037	9.1831
$GCD(I_a, I_b)$	1.1147	4.5920	11.8695
$DR(I_a, I_b)$	0.1498	1.0113	1.1600

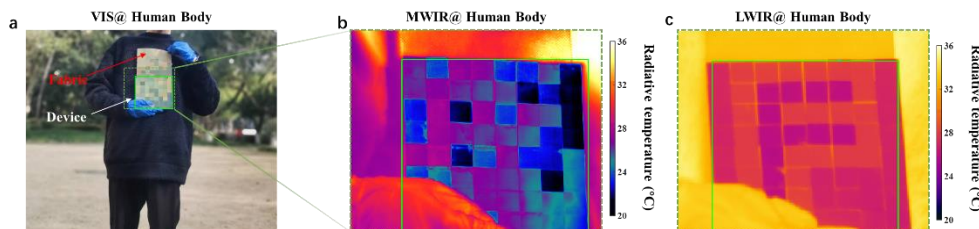
Supplementary Note 14. Thermal IR digital camouflage demonstration

To demonstrate the device's best digital camouflage effect at a far distance, we conducted MWIR imaging at different indoor distances. At 0.5 m (Supplementary Fig. 16a), the MWIR digital camouflage pattern is clearly visible. At approximately 5 m (Supplementary Fig. 16b), which exceeds the camera's lock-on range (background $\sim 25\ ^\circ\text{C}$, while the lock-on distance for practical applications is about three orders of magnitude higher), the digital camouflage pattern begins to blend into the background intensity. At approximately 10 m (Supplementary Fig. 16c), which exceeds both the camera's lock-on range and maximum object distance, individual pixels of the digital camouflage pattern start to blur, and adjacent pixels begin to merge, achieving the optimal camouflage effect.

To demonstrate the device's potential for individual combat, it is affixed alongside a fabric reference on the human body (Supplementary Fig. 17a). The samples not only exhibit flexibility but also showcase infrared digital camouflage capabilities. The device can lower the radiation temperature of clothing on the human body from $36\ ^\circ\text{C}$ to an average of approximately $25\ ^\circ\text{C}$ (Supplementary Fig. 17b and 17c).



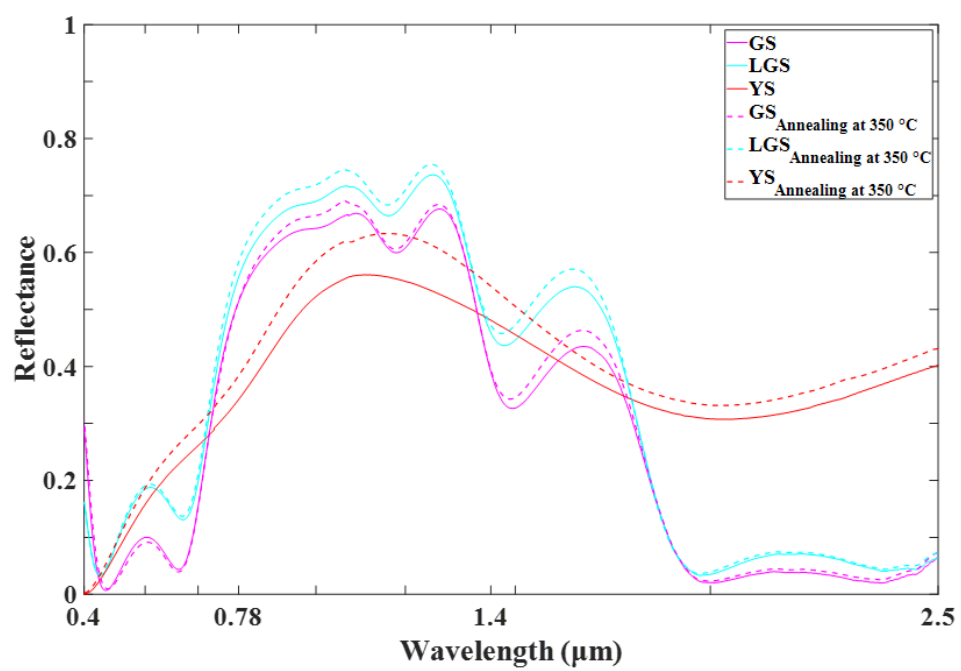
Supplementary Fig. 16 | Demonstration of MWIR digital camouflage effectiveness. IR images captured at different distances: a. 0.5 m, b. 5 m, and c. 10 m.



Supplementary Fig. 17 | Thermal IR human body demonstration. a. Human body demonstration in jungle environment. b. MWIR demonstration. c. LWIR demonstration.

Supplementary Note 15. High temperature illustration

The samples (GS, LGS, and YS) are annealed on a heating stage in an air atmosphere to assess their thermal stability. A thermocouple is employed to measure the surface temperature of the samples. The annealing process lasts for 10 minutes after reaching the specified temperature, and the entire process for each sample took approximately 20 minutes. As can be seen from Supplementary Fig. 18, the spectral changes of the multilayer structure before and after high-temperature annealing and cooling to room temperature are minimal, maintaining its original camouflage capability. This confirms its high-temperature stability and potential applications in targets containing electrical components or engines.



Supplementary Fig. 18 | High temperature annealing demonstration.

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