

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

Corresponding Author: Professor Qiang Li

This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)

Modern reconnaissance technologies, including hyperspectral and multispectral intensity imaging across optical, thermal infrared, and electromagnetic bands, can detect the shape, material composition, and temperature of targets. Consequently, developing a camouflage technique that seamlessly integrates both spatial and spectral dimensions across all key atmospheric windows to outsmart advanced surveillance has yet to be effectively developed and remains a significant challenge. Thus, a digital camouflage material was created. The work is just simple repetition. Unfortunately, the manuscript does not meet the standards of novelty and significance required. Rejection is suggested. I would like to give some advices.

1. The innovation is not prominent.

The expansion of wide-spectrum camouflage, especially in regard to the terahertz band, was regarded as an innovative element. However, the article contains minimal characterization of terahertz, merely presenting one spectral image and three terahertz images. This has left me in a rather conflicted state. Additionally, concerning terahertz camouflage, it should be noted that the author is not a pioneer. In fact, Zhejiang University had a dedicated article on terahertz stealth published in *Advanced Materials* in 2022. Hence, I harbor doubts regarding the innovation level of this article.

2. Weak innovation in materials.

At present, the multi-layer structure and unit recombination form is no longer novel. For instance, the one cited by the author from *Nature Communications* in 2022 (Fig. S1.) also adopts this kind of structure.

3. Performance falls short of exceptional standards.

The hyperspectral simulation, which is the core emphasis of the article, lags behind that of *Advanced Materials* (Fig. S1.) in certain aspects. Adv. Mater concentrates on modulating the details of green peak and red edge, albeit with a relatively weak simulation of water absorption bands. In contrast, the author's simulation of water peaks is marginally better, yet there is a dearth of in-depth discussion regarding the details of green peak and red edge.

Secondly, the author primarily centers on the hyperspectral simulation performance of three fundamental units in comparison to natural leaves. Although the overall average spectrum is presented, it fails to stand out prominently. In fact, a comprehensive spectrum would carry more persuasive power.

Furthermore, I am rather at a loss when it comes to the performance comparison chart. Firstly, the article selection seems inappropriate as the author is engaged in digital camouflage, yet has made a comparison of the performance of two types of materials that are mainly oriented towards hyperspectral stealth (The first two parts in Fig. S1.). The third article from *Science Advance*, although also achieving hyperspectral and infrared camouflage through unit construction. It lays emphasis on microscale thermal signal control rather than performance per se. Secondly, in terms of the analysis of performance and the choice of indicators in the literature, I contend that the crux lies not in their existence but in the deviation rate.

4. When discussing the three aspects of imaging technology in the Introduction, why does it emphasize the low stability of the existing hyperspectral camouflage material? Moreover, I feel that the expression "ultra multilayer" is also incorrect.

5. Why is the electromagnetic band parallel to optics and thermal infrared when expressed ?

6. "Specifically, in the optical band, hyperspectral, imaging excels in detecting vegetation due to the spectral characteristics of plants, including the green peak, red edge, NIR plateau, and NIR/SWIR water absorption bands, (Fig. 2e), posing an extreme threat to targets in vegetational backgrounds."

There is a problem with this statement. Hyperspectral imaging performs well in detecting vegetation, not because of the disguised target, but because of the superior technology of hyperspectral imaging.

7. The title is incorrect. Merely using "hyperspectral" would have sufficed instead of adding "optical". Additionally, in the text, the camouflage effects of terahertz and microwave bands are discussed separately, so it is illogical to directly combine them in the title.

Reviewer #2

(Remarks to the Author)

In the manuscript "Digital camouflage encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands" Rongxuan Zhu et al. study performance of a designed multilayer structure serving as a digital camouflage. The authors provide a thorough introduction covering the existing challenges and up-to-date advancements in the field. Next, the principle of digital camouflage is introduced with a focus on a theoretical background in image processing. Note that we found that it requires additional explanations and is more suitable for supplement materials (see below). Then, the authors show a designed digital camouflage device. It consists of three different layered structures mimicking green, light green and yellow colors correspondingly. Numerically, electric fields in two structures are calculated. However, it remains unclear whether results shown in Fig.2e-h are numerical or experimental (see below). Finally, analysis based on the experimental measurements in visible, infrared, THz and microwave spectral range is performed to determine the effectiveness of the device.

This manuscript proposes a new design for the digital camouflage device aiming for broadband performance and validation of its performance in optical, infrared, THz and microwave spectral ranges. Thus, we believe this paper might be of interest for a broader community of Nature Communications readers. However, we find a lot of missing details and unclear points which should be addressed by the authors before this manuscript can be published. So, our recommendation is major revision required.

Major comments:

1. Clarity.

A manuscript requires thorough revision since we find it is very hard to follow the main text. For instance, classification procedure is introduced in Lines 127-132 and different classes LH1, LH2, LH3 are shown Figure 1b. However, the meaning of these classes is explained first in Line 216. What is the meaning of "recorded" spectra in Fig. e-h? Are they obtained numerically or experimentally? In either case, additional clarification is required. Even though the list of references covers a huge number of articles, additional references are required for clarity. For example, provide the source of "military specifications". Additionally, references should be added in Supplementary Note S3.

2. No pattern analysis.

As mentioned in the manuscript, pattern is one of the fundamental components of digital camouflage. However, there is no discussion why the chosen pattern can serve for real applications. Moreover, it is clearly seen in Fig.3-4, that pixels are distinguishable in the meaning that they do not form any object (e.g. leaf). If it is beyond the scope of the manuscript, authors should mention it explicitly and provide examples and references to the digital camouflage patterns studies.

3. Application.

Fig.4a and Fig. 4c show a dramatic difference between the pixels and background. Please, explain why the device works even though pixels are distinguishable from the background. What are the possible applications of creating different patterns as in Fig. 4b?

4. "Principles of digital camouflage" is focused on the image processing having a limited applicability in the following text. Instead, we recommend adding a paragraph covering the design optimization strategy. In "Methods. Design" it is mentioned that "The initial sample structures are generated randomly". What were the parameters to optimize? Did you vary materials, layers, thickness? What was the quantity to judge whether the sample is more optimal or less?

5. Comparison between Device, Fabric, and Paint.

Visually, the colors of the fabric are green, yellow and orange. However, they were used to classify them into green, light green and yellow. Therefore, we think that the classification was performed properly and there are no misidentifications in 0.4-1um classification. Both yellow and orange cells are identified as LH3, while green is LH1. A more suitable combination of fabric colors should be used for clear comparison between device and fabric. Also, both paint green colors are much lighter than dark green color of leaves and fabric. Possibly, that is the reason they both are identified as light green. A more suitable combination of paint colors should be used for a clear comparison between the device and paint. All the colors should be consistent with each other.

There is a deterministic criterion GCD used to classify different elements.

What is the reason that part of Paint is an unidentified region in 0.4-1um classification? If the paint on aluminum plate is uniformly distributed, why there are two different regions? Similar question is for 1-2.5um Fabric classification. If the fabric squares are identical, why some of them are unidentifiable forming two rectangles?

What is the reason 1-2.5um classification leads to worse results than 0.4-1um classification?

6. Classification algorithm

Fig. 1b includes the image of a deep neural network (DNN) architecture. Did you use DNN for the classification? What is the purpose? In the main text it is mentioned, that "a specific GCD range" is utilized to identify pixel labels. It looks like to me that DNN is not needed for this process. Please, change the corresponding figure if DNN was not used. If it is indeed used, please provide more discussion about this part.

7. Image processing equations.

Firstly, this topic is covered much in both main text and supplemental notes. We recommend moving it entirely to supplemental notes since the results of the calculations are not the most important outcomes of this work. They are shown only in a table in Fig.3d and have very limited significance for a broader community. Instead, a description of design optimization can be included in the main text (see other comments). Moreover, we recommend rewriting a paragraph from the abstract where different metrics are covered since such information in the abstract might be confusing for readers. Some of the quantities, such as SD, SAM, SID, SSIM, are widely used. However, it remains unclear whether GCD and SWD are introduced by the authors or taken from other studies. In the former scenario, the meaning of these quantities and

corresponding equations (Eq. 2, Eq. S4, Eq. S5) should be explained. Otherwise, relevant references might be useful. In either case, it is unclear why alphas and betas in Eq. S4 have their values (as well as k and b in Eq. S5). With the chosen values, calculations are equivalent to adding a factor of 100 to SID and keeping SD as it is. What is the purpose of these manipulations?

8. Human body Thermal IR demonstration. we think this part is a little misleading regarding the statement “The device can lower the body’s radiation temperature from 36.8 °C to an average of approximately 25 °C”. The IR image was taken for a human wearing a jacket and holding the sample close to the jacket. The IR images (Fig. S7 B and C) indicate the human coat temperature to be 36 deg C. We believe the authors adjusted the emissivity value of the infrared camera such that the human coat temperature was 36, equal to human body temperature. But we do not think this is correct. The coat should have a lower temperature than the human body temperature.

Minor comments:

1. “Each GS, LGS, and YS pixel contains approximately 400 (20 × 20) rectangular sub-pixels”. Do you have different number of sub-pixels in pixels?

2. Note S2. It will be interesting to readers if the ranges of frequency/wavelength of the typical atmospheric windows not covered in this study are explicitly mentioned.

3. What are the units of intensity in equations? Why there is no units for SD?

What is C_N in Eq.3?

4. Reference/-s is recommended for the paragraph regarding the human vision and eye in Notes S3.

5. Fig. 2d shows t_1 , t_2 , etc. with no explanation.

6. Fig. 2h shows spectra only between 8 and 12 GHz. Why there is no information about R/T for 5-8 GHz and 12-60 GHz? What is the meaning of “Average Transmittance” line?

7. “The LM4 spectrum is created by the total structural resonance between GS and LGS pixels, which is evident from the electric field distribution and resistive loss plots at approximately 4 μ m wavelength (Fig. 2d).” In Fig. 2d there is no electric field for LGS.

8. In Note S10, the authors show that the device performance is similar at 350 degC. Is this heating process reversible, meaning that after heating and then cooling, will the performance of the optical device be identical to the original one?

Reviewer #3

(Remarks to the Author)

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

Reviewer #4

(Remarks to the Author)

This work reports a broadband camouflage strategy across the visible, near-infrared, shortwave infrared, mid-wave infrared, long-wave infrared, terahertz, and microwave bands, which covers over 80% of the atmospheric windows. It addresses a lingering challenge in creating an adaptable camouflage solution for diverse surveillance threats. A novelty, I believe, is its seamless integration of optical (visible, near-infrared, and shortwave infrared) hyperspectral adjustment with multispectral intensity modulation. In the optical range, the camouflage replicates vegetational spectral features with high fidelity, while in the thermal infrared, terahertz, and microwave bands, it produces multilevel intensity camouflage to counter imaging systems working across those bands. While I find the manuscript somewhat interesting and recommendable for publication in Nature Communications, I believe that several major flaws need to be resolved in revision.

1. The text is challenging to read, which is due to a lack of logical flow between paragraphs. The authors should improve the narrative for better coherence. Additionally, the quality of the figures (I should say all the figures including data) needs improvement. Spacing, axis and legend labeling, and overall visual clarity should be improved. For example, Figures 2e, 2f, 2g, and 2h are difficult to interpret because it is unclear which plot corresponds to which dataset. Enhancing the quality of both the text and figures throughout the manuscript will promise its readability.

2. The terms like SD, SAM, SID, SWD, and GCD may not be familiar to general readers. The authors should provide clearer definitions and explanations of these terms, highlighting their distinctions. Furthermore, the values mentioned in the abstract could sound unattractive. Replacing them with more widely understood metrics would make the work accessible to a broader audience. Similarly, the tables in Figure 3d are difficult to interpret, so the purpose and meaning of the numerical values should be clarified.

3. The manuscript frequently refers to “spatial” texture and “spatial” resolution, but these terms are not clearly explained. The authors should clarify what is meant by “spatial” and what specific efforts were made to mimic “spatial” texture and improve “spatial” resolution.

4. Figure 2d shows the electric field distribution and resistive loss within the multilayers at the target wavelengths. The authors should provide a more detailed discussion of these results, including the physics behind them.

5. The authors should explain the selection rules of ZnS, Ge, and Ti in the designed multilayers. Additionally, the manuscript

can benefit from a thorough description of the machine learning model, including how it was trained and validated.

6. What specific spectra of natural vegetation were used as targets for the multilayer design? The target spectra should be shown in the spectra in Figures 2e, 2f, 2g, and 2h, which help readers recognize how closely the multilayers replicate the desired natural creatures.

7. For the MWIR and THz bands, the authors fabricated four samples instead of three. Please clarify the rationale for introducing an additional sample for these bands.

8. In Figure 3a, the multilayer devices appear partly transparent in the visible range. Please provide their transmittance spectra. It would be helpful to discuss the visual appearance of the devices, particularly how the combination of transmission and reflection colors seems to the naked eye.

9. In Figure 4c, while the multilayer devices successfully conceal the underlying metallic object, none of the pixels seem to match the background. The authors should point out this discrepancy and discuss potential improvements.

10. The manuscript should explain in detail how intensity modulation in the thermal infrared and terahertz bands is achieved by adjusting the interspacing of the pixels.

Version 1:

Reviewer comments:

Reviewer #2

(Remarks to the Author)

Rongxuan Zhu et al. made suitable corrections to their manuscript "Digital camouflage encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands". However, not all questions and comments were fully addressed in the response letter. Additionally, we have identified new points of confusion in the revised manuscript that should be clarified by the authors before the manuscript can be considered for publication. So, our recommendation is minor revision required.

Major comments:

1. Deviation rate. Starting from the abstract, authors claim that with a proposed design they achieve deviation rates which vary from 0.1343 to 0.1825. Why are these values considered acceptable? Additional discussion (examples) will be helpful.

2. Optimization. In the "Strategy of the digital camouflage" authors mention that camouflage patterns are "not fully optimized". In the "Discussion", that performance can be improved "by pattern design or structure optimization". These points are unclear, since the manuscript contains both pattern design method (Suppl 6) and structure design method (Suppl 8). It is clear that optimization is very challenging. In the "Discussion" and "Strategy of the digital camouflage", more examples of possible improvement strategies and limitations of the current optimization methods are required for clarification.

3. IR and THz performance distance. Lines 239-247 and supplements explain why camouflage is distinguishable from the background in Fig.5a and c. However, it remains unclear why Fig.5a is shown as a main result even though there are Fig.S14 b and c, where camouflage is similar to background. In response to the reviewers, authors provide simulated THz images at a longer object distance. If it is impossible to get experimental images at longer distances, simulations for both short and longer distances should be included either in main or supplementary figures to clarify the difference between camouflage and background in the experimental images. Distance values should be included as it is done for the IR images.

Minor comments:

1. Line 97. CMOS, CCD and SAR should be written in full first.

2. Line 131. "the thickness (t_1 , t_2 , etc.) in Fig. 2d are optimized spectrally according to Supplement 7" should be paraphrased. It is not clear what is the meaning of spectral optimization and Supplement 7 does not provide any optimization information.

3. Line 139. Erase "approximately".

4. Line 155-156. "and the decreasing intrinsic loss of Ge decreases." should be paraphrased.

5. Line 157-158. "resulting from all layers' the resonances of all layers." should be paraphrased.

6. Line 182. SSIM should be written in full first.

7. Line 192. SID should be written in full first.

8. Supplement 7. "showingleading" and "bebecome" should be modified.

Reviewer #3

(Remarks to the Author)

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

Reviewer #4

(Remarks to the Author)

Overall, the authors have faithfully addressed all the concerns raised by the reviewers. I hope the authors will pay more attention to organizing and clarifying the plots in the figures before publication.

Version 2:

Reviewer comments:

Reviewer #2

(Remarks to the Author)

All the questions and comments were addressed and discussed in the revised version of this manuscript and we have no further questions or comments on it. It is now in a good shape for publication in Nature Communications.

Reviewer #3

(Remarks to the Author)

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

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The Reviewer #1's comments

Reviewer's general remarks:

Modern reconnaissance technologies, including hyperspectral and multispectral intensity imaging across optical, thermal infrared, and electromagnetic bands, can detect the shape, material composition, and temperature of targets. Consequently, developing a camouflage technique that seamlessly integrates both spatial and spectral dimensions across all key atmospheric windows to outsmart advanced surveillance has yet to be effectively developed and remains a significant challenge. Thus, a digital camouflage material was created. The work is just simple repetition. Unfortunately, the manuscript does not meet the standards of novelty and significance required. Rejection is suggested. I would like to give some advices.

Response:

We appreciate the reviewer's evaluation of our work on digital camouflage strategy encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands. We are sincerely grateful to the reviewer for their helpful comments and suggestions. We have revised the manuscript accordingly. Below is a point-by-point response.

1. The innovation is not prominent. The expansion of wide-spectrum camouflage, especially in regard to the terahertz band, was regarded as an innovative element. However, the article contains minimal characterization of terahertz, merely presenting one spectral image and three terahertz images. This has left me in a rather conflicted state. Additionally, concerning terahertz camouflage, it should be noted that the author is not a pioneer. In fact, Zhejiang University had a dedicated article on terahertz stealth published in Advanced Materials in 2022. Hence, I harbor doubts regarding the innovation level of this article.

Response:

We thank the reviewer for the comments.

The innovation is this work lies in the following:

First, our study spans the main atmospheric windows across VIS, NIR, SWIR, MWIR, LWIR, THz, and MW bands (Fig. R1.1). Second, we applied digital camouflage to blend with the background texture across all the investigated bands.

In contrast, the work cited by the reviewer [Ref. R1.1] focuses solely on camouflage in the THz band.

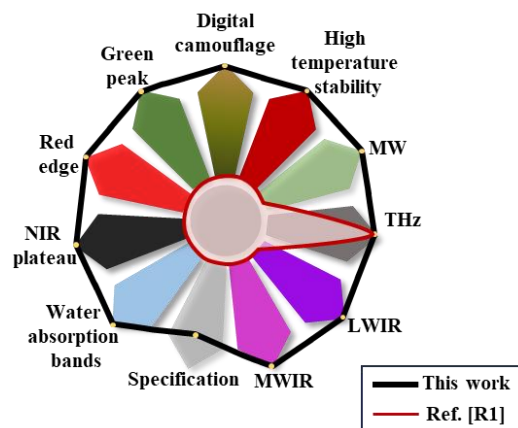


Fig. R1.1 | Comparison with other work.

[R1.1] Cai, T. *et al.* Experimental Realization of a Superdispersion-Enabled Ultrabroadband Terahertz Cloak. *Advanced Materials* **34**, 2205053 (2022).

2. (i) *Weak innovation in materials. At present, the multi-layer structure and unit recombination form is no longer novel.* (ii) *For instance, the one cited by the author from Nature Communications in 2022 (Fig. S1.) also adopts this kind of structure.*

Response:

We sincerely thank the reviewer for the comment.

(i) Our main innovation lies in digital camouflage encompassing optical hyperspectral, thermal IR, THz, and MW bands rather than in materials. Ge, with a high refractive index, and ZnS, with a low refractive index, are widely used conventional infrared materials. In our previous works, we employed Ge/ZnS multi-layer structure for camouflage [Refs. R1.2, *Nature Communications* **12**, 1805 (2021)] and thermal management [Refs. R1.3, *Light: Science & Applications* **12**, 268 (2023)].

In this work, aiming at digital camouflage spanning optical hyperspectral, thermal IR, THz, and MW bands, we designed a multi-layer film structure incorporating Ge, ZnS and Ti, with a total thickness of ~700 nm. The inclusion of Ti introduces multiple resonances in optical band and reduces emissivity in the thermal IR band.

(ii) The reviewer mentioned “*the one cited by the author from Nature Communications in 2022*”. However, our manuscript does not contain any references from Nature Communications in 2022. We assume the reviewer is referring to [Refs. R1.4, *Ultrahigh-efficient material informatics inverse design of thermal metamaterials for visible-infrared-compatible camouflage. Nature Communications* **14**, 4694 (2023).] by Prof. Run Hu’s group. This work focuses on material informatics inverse design for visible-infrared camouflage. It uses a Ge/ZnS multi-layer structure with a total thickness of ~2300 nm, which cannot achieve optical hyperspectral camouflage and thermal MWIR (3-5 μm) camouflage.

Therefore, our work presents novelty in both structure and function. We have revised our manuscript to include a detailed physical analysis of how Ti participates in multiple resonances to aid optical hyperspectral camouflage.

Supplement 11. Simulations of optical hyperspectra, thermal IR, and THz bands

Using GS as an example (similar for LGS, LYS, RS, and BGS), its electric field (Fig. S10a) and loss (Fig. S10b) from short to long wavelengths are analyzed as follows: (i) For the upper ZnS/Ge/ZnS/Ti layers, an F-P cavity forms 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 relatively high reflection green peak at 550 nm. (ii) At longer wavelengths, the cavity length is insufficient to support the F-P mode. As the loss of Ge decreases (Fig. S10c), the high reflectivity of Ti dominates 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 $1/4+n/2$ anti-reflection effect of all layers and the absorption of the Ti layer.

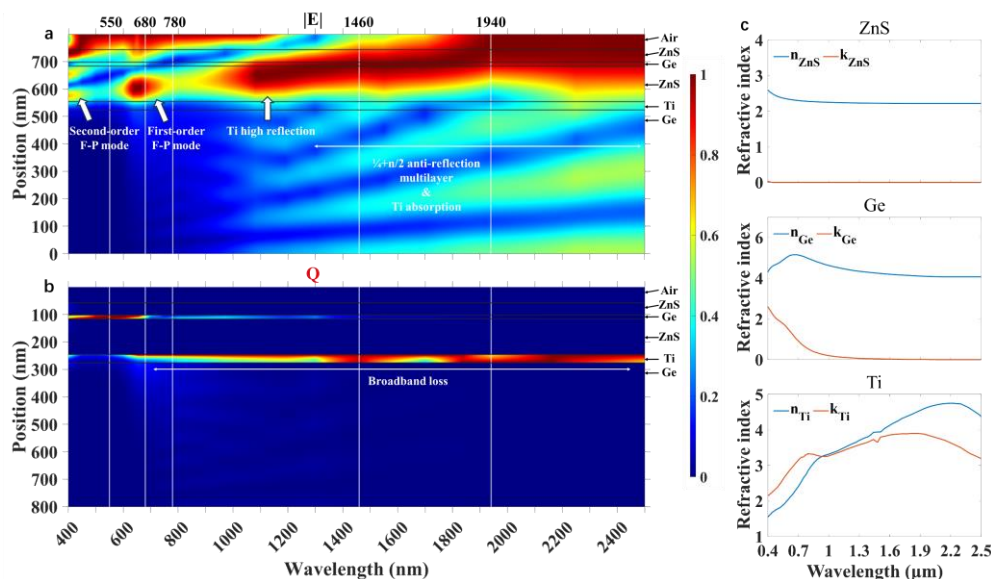


Fig. S10. Simulated optical hyperspectral properties of GS. a. Electric field distribution ($|E|$). b. Resistive loss (Q). c. Refractive indices of the materials.

[R1.2] Zhu, H. *et al.* Multispectral camouflage for infrared, visible, lasers and microwave with radiative cooling. *Nature Communications* **12**, 1805 (2021).

[R1.3] Zhu, Y. *et al.* Night-time radiative warming using the atmosphere. *Light: Science & Applications* **12**, 268 (2023).

[R1.4] Xi, W. *et al.* Ultrahigh-efficient material informatics inverse design of thermal metamaterials for visible-infrared-compatible camouflage. *Nature Communications* **14**, 4694 (2023).

3. Performance falls short of exceptional standards. (i) The hyperspectral simulation, which is the core emphasis of the article, lags behind that of Advanced Materials (Fig. S1.) in certain aspects. Adv. Mater concentrates on modulating the details of green peak and red edge, albeit with a relatively weak simulation of water absorption bands. In contrast, the author's simulation of water peaks is marginally better, yet there is a dearth of in-depth discussion regarding the details of green peak and red edge. (ii) Secondly, the author primarily centers on the hyperspectral simulation performance of three fundamental units in comparison to natural leaves. Although the overall average spectrum is presented, it fails to stand out prominently. In fact, a comprehensive spectrum would carry more persuasive power. (iii) Furthermore, I am rather at a loss when it comes to the performance comparison chart. Firstly, the article selection seems inappropriate as the author is engaged in digital camouflage, yet has made a comparison of the performance of two types of materials that are mainly oriented towards hyperspectral stealth (The first two parts in Fig. S1.). The third article from Science Advance, although also achieving hyperspectral and infrared camouflage through unit construction. It lays emphasis on microscale thermal signal control rather than performance perse. (iv) Secondly, in terms of the analysis of performance and the choice of indicators in the literature, I contend that the crux lies not in their existence but in the deviation rate.

Response:

We thank the reviewer for the comments and suggestions.

(i) We have conducted an in-depth discussion on the formation mechanism of the green peak and red edge in Fig. R1.2 in the multilayer structure:

Taking the GS multilayer structure (Fig. R1.3a) as an example, the green peak at 550 nm exhibits relatively high reflectance (Fig. R1.2). That's because the 550 nm green peak lies between the strong absorption regions of the second-order and first-order F-P modes in the topmost ZnS/Ge/ZnS/Ti stack (Fig. R1.3b).

For the red edge, at longer wavelengths, the F-P mode ceases to dominant. As the intrinsic loss of Ge decreases (Fig. R1.3c), the high reflectivity of Ti dominates the ZnS/Ge/ZnS/Ti stack, leading to a rapid increase in reflectance and formation of the red edge.

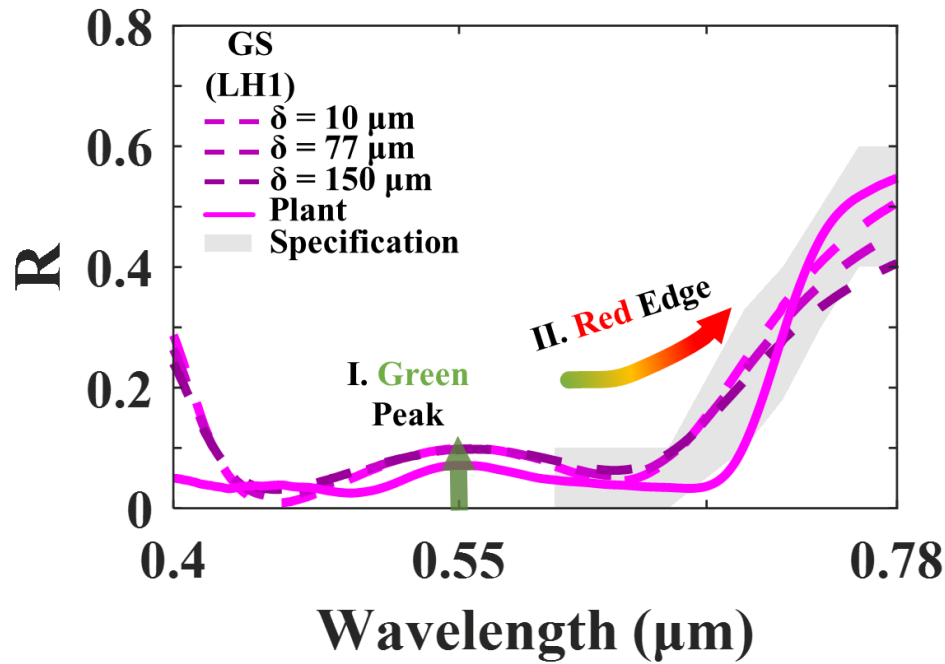


Fig. R1.2 | VIS spectra of GS and plant.

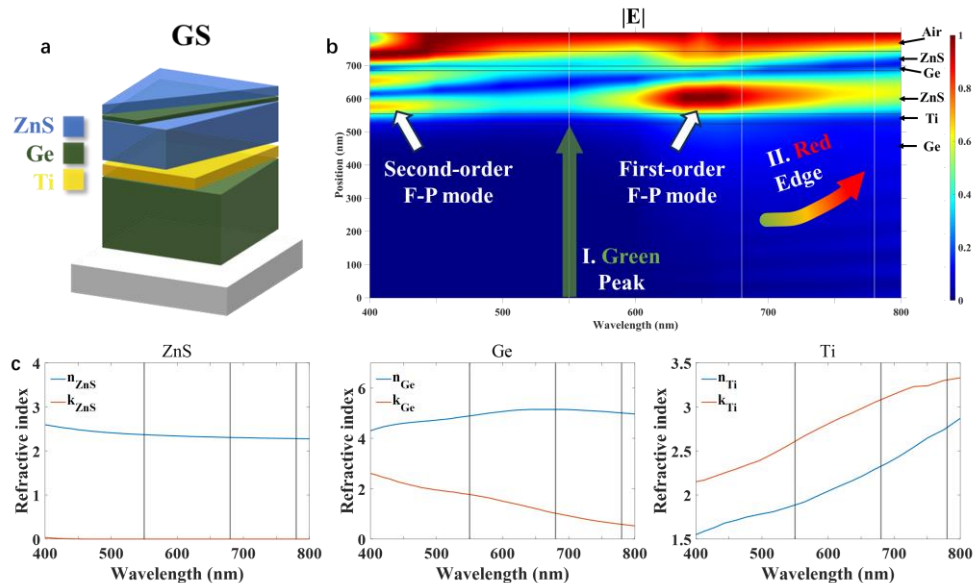


Fig. R1.3 | Electric field analysis of GS at the green peak and red edge. a. Multilayer structure diagram of GS. **b.** Simulated electric field distribution ($|E|$) of GS in the 400-800 nm range. **c.** Refractive indices of ZnS, Ge, and Ti.

We have revised the manuscript as:

(Page 8, lines 151-158)

For GS/LGS, they have similar structures and exhibit comparable spectral performance (a detailed physical analysis is shown in Supplement 11): (i) The green peak is precisely aligned at 0.55 μm , formed by the F-P resonance and antireflection effects of the four-layer ZnS/Ge/ZnS/Ti structure. (ii) The red edge and NIR plateau ($\sim 1.1 \mu\text{m}$) meet military specifications, which is formed by the high reflectance of the Ti layer and the decreasing intrinsic loss of Ge decreases. (iii) The four water absorption bands in the NIR/SWIR exhibit increasing absorption from shortwave to longwave, resulting from all layers' the resonances of all layers.

Supplement 11. Simulations of optical hyperspectra, thermal IR, and THz bands

Using GS as an example (similar for LGS, LYS, RS, and BGS), its electric field (Fig. S10a) and loss (Fig. S10b) from short to long wavelengths are analyzed as follows: (i) For the upper ZnS/Ge/ZnS/Ti layers, an F-P cavity forms 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 relatively high reflection green peak at 550 nm. (ii) At longer wavelengths, the cavity length is insufficient to support the F-P mode. As the loss of Ge decreases (Fig. S10c), the high reflectivity of Ti dominates 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 $1/4+n/2$ anti-reflection effect of all layers and the absorption of the Ti layer.

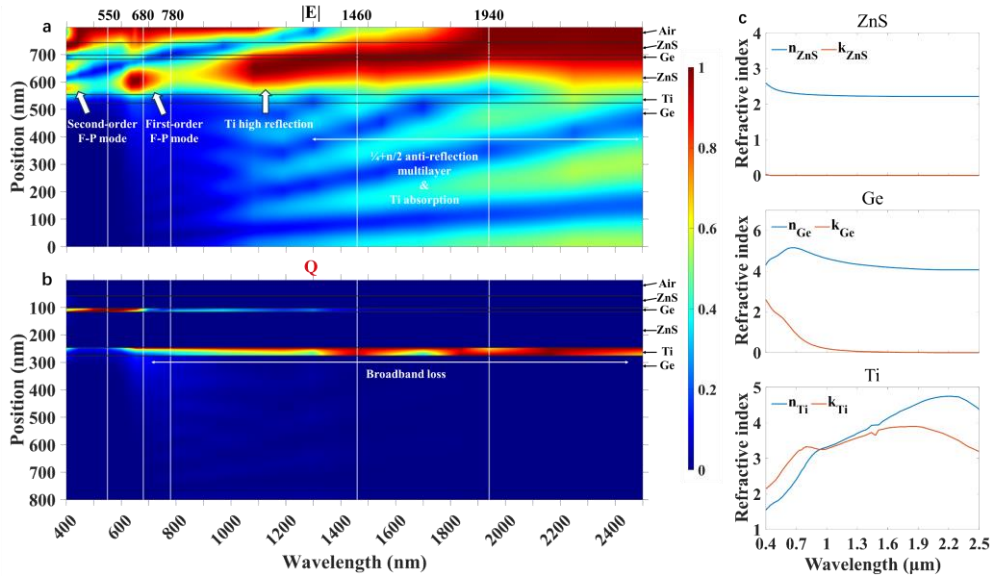


Fig. S10. Simulated optical hyperspectral properties of GS. a. Electric field distribution ($|E|$). b. Resistive loss (Q). c. Refractive indices of the materials.

(ii) The overall spectrum is used to display the average spectrum formed by spatial color mixing in digital camouflage. The spectrum for each original pixel with different sub-pixel line widths has also been provided (colored dashed lines) as follows:

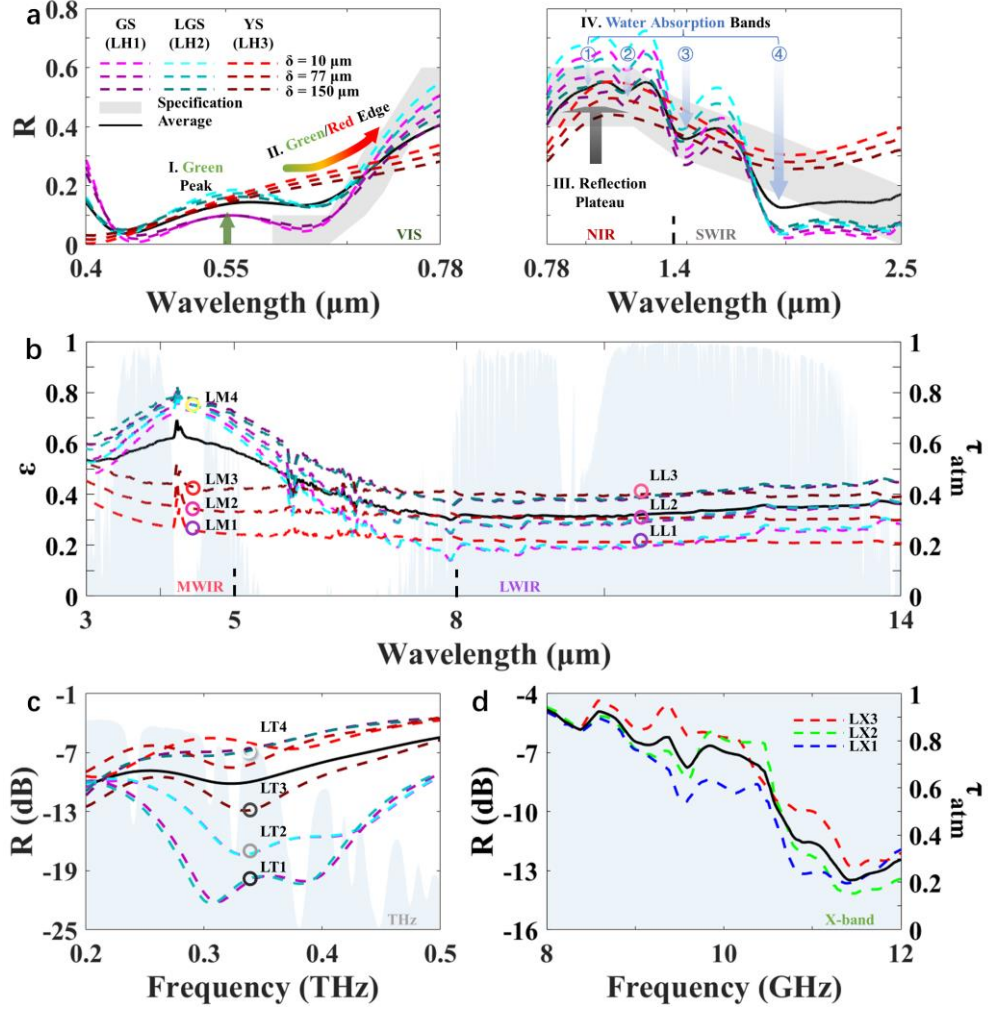


Fig. 3 | Multilevel reflectance, transmittance, and emissivity spectra of pixels. a. Experimental reflectance spectra of the three structures (GS, LGS, and YS) in the VIS, NIR, and SWIR bands. **b.** Experimental emissivity spectra of the three structures in the MWIR and LWIR bands, categorized into four levels (LM1-4) for the MWIR band and three levels (LL1-3) for the LWIR band. **c.** Experimental reflectance spectra of the three structures in the THz band, showing four levels (LT1-4). **d.** Experimental reflectance spectra of the whole device (including the structures and the MW-absorbing substrate) and average transmittance spectra of the microwave-absorbing substrate. The inset shows the zoomed-in X-band spectra and the corresponding three levels (LX1-3).

(iii) Our main innovation lies in combining digital camouflage with ultra-wideband multispectral camouflage. Therefore, it is necessary to compare the digital camouflage and multispectral performance.

The reviewer mentioned “*The third article from Science Advance, although also achieving hyperspectral and infrared camouflage through unit construction*”. There are three references from Science Advance in our manuscript, which are listed as follows:

[R1.5, Li, Z. *et al.* Brochosome-inspired binary metastructures for pixel-by-pixel thermal signature control. *Science Advances* **10**, ead14027 (2024).]

[R1.6, Fang, S. *et al.* Self-assembled skin-like metamaterials for dual-band camouflage. *Science Advances* **10**, ead1896 (2024).]

[R1.7, Li, M. *et al.* Manipulating metals for adaptive thermal camouflage. *Science Advances* **6**, eaba3494 (2020).]

These three works focus on active thermal infrared regulation and does not mention optical hyperspectral camouflage. Therefore, they are not included in the performance comparison chart.

(iv) In response to the reviewer's suggestion and to make the manuscript more accessible to a broader audience, we have replaced the original spectral evaluation metrics (SD, SAM, etc.) with the deviation rate[Ref. R1.8]:

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

The original metrics and deviation rate have been shown in Supplement 13:

Table. S6 | Detailed spectral parameter comparison among green samples.

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

Table. S7 | Detailed spectral parameter comparison among light-green samples.

	Device	Fabric	Paint
<u>SD(I_a, I_b)</u>	2.2183	16.6483	15.2274
<u>cos[SAM(I_a, I_b)]</u>	99.31%	91.49%	79.78%
<u>SID(I_a, I_b)</u>	0.0202	0.3409	0.5403
<u>SID_{0.4-1 μm}(I_a, I_b)</u>	0.0056	0.1278	0.1543
<u>SID_{1-2.5 μm}(I_a, I_b)</u>	0.0146	0.2131	0.3860

$\underline{SWD}(I_a, I_b)$	1.1062	8.3242	7.6137
$\underline{GCD}(I_a, I_b)$	1.1155	10.8004	17.9933
$\underline{DR}(I_a, I_b)$	0.1343	0.9425	0.8488

Table. S8 | Detailed spectral parameter comparison among yellow samples.

	Device	Fabric	Paint
$\underline{SD}(I_a, I_b)$	2.1990	15.6074	18.3661
$\underline{\cos}[SAM(I_a, I_b)]$	99.25%	97.93%	91.05%
$\underline{SID}(I_a, I_b)$	0.0301	0.4265	0.5673
$\underline{SID}_{0.4-1\mu m}(I_a, I_b)$	0.0064	0.1229	0.1707
$\underline{SID}_{1-2.5\mu m}(I_a, I_b)$	0.0237	0.3035	0.3966
$\underline{SWD}(I_a, I_b)$	1.100	7.8037	9.1831
$\underline{GCD}(I_a, I_b)$	1.1147	4.5920	11.8695
$\underline{DR}(I_a, I_b)$	0.1498	1.0113	1.1600

[R1.8] Dinwoodie, I. H. Identifying a large deviation rate function. *The Annals of Probability* **21**, 216-231 (1993).

4. (i) When discussing the three aspects of imaging technology in the Introduction, why does it emphasize the low stability of the existing hyperspectral camouflage material? (ii) Moreover, I feel that the expression “ultra multilayer” is also incorrect.

Response:

We thank the reviewer for the comments and suggestions.

(i) Existing hyperspectral camouflage works have poor stability due to water content. Especially at high temperatures, water evaporation leads to camouflage failure. The stability is therefore important for hyperspectral camouflage [Refs. R1.9-R1.10].

[R1.9] Yang, P. *et al.* Hyperspectral and Weather Resistant Biomimetic Leaf Enabled by Interlayer Confinement. *Advanced Functional Materials*, 2405908 (2024).

[R1.10] Yang, P. *et al.* Weatherability and heat resistance enhanced by interaction between AG25 and Mg/Al-LDH. *Rare Metals* **43**, 2758-2768 (2024).

(ii) We thank the reviewer’s suggestion and have changed “ultra multilayer” to “multilayer” (Page 4, line 67”).

5. Why is the electromagnetic band parallel to optics and thermal infrared when expressed ?

Response:

We thank the reviewer for the thoughtful question.

The “electromagnetic band” conventionally refers to the terahertz-microwave bands [Refs. R1.11-R1.14] in some fields (e.g., electrical engineering). To avoid any misunderstanding, we have revised the manuscript by changing “electromagnetic band” to “terahertz and microwave bands” (Page 1, lines 18; Page 4, lines 68)”.

[R1.11] Schurig, D. *et al.* Metamaterial electromagnetic cloak at microwave frequencies. *Science* **314**, 977-980 (2006).

[R1.12] Lv, H. *et al.* A flexible electromagnetic wave-electricity harvester. *Nature communications* **12**, 834 (2021).

[R1.13] Qin, M. *et al.* Dielectric loss mechanism in electromagnetic wave absorbing materials. *Advanced Science* **9**, 2105553 (2022).

[R1.14] Li, Q. *et al.* Toward the application of high frequency electromagnetic wave absorption by carbon nanostructures. *Advanced Science* **6**, 1801057 (2019).

6. “Specifically, in the optical band, hyperspectral, imaging excels in detecting vegetation due to the spectral characteristics of plants, including the green peak, red edge, NIR plateau, and NIR/SWIR water absorption bands, (Fig. 2e), posing an extreme threat to targets in vegetational backgrounds.” There is a problem with this statement. Hyperspectral imaging performs well in detecting vegetation, not because of the disguised target, but because of the superior technology of hyperspectral imaging.

Response:

We thank the reviewer for the comments and suggestions.

We have revised the manuscript accordingly:

(Pages 3-4, lines 61-65)

Specifically, in the optical band, hyperspectral imaging excels in detecting vegetation due to the combination of high spectral resolution and spectral characteristics of plants, including the green peak, red edge, NIR plateau, and NIR/SWIR water absorption bands (Fig. 3a). This capability poses a significant threat to targets in vegetational backgrounds.

7. The title is incorrect. Merely using “hyperspectral” would have sufficed instead of adding “optical”. Additionally, in the text, the camouflage effects of terahertz and microwave bands are discussed separately, so it is illogical to directly combine them in the title.

Response:

We thank the reviewer for the comment and suggestion.

Beyond optical hyperspectral imaging, infrared hyperspectral imaging has also emerged due to rapid development of infrared technology (see [Refs. R1.15-R1.19] below). Therefore, we use the term “optical hyperspectral” to avoid misunderstandings.

Additionally, although the thermal infrared, terahertz, and microwave bands are discussed separately in the main text, they all focus on intensity camouflage rather than hyperspectral camouflage. Thus, we group them together in the title.

[R1.15] Fang, J. *et al.* Wide-field **mid-infrared hyperspectral** imaging beyond video rate. *Nature Communications* **15**, 1811 (2024).

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- [R1.16] Amenabar, I. *et al.* **Hyperspectral infrared** nanoimaging of organic samples based on Fourier transform infrared nanospectroscopy. *Nature communications* **8**, 14402 (2017).
- [R1.17] Paterova, A.V. *et al.* **Hyperspectral infrared** microscopy with visible light. *Science advances* **6**, eabd0460 (2020).
- [R1.18] Tournié, A. *et al.* Ancient Greek text concealed on the back of unrolled papyrus revealed through **shortwave-infrared hyperspectral** imaging. *Science Advances* **5**, eaav8936 (2019).
- [R1.19] Lee C.M. *et al.* An introduction to the NASA **Hyperspectral InfraRed** Imager (HyspIRI) mission and preparatory activities. *Remote Sensing of Environment* **167**, 6-19 (2015).

The Reviewer #2's comments

Reviewer's general remarks:

In the manuscript "Digital camouflage encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands" Rongxuan Zhu et al. study performance of a designed multilayer structure serving as a digital camouflage. The authors provide a thorough introduction covering the existing challenges and up-to-date advancements in the field. Next, the principle of digital camouflage is introduced with a focus on a theoretical background in image processing. Note that we found that it requires additional explanations and is more suitable for supplement materials (see below). Then, the authors show a designed digital camouflage device. It consists of three different layered structures mimicking green, light green and yellow colors correspondingly. Numerically, electric fields in two structures are calculated. However, it remains unclear whether results shown in Fig.2e-h are numerical or experimental (see below). Finally, analysis based on the experimental measurements in visible, infrared, THz and microwave spectral range is performed to determine the effectiveness of the device.

This manuscript proposes a new design for the digital camouflage device aiming for broadband performance and validation of its performance in optical, infrared, THz and microwave spectral ranges. Thus, we believe this paper might be of interest for a broader community of Nature Communications readers. However, we find a lot of missing details and unclear points which should be addressed by the authors before this manuscript can be published. So, our recommendation is major revision required.

Response:

We appreciate the reviewer's positive evaluation of our digital camouflage strategy encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands. We are grateful for the reviewer's helpful comments and suggestions. In response, we have revised the manuscript accordingly. Below is a point-by-point response.

Major comments:

1. Clarity. (i) A manuscript requires thorough revision since we find it is very hard to follow the main text. For instance, classification procedure is introduced in Lines 127-132 and different classes LH1, LH2, LH3 are shown Figure 1b. However, the meaning of these classes is explained first in Line 216. (ii) What is the meaning of "recorded" spectra in Fig. e-h? Are they obtained numerically or experimentally? (iii) In either case, additional clarification is required. Even though the list of references covers a huge number of articles, additional references are required for clarity. For example, provide the source of "military specifications". Additionally, references should be added in Supplementary Note S3.

Response:

We thank the reviewer for the comments and suggestions.

(i) In response to the reviewer's suggestion, we have added a description of the multi-level digital camouflage (LH1-3, LM1-4, etc.) when explaining the classification in Fig. 1b.

(Pages 5-6, lines 103-106)

For optical hyperspectral digital camouflage, the primary colors are defined based on the main vegetational regions of interest (ROI) classification (the details of design method can be found in the Supplement 5 and 6). This include LH1 (fresh green vegetation), LH2 (fresh light-green vegetation), and LH3 (withered yellow vegetation) (Fig. 1b).

(ii) Here, the "recorded" spectra refers to the experimental spectra.

To avoid any misunderstanding, we have also revised the manuscript accordingly:

(Page 29, lines 523-530) **Fig. 3. Multilevel reflectance, transmittance, and emissivity spectra of pixels. a. Experimental reflectance spectra of the three structures (GS, LGS, and YS) in the VIS, NIR, and SWIR bands...**

(iii) We thank the reviewer again for their suggestion. We carefully checked the entire text, including the supplementary information, and added relevant references.

For example, the “military specifications” mentioned by the reviewer originate from [Ref. R2.1]. Additionally, the references added in Supplementary Note S3 are sourced from [Refs. R2.2-R2.9].

[R2.1] MIL-PRE-53134. Ultra lightweight camouflage net system (ULCANS). *Military Specification of USA*, USA.

[R2.2] Jovanović, I. *et al.* Spectral distances of graphs. *Linear Algebra and its Applications* **436**, 1425-1435 (2012).

[R2.3] Konukoglu, E. *et al.* WESD--Weighted Spectral Distance for measuring shape dissimilarity. *IEEE transactions on pattern analysis and machine intelligence* **35**, 2284-2297 (2013).

[R2.4] Chakravarty, S. *et al.* Hyperspectral Image Classification using Spectral Angle Mapper. *2021 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE)*, 87-90 (2021).

[R2.5] Park, B. *et al.* Contaminant Classification of Poultry Hyperspectral Imagery using a Spectral Angle Mapper Algorithm. *Biosystems Engineering* **96**, 323-333 (2007).

[R2.6] Chang, C.-I. Spectral information divergence for hyperspectral image analysis. *IEEE 1999 International Geoscience and Remote Sensing Symposium. IGARSS'99 (Cat. No. 99CH36293)* **1**, 509-511 (1999).

[R2.7] Dinwoodie, I. H. Identifying a large deviation rate function. *The Annals of Probability* **21**, 216-231 (1993).

[R2.8] Xu, C. *et al.* The relationship between spatial color mixing with color and radiation similarity in digital camouflage study. *Infrared Physics & Technology* **130**, 104593 (2023).

[R2.9] Wang, Z. *et al.* Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing* **13**, 600-612 (2004).

2. No pattern analysis. (i) As mentioned in the manuscript, pattern is one of the fundamental components of digital camouflage. However, there is no discussion why the chosen pattern can serve for real applications. (ii) Moreover, it is clearly seen in Fig.3-4, that pixels are distinguishable in the meaning that they do not form any object (e.g. leaf). If it is beyond the scope of the manuscript, authors should mention it explicitly and provide examples and references to the digital camouflage patterns studies.

Response:

We thank the reviewer for the comments and suggestions.

(i) The pattern in this manuscript is selected by **extracting texture pixels from the actual background** and incorporating small templates to enhance the camouflage layers. The pattern that most closely resembles the background texture is then chosen. As a result, this approach enables the camouflage pattern to blend with the background texture even beyond the maximum object distance. Taking 400-1000 nm hyperspectral digital camouflage as an example, the detailed process of pattern selection is shown as follows (Fig. R2.1):

-
1. 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).
 2. 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.
 3. 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 pattern [Ref. R2.10].
 4. 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.
 5. 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.
 6. 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.

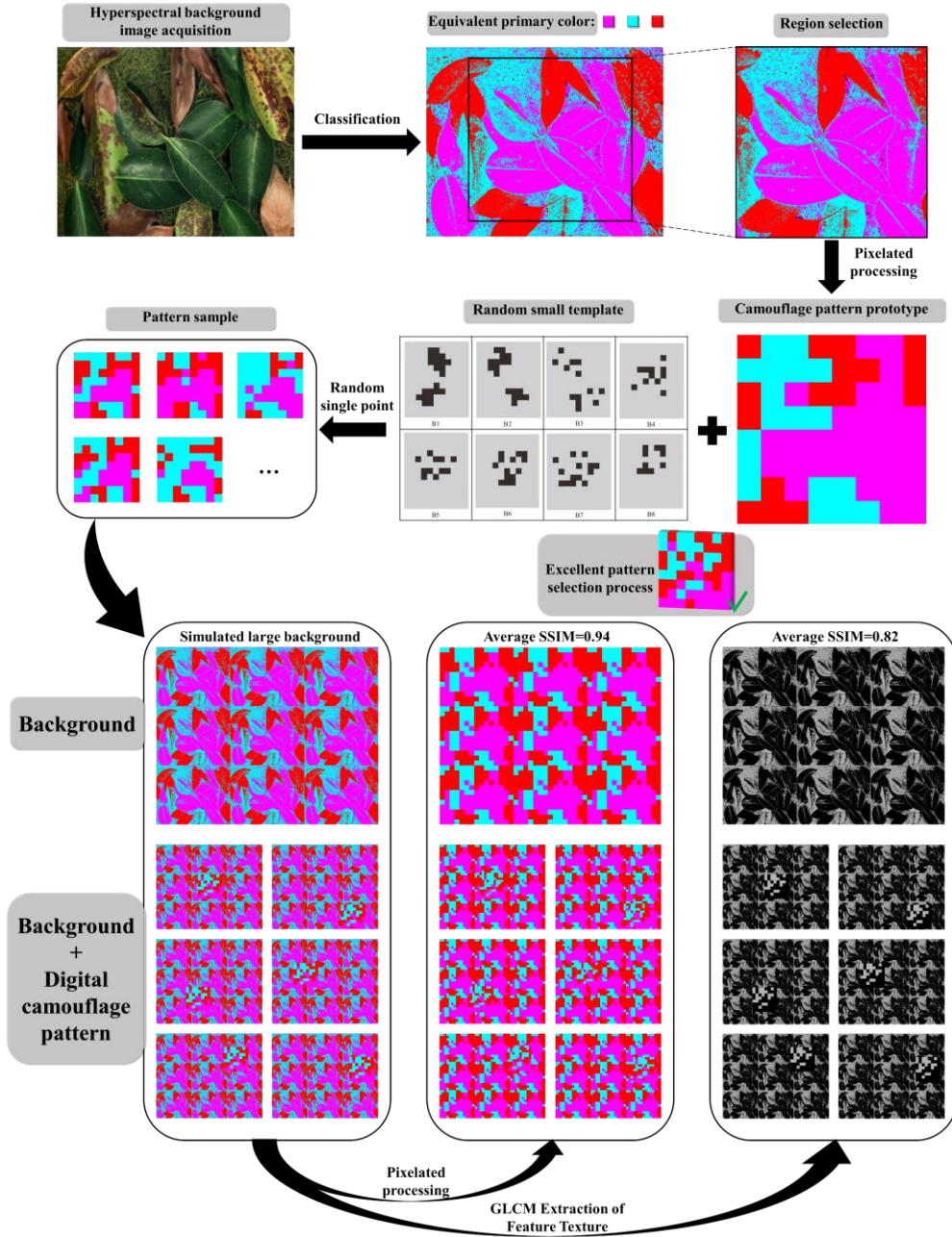


Fig. R2.1 | Digital camouflage pattern design process.

[R2.10] Xue, F. *et al.* Design of digital camouflage by recursive overlapping of pattern templates. *Neurocomputing* **172**, 262-270, (2016).

(ii) To evaluate **real-world application performance**, we use MWIR band as an example and construct a real scenario (Fig. R2.2d):

In the MWIR band, at an imaging distance of 0.5 m (Fig. R2.2a), the MWIR digital camouflage pattern is **clearly distinguishable**. This is because the imaging distance is smaller than the maximum object distance (~5 m for our MWIR camera, with detailed calculations in Supplement 3[Ref. R2.11]), so the pattern's texture remains sharp and spatial color mixing has not yet occurred. At the same time, the imaging distance is also smaller than the lock-on range (~10 m for our MWIR camera, with detailed calculations in Supplement 4[Refs. R2.12]), meaning the pattern's color is still distinguishable from the background and can be locked onto.

In contrast, at approximately 5 m (Fig. R2.2b), which exceeds the camera's lock-on range (background $\sim 25^{\circ}\text{C}$), the digital camouflage pattern's color begins to blend into the background intensity. At approximately 10 m (Fig. R2.2c), 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 (spatial color mixing, **not clearly distinguishable anymore**), achieving the optimal camouflage effect.

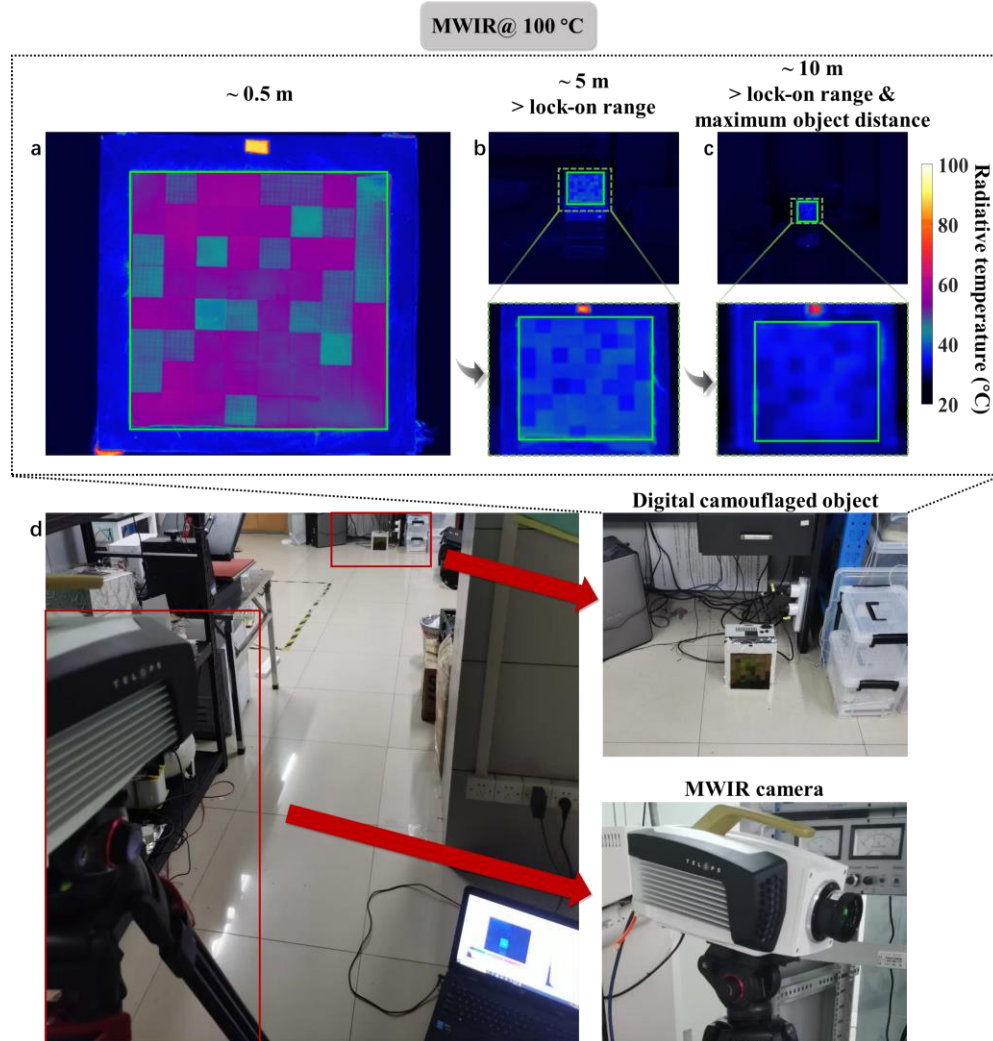


Fig. R2.2 | MWIR digital camouflage effect demonstration. IR images at different distances: **a.** 0.5 m, **b.** 5 m, and **c.** 10 m. **d.** Indoor experimental scene.

We have added a section of discussion about digital camouflage color and pattern in “Strategy of digital camouflage”

(Page 6, lines 111-115).

The optical hyperspectral digital camouflage pattern, composed of primary color pixels, replicates to the texture of vegetation in the hyperspectral image within the optical band (Fig. 1a). Therefore, optical hyperspectral camouflage pattern (spanning VIS, NIR, and SWIR bands in Fig. 1b) can be designed by integrating hyperspectral classification, background texture detection, pixelation, and patch templates (see Supplement 6).

We have revised the manuscript accordingly:

Supplement 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 . 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 by:

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

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.

Supplement 4. Lock-on range calculation

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

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

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:

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

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.

Additionally, to better demonstrate the functionality of the digital camouflage pattern and help readers understand, we have included the algorithm used for the digital camouflage pattern design in this manuscript in Supplement 6.

Supplement 6. Digital camouflage pattern design method

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 Fig. S4:

(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 pattern.

(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) (Table S2). In Fig. S4, 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 Table S2, 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.

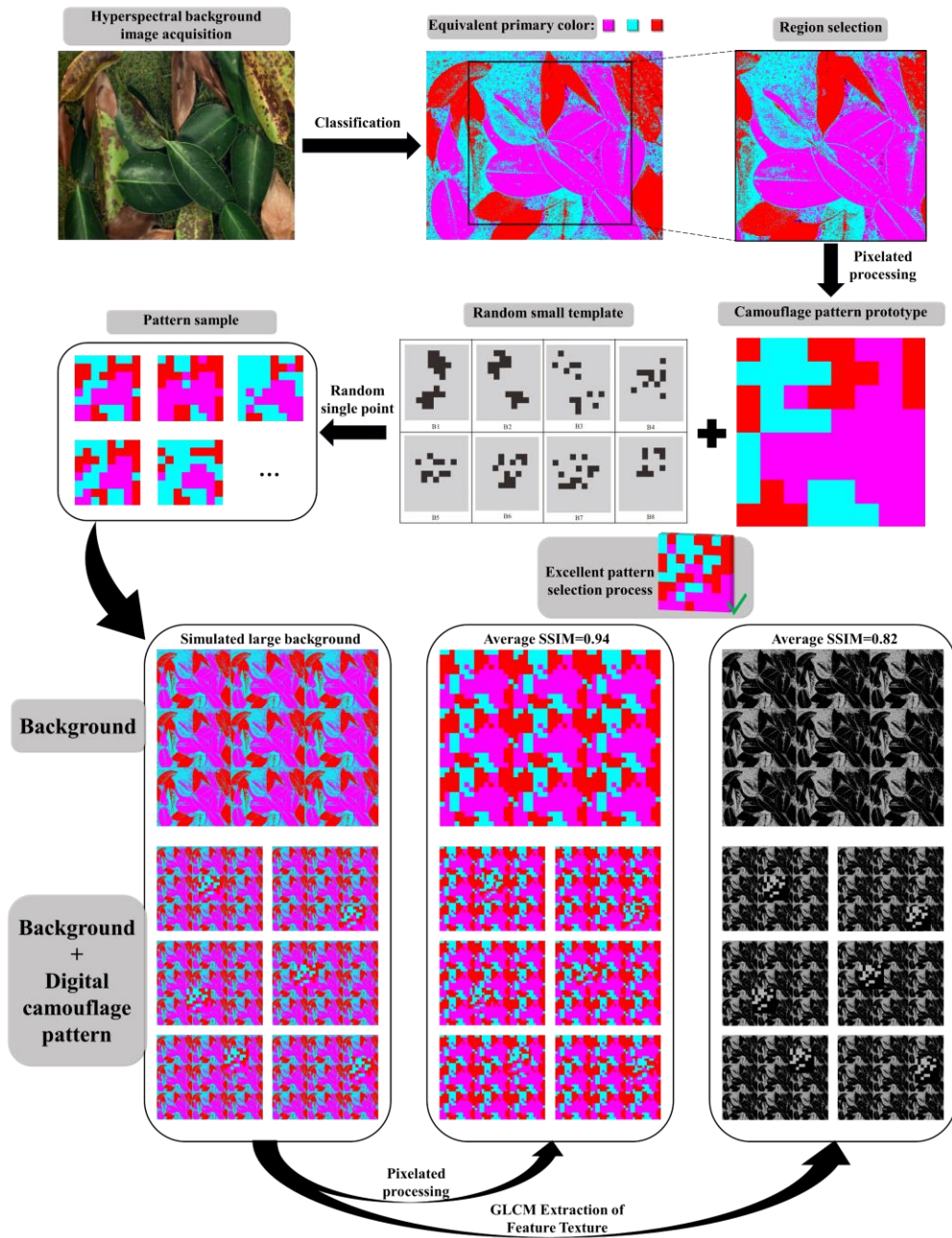


Fig. S4 | Digital camouflage pattern design process.

Table. S2 | Time taken to find targets in simulated scenes.

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

Supplement 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 (Fig. S14a), the MWIR digital

camouflage pattern is clearly visible. At approximately 5 m (Fig. S14b), 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 (Fig. S14c), 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.

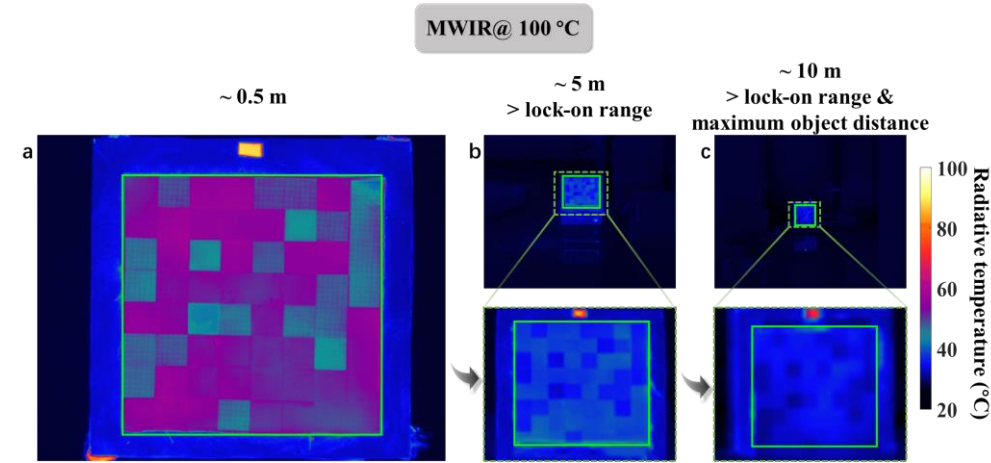


Fig. S14 | MWIR digital camouflage effect demonstration. IR images at different distances: **a.** 0.5 m, **b.** 5 m, and **c.** 10 m.

[R2.11] Xu, C. *et al.* The relationship between spatial color mixing with color and radiation similarity in digital camouflage study. *Infrared Physics & Technology* **130**, 104593 (2023).

[R2.12] Rao, A. *et al.* Aircraft powerplant and plume infrared signature modelling and analysis. *43rd AIAA Aerospace Sciences Meeting and Exhibit*, 221 (2005).

3. Application. (i) Fig.4a and Fig. 4c show a dramatic difference between the pixels and background. Please, explain why the device works even though pixels are distinguishable from the background. (ii) What are the possible applications of creating different patterns as in Fig. 4b?

Response:

We thank the reviewer for the thoughtful comments and insightful questions.

(i) In the MWIR band, at 0.5 m imaging distance (Fig. R2.3a), the MWIR digital camouflage pattern is clearly distinguishable. This is because the imaging distance is smaller than the maximum object distance (~ 5 m for our MWIR camera, with detailed calculations in Supplement 3[Refs. R2.13-R2.14]), so the pattern's texture remains sharp and spatial color mixing has not yet occurred. At the same time, the imaging distance is also smaller than the lock-on range (~ 10 m for our MWIR camera, with detailed calculations in Supplement 4[Refs. R2.15]), meaning the pattern's color is still distinguishable from the background and can be locked onto.

In a real-world scenario (Fig. R2.3d), at approximately 5 m (Fig. R2.3b), which exceeds the camera's lock-on range (background $\sim 25^\circ\text{C}$), the digital camouflage pattern's color begins to blend into the background intensity. At approximately 10 m (Fig. R2.3c), 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 (spatial color mixing), achieving the optimal camouflage effect.

In THz band, due to imaging method limitations, we provide simulated images at the maximum object distance (Fig. R2.4b). The conclusion is similar to that of the MWIR band. Comparing Fig. R2.4a, at the maximum object distance, the camouflage effect of the pattern is enhanced due to the spatial color mixing effect, blending with the background.

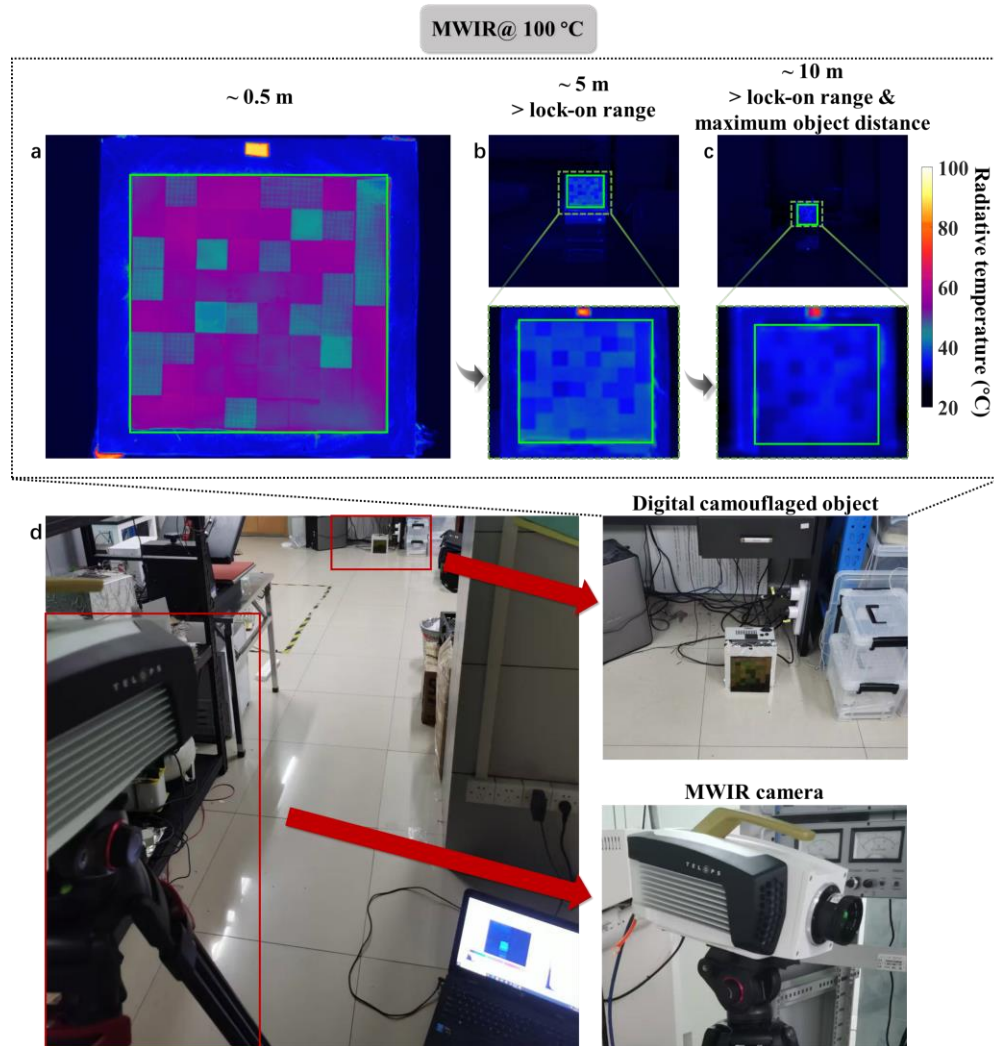


Fig. R2.3 | MWIR digital camouflage effect demonstration. IR images at different distances: **a.** 0.5 m, **b.** 5 m, and **c.** 10 m. **d.** Indoor experimental scene.

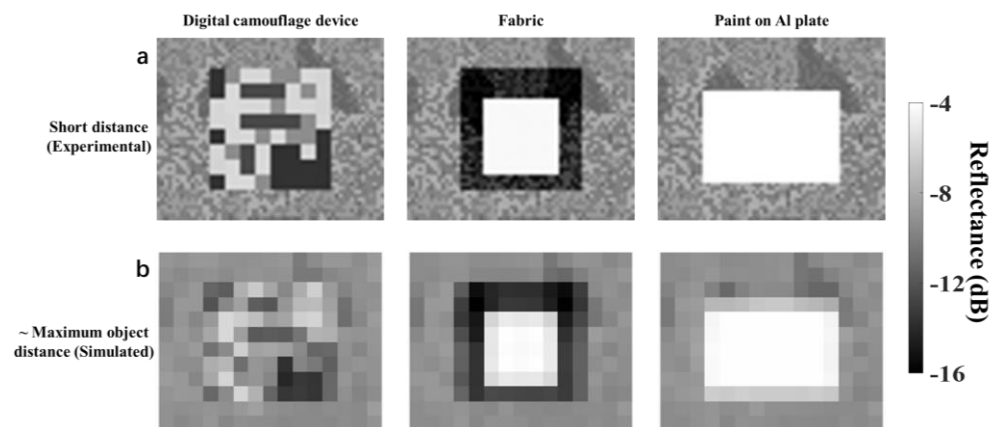


Fig. R2.4 | Comparison of THz images at different distances: **a.** Experimental THz images at a short distance. **b.** Simulated THz images at the maximum object distance.

We have revised the manuscript accordingly:

(Page 12, lines 239-247)

Additionally, it should be noted that in Fig. 5a and Fig. 5c, camouflage patterns do not blend well with the background. As mentioned earlier, passive camouflage cannot perfectly adapt to all background environments (factors such as temperature and moisture can affect the background's reflectance or emissivity response). The patterns still maintain camouflage effectiveness, although they require greater distance than perfect pattern, to escape detection by the sensor (see Supplement 3 for maximum object distance calculation, Supplement 4 for lock-on range calculation). Furthermore, there are potential improvements, such as decoupling and independently designing patterns for the thermal IR and THz bands (see Supplement 10 and 11), which would allow them to perfectly align with the background.

Supplement 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. 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 by:

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

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.

Supplement 4. Lock-on range calculation

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

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

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.

Supplement 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 (Fig. S14a), the MWIR digital camouflage pattern is clearly visible. At approximately 5 m (Fig. S14b), which exceeds the camera's lock-on range (background ~25 °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 (Fig. S14c), 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.

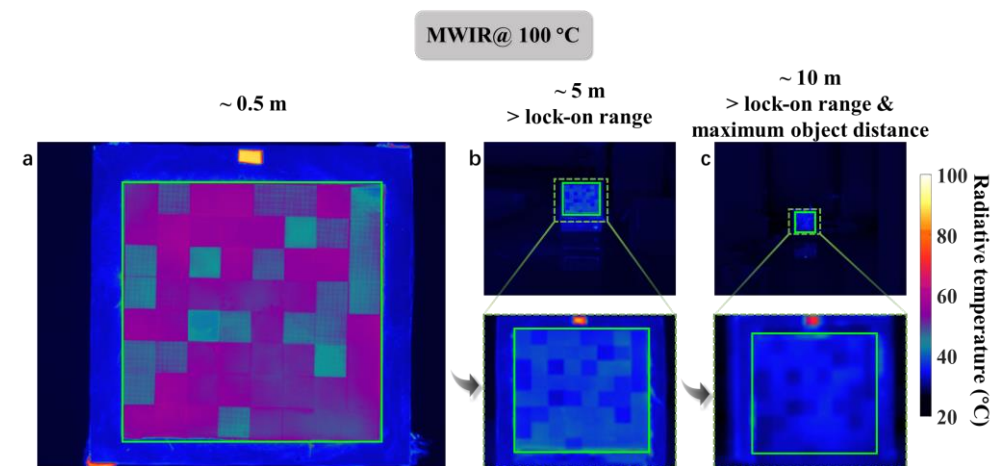


Fig. S14 | Demonstration of MWIR digital camouflage effectiveness. IR images captured at different distances: **a.** 0.5 m, **b.** 5 m, and **c.** 10 m.

[R2.13] Zhou, Z. *et al.* A comprehensive multimodal eye recognition. *Signal, Image and Video Processing* **7**, 619-631 (2013).

[R2.14] Xu, C. *et al.* The relationship between spatial color mixing with color and radiation similarity in digital camouflage study. *Infrared Physics & Technology* **130**, 104593 (2023).

[R2.15] Rao, A. *et al.* Aircraft powerplant and plume infrared signature modelling and analysis. *43rd AIAA Aerospace Sciences Meeting and Exhibit*, 221 (2005).

(ii) In Fig. 4b, the LWIR pattern displaying the letter ‘F’ demonstrates that (1) the design allows independent control of the pattern without coupling to the optical band, and (2) it can be applied for thermal signal encryption.

We have revised the manuscript accordingly.

(Page 11, lines 226-227)

The LWIR pattern of the letter “F” demonstrates the ability to design independent patterns across multiple bands.

4. (i) “Principles of digital camouflage” is focused on the image processing having a limited applicability in the following text. Instead, we recommend adding a paragraph covering the design optimization strategy. (ii) In “Methods. Design” it is mentioned that “The initial sample structures are generated randomly”. What were the parameters to optimize? Did you vary materials, layers, thickness? What was the quantity to judge whether the sample is more optimal or less?

Response:

We sincerely thank the reviewer for the insightful suggestions and questions.

(i) We have revised the original section “Principles of digital camouflage” to “Strategy of digital camouflage”, including **the process of primary color classification** and **the method of texture design**. Also, the detailed description of the digital camouflage method is added in Supplement 6. Moreover, **the multilayer structure design** method is briefly mentioned in the section “Structure of the digital camouflage device”.

(Pages 5-6, lines 95-125)

Strategy of digital camouflage

Digital camouflage fundamentally relies on the manipulation of color and pattern to counter detector arrays (e.g., CMOS, CCD, SAR arrays). The digital camouflage pattern can operate at optimal performance, with its colors and textures starting to blend into the background after reaching a certain distance from the detector (see Supplement 3 for maximum object distance calculation and Supplement 4 for lock-on range calculation). The method by which the digital camouflage device operates in the optical hyperspectral and thermal infrared-terahertz-microwave tri-bands is outlined as follows.

Primary color classification process. For optical hyperspectral digital camouflage, the primary colors are defined based on the main vegetational regions of interest (ROI) classification (the details of design method can be found in the Supplement 5 and 6). This include LH1 (fresh green vegetation), LH2 (fresh light-green vegetation), and LH3 (withered yellow vegetation) (Fig. 1b). Additionally, this study introduces a new theoretical framework and relevant parameter indicators for calculating spectral differences in digital camouflage (see Supplement 5). As shown in Fig. 1b, a simple deep neural network (DNN) is trained to rapidly compute various hyperspectral image parameters and assist in classification algorithms (see Supplement 5).

Texture design method. The optical hyperspectral digital camouflage pattern, composed of primary color pixels, replicates the texture of vegetation in the hyperspectral image within the optical band (Fig. 1a). Therefore, optical hyperspectral camouflage pattern (spanning the VIS, NIR, and SWIR bands in Fig. 1b) can be designed by integrating hyperspectral classification, background texture detection, pixelation, and patch templates (see Supplement 6).

Primary color determination of tri-bands. For thermal infrared-terahertz-microwave tri-band digital camouflage, the primary color is referenced from Supplement 7 and mapped to a color bar 15. Here, the MWIR band is divided into 4-level (LM1-4), the LWIR band into 3-level (LL1-3), the THz band into 4-level (LT1-4), and the X-band into 3-level (LX1-3) (Fig. 1c).

Texture discussion of tri-bands. The thermal infrared-terahertz-microwave camouflage patterns for the three bands are not fully optimized in this study. Due to the greater variability of signals in these bands (see Supplement 7), obtaining accurate and effective background textures is challenging. Furthermore, in Fig. 1c, the LWIR band pattern is designed in the shape of the letter “F” to preliminarily demonstrate the decoupling performance of the device. The coupling and decoupling methods for each band are discussed in detail in the Supplements 5, 10, and 11.

(Page 7, lines 135-138)

“Structure of the digital camouflage device”

Multilayer structure design method. Designing hyperspectral camouflage is challenging, as it requires the simultaneous optimization of numerous structural parameters and materials. To address this, a machine learning method based on the quadratic unconstrained binary optimization (QUBO) model is used to determine the optimal layer distribution (see Supplement 8 for details).

(ii) We optimized the **materials, layers, and thickness** of the multilayer structure using the mentioned algorithm. We used a figure of merit (FOM) that includes spectral angle mapping (SAM) and spectral distance (SD) to judge the sample, which is given by

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

We have revised the original “Design” subsection and moved it to Supplement 8, where detailed flowcharts and explanations are provided.

Supplement 8. Multilayer structure design method

The multilayer structures are designed using the QUBO model and employing the factorization machine (FM) model. As shown in Fig. S7, 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 Table S3, 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 Table S4, 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.

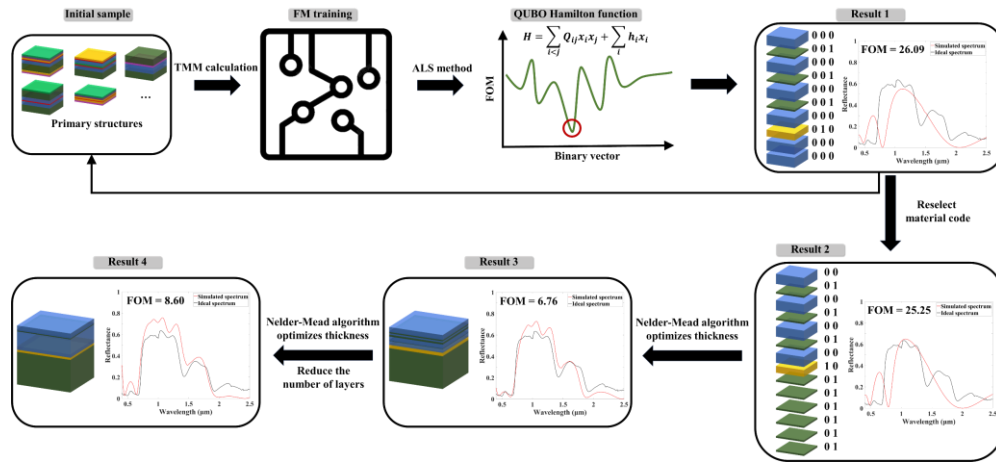


Fig. S7 | Multilayer structure design method

Table. S3 | Material code 1

Material	Binary code	Thickness (nm)
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<u>ZnS</u>	<u>0 0 0</u>	<u>50</u>
<u>Ge</u>	<u>0 0 1</u>	<u>5</u>
<u>Ti</u>	<u>0 1 0</u>	<u>30</u>
<u>Au</u>	<u>0 1 1</u>	<u>5</u>
<u>Ag</u>	<u>1 0 0</u>	<u>10</u>
<u>SiO₂</u>	<u>1 0 1</u>	<u>50</u>
<u>MgF₂</u>	<u>1 1 0</u>	<u>50</u>
<u>None</u>	<u>1 1 1</u>	<u>0</u>

Table. S4 | Material code 2

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

5. Comparison between Device, Fabric, and Paint. (i) Visually, the colors of the fabric are green, yellow and orange. However, they were used to classify them into green, light green and yellow. Therefore, we think that the classification was performed properly and there are no misidentifications in 0.4-1um classification. Both yellow and orange cells are identified as LH3, while green is LH1. A more suitable combination of fabric colors should be used for clear comparison between device and fabric. Also, both paint green colors are much lighter than dark green color of leaves and fabric. Possibly, that is the reason they both are identified as light green. A more suitable combination of paint colors should be used for a clear comparison between the device and paint. All the colors should be consistent with each other. (ii) There is a deterministic criterion GCD used to classify different elements. What is the reason that part of Paint is an unidentified region in 0.4-1um classification? If the paint on aluminum plate is uniformly distributed, why there are two different regions? Similar question is for 1-2.5um Fabric classification. If the fabric squares are identical, why some of them are unidentifiable forming two rectangles? What is the reason 1-2.5um classification leads to worse results than 0.4-1um classification?

Response:

We thank the reviewer for the comments and suggestions.

We sincerely thank the reviewer for the insightful comments, suggestions, and questions.

(i) The existing color difference arises because the hyperspectral camera automatically maps signals at 640 nm, 550 nm, and 470 nm to generate RGB values, forming a false color image (also called “metamerism” [Ref. R2.16]).

Actually, we customized fabrics and paints to match the same color. We calibrate the original images (Fig. R2.5) by referencing images taken at the same angle with a smartphone camera. Additionally, we provide the calculated colors based on the hyperspectral camera data (Table. R2.1, using the CIE 1931 2° standard observer with a D50 illuminant), demonstrating the same color of digital camouflage device, fabric reference, and paint reference.

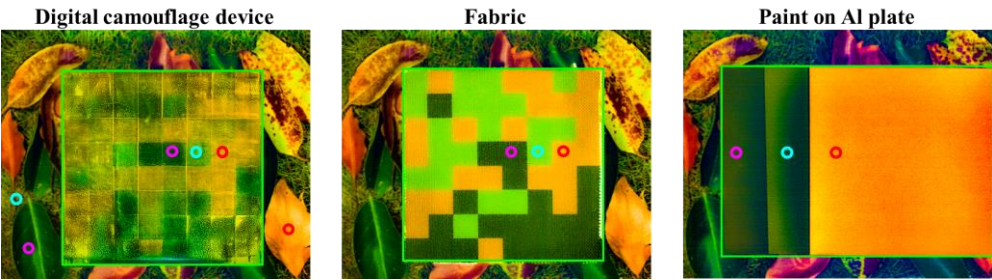


Fig. R2.5 | Calibrated VIS images.

Table. R2.1 | Visible color of plant and samples.

	Digital Camouflage device	Fabric	Paint on Al plate
	(71.82, 86.25, 72.08)	(79.03, 88.98, 71.17)	(79.35, 83.33, 78.20)
Green			
	(112.24, 117.57, 59.79)	(115.99, 117.61, 82.46)	(88.23, 90.58, 71.40)
Light- green			
	(137.66, 117.40, 88.68)	(126.75, 99.65, 70.48)	(173.77, 134.57, 95.51)
Yellow			

[R2.16] Foster, D.H. *et al.* Frequency of metamerism in natural scenes. *Journal of the Optical Society of America A* **23**, 2359-2372, (2006).

(ii) The reason for different classification results within the same sample area is that the **lighting on the sample surface is not completely uniform** due to the experimental setup. The optical hyperspectral demonstration is conducted inside a black box, where the illumination is provided by four halogen lamps positioned at the top of the box, approximately 50 cm above the surface. In areas near the classification threshold, this uneven lighting can lead to variations in classification results.

The worse result in the 1-2.5 μm range, compared to the 0.4-1 μm range, are attributed to the fact that the pigments in the fabric and paint can only camouflage the VIS color (Fig. R2.6). In contrast, in the 1-2.5 μm NIR-SWIR, the lack of water absorption bands does not create distinct classification result.

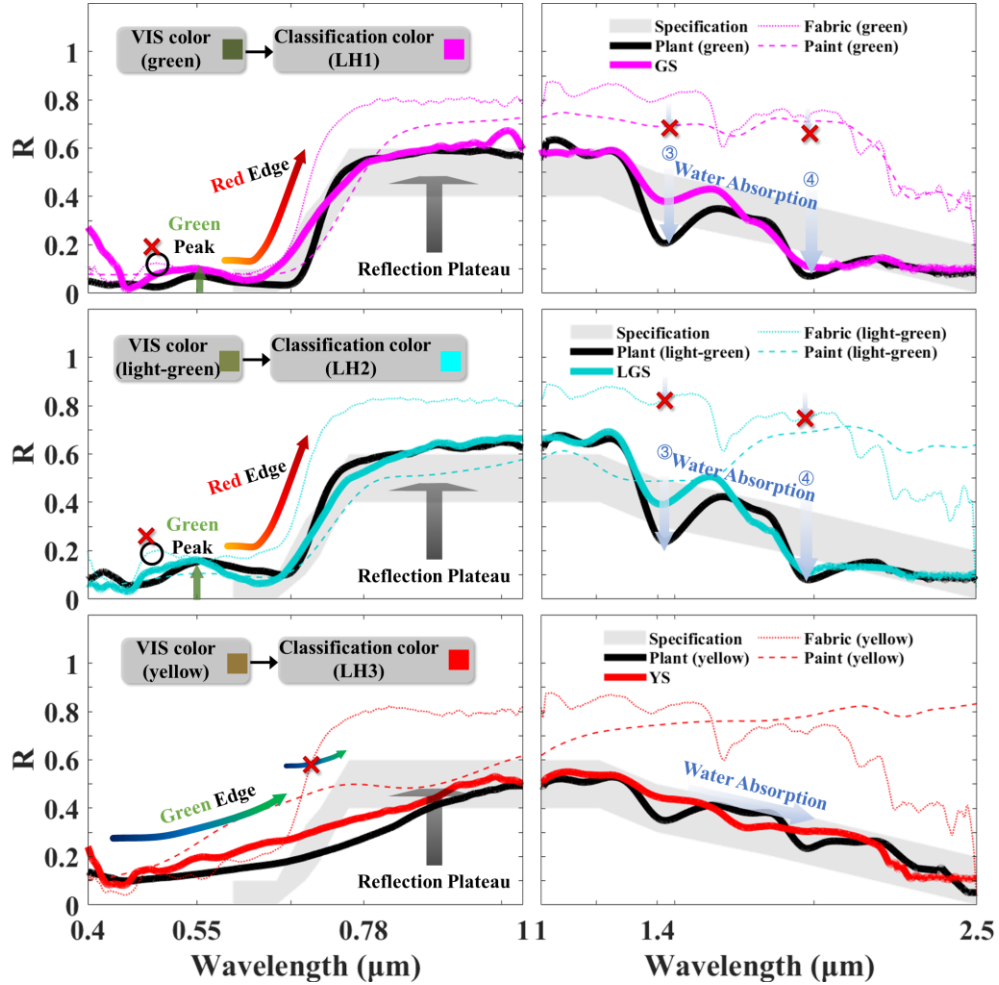


Fig. R2.6 | Spectral diagrams illustrating three types of vegetation and various camouflage samples.

6. Classification algorithm. Fig. 1b includes the image of a deep neural network (DNN) architecture. Did you use DNN for the classification? What is the purpose? In the main text it is mentioned, that “a specific GCD range” is utilized to identify pixel labels. It looks like to me that DNN is not needed for this process. Please, change the corresponding figure if DNN was not used. If it is indeed used, please provide more discussion about this part.

Response:

We thank the reviewer for the comments and suggestions.

We used a simple deep neural network (DNN) to rapidly calculate the relevant parameters (SD, SAM, SID, SWD, GCD) and classify them efficiently. The computational bottleneck arises from the parameter, $\beta_{i,j}$, which significantly slows down the calculation of image parameters. By employing the DNN, the computation speed increased approximately 70,000-fold. Moreover, the histogram of the dataset (Fig. R2.7) helps to better determine the suitable classification method. From the figure, GCD classification appears appropriate because there are three peaks in the histograms corresponding to the all three ROIs. However, GCD, as a newly proposed metric in this

paper, may not yet be widely accepted by a broader audience. Therefore, SID classification is used in this manuscript.

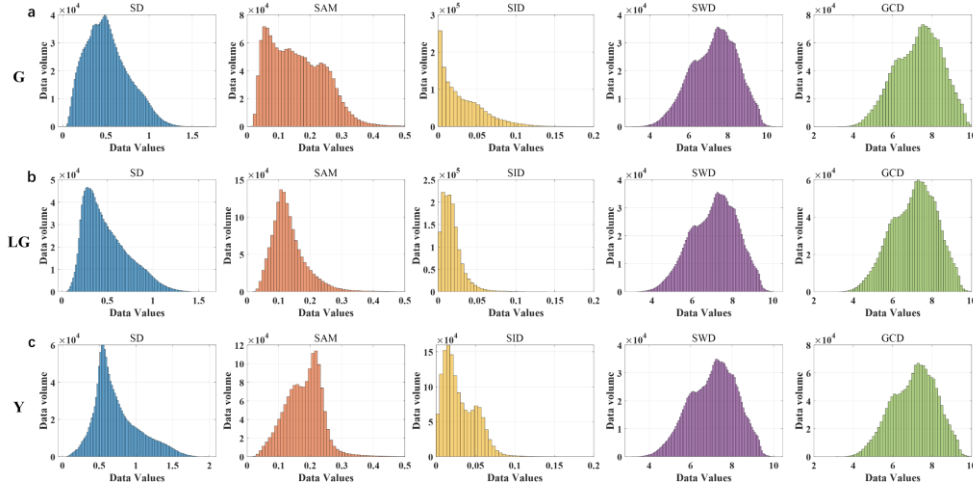


Fig. R2.7 | Histograms of dataset parameters for different ROIs: a. Green plant, b. Light-green plant, and c. Yellow plant.

We have revised the relative discussion in Supplement 5.

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 (Fig. S3) 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.

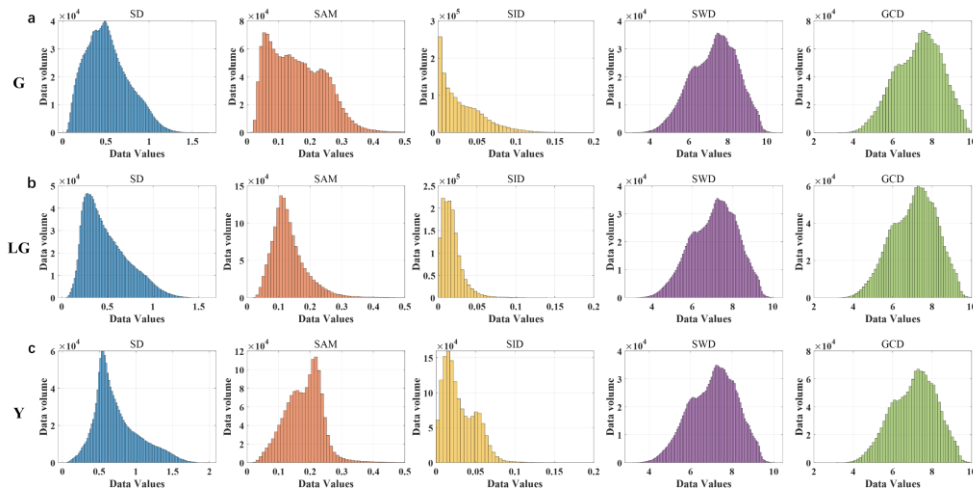


Fig. S3 | Histograms of dataset parameters for different ROIs: a. Green plant, b. Light-green plant, and c. Yellow plant.

7. Image processing equations. (i) Firstly, this topic is covered much in both main text and supplemental notes. We recommend moving it entirely to supplemental notes since the results of the calculations are not the most important outcomes of this work. They are shown only in a table in Fig.3d and have very limited significance for a broader community. (ii) Instead, a description of design optimization can be included in the main text (see other comments). (iii) Moreover, we recommend rewriting a paragraph from the abstract where different metrics are covered since such information in the abstract might be confusing for readers. (iv) Some of the quantities, such as SD, SAM, SID, SSIM, are widely used. However, it remains unclear whether GCD and SWD are introduced by the authors or taken from other studies. In the former scenario, the meaning of these quantities and corresponding equations (Eq. 2, Eq. S4, Eq. S5) should be explained. Otherwise, relevant references might be useful. (v) In either case, it is unclear why alphas and betas in Eq. S4 have their values (as well as k and b in Eq. S5). With the chosen values, calculations are equivalent to adding a factor of 100 to SID and keeping SD as it is. What is the purpose of these manipulations?

Response:

We sincerely thank the reviewer for their insightful comments, valuable suggestions, and thoughtful questions.

(i) We have moved all the equations to Supplement 5 and added explanations for the parameters (e.g., SD, SAM, SID, SSIM, etc.). The tables in Fig. 3d have also been moved to Supplement 13.

(ii) We have revised the original section “Principles of digital camouflage” to “Strategy of digital camouflage”, including **the process of primary color classification** and **the method of texture design**. Also, a detailed description of the digital camouflage method has been added in Supplement 6.

(Page 5-6, lines 95-125)

Strategy of digital camouflage

Digital camouflage fundamentally relies on the manipulation of color and pattern to counter detector arrays (e.g., CMOS, CCD, SAR arrays). The digital camouflage pattern can operate at optimal performance, with its colors and textures starting to blend into the background after reaching a certain distance from the detector (see Supplement 3 for maximum object distance calculation and Supplement 4 for lock-on range calculation). The method by which the digital camouflage device operates in the optical hyperspectral and thermal infrared-terahertz-microwave tri-bands is outlined as follows.

Primary color classification process. For optical hyperspectral digital camouflage, the primary colors are defined based on the main vegetational regions of interest (ROI) classification (the details of design method can be found in the Supplement 5 and 6). This include LH1 (fresh green vegetation), LH2 (fresh light-green vegetation), and LH3 (withered yellow vegetation) (Fig. 1b). Additionally, this study introduces a new theoretical framework and relevant parameter indicators for calculating spectral differences in digital camouflage (see Supplement 5). As shown in Fig. 1b, a simple deep neural network (DNN) is trained to rapidly compute various hyperspectral image parameters and assist in classification algorithms (see Supplement 5).

Texture design method. The optical hyperspectral digital camouflage pattern, composed of primary color pixels, replicates the texture of vegetation in the hyperspectral image within the optical band (Fig. 1a). Therefore, optical hyperspectral camouflage pattern (spanning the VIS, NIR, and SWIR bands in Fig. 1b) can be designed by integrating hyperspectral classification, background texture detection, pixelation, and patch templates (see Supplement 6).

Primary color determination of tri-bands. For thermal infrared-terahertz-microwave tri-band digital camouflage, the primary color is referenced from Supplement 7 and mapped to a color bar 15. Here, the MWIR band is divided into 4-level (LM1-4), the LWIR band into 3-level (LL1-3), the THz band into 4-level (LT1-4), and the X-band into 3-level (LX1-3) (Fig. 1c).

Texture discussion of tri-bands. The thermal infrared-terahertz-microwave camouflage patterns for the three bands are not fully optimized in this study. Due to the greater variability of signals in these bands (see Supplement 7), obtaining accurate and effective background textures is challenging. Furthermore, in Fig. 1c, the LWIR band pattern is designed in the shape of the letter “F” to preliminarily demonstrate the decoupling performance of the device. The coupling and decoupling methods for each band are discussed in detail in the Supplements 5, 10, and 11.

Supplement 6. Digital camouflage pattern design method

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 Fig. S4:

(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 pattern.

(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) (Table S2). In Fig. S4, 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 Table S2, 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.

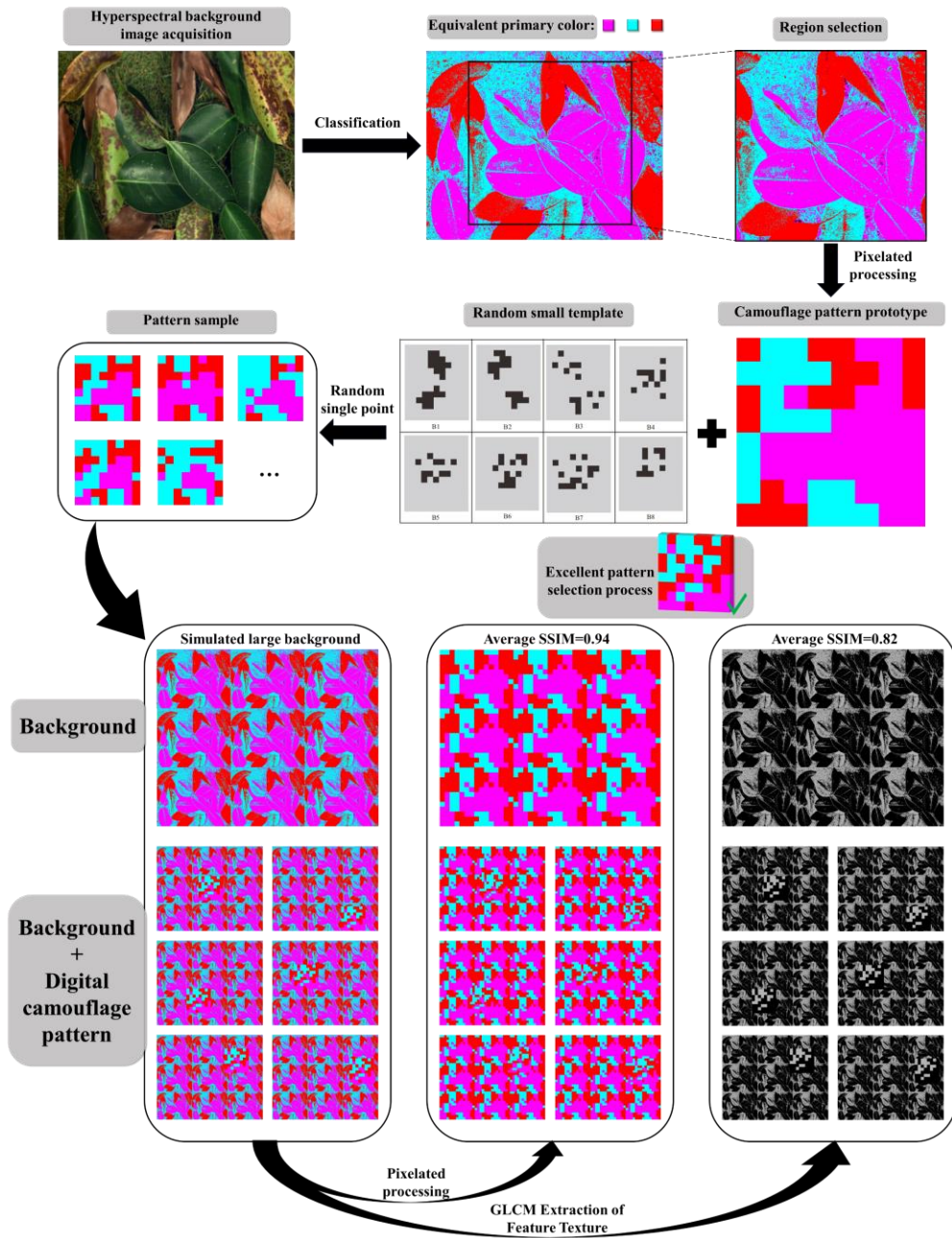


Fig. S4 | Digital camouflage pattern design process.

Table. S2 | Time taken to find targets in simulated scenes.

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

Moreover, **the design method of the multilayer structure** is briefly mentioned in the section “Structure of the digital camouflage device”.

(Page 7, lines 137-140)

Designing hyperspectral camouflage is challenging, as it requires the simultaneous optimization of numerous structural parameters and materials. To address this, a machine learning method based on the quadratic unconstrained binary optimization (QUBO) model is used to determine the optimal layer distribution (see Supplement 8 for details).

Supplement 8. Multilayer structure design method

The multilayer structures are designed using the QUBO model and employing the factorization machine (FM) model. As shown in Fig. S7, 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 Table S3, 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 Table S4, 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.

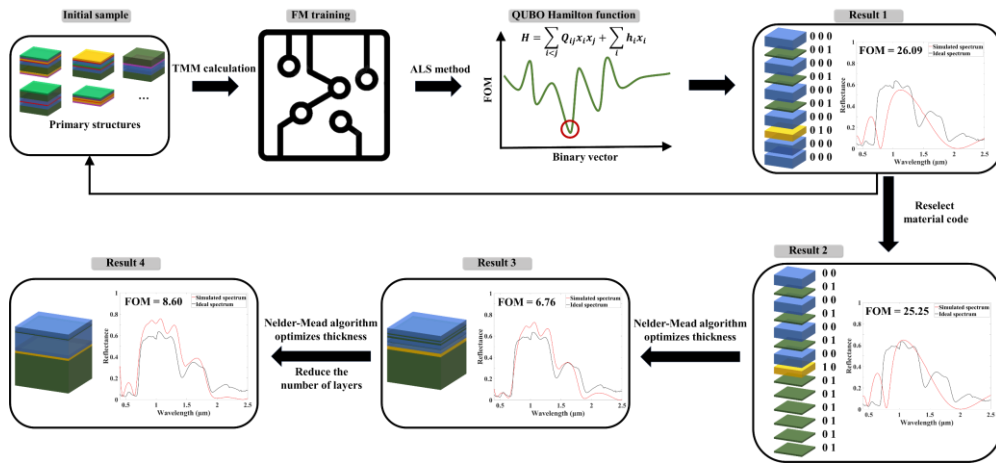


Fig. S7 | Multilayer structure design method

Table. S3 | Material code 1

<u>Material</u>	<u>Binary code</u>	<u>Thickness (nm)</u>
<u>ZnS</u>	<u>0 0 0</u>	<u>50</u>
<u>Ge</u>	<u>0 0 1</u>	<u>5</u>
<u>Ti</u>	<u>0 1 0</u>	<u>30</u>
<u>Au</u>	<u>0 1 1</u>	<u>5</u>
<u>Ag</u>	<u>1 0 0</u>	<u>10</u>
<u>SiO₂</u>	<u>1 0 1</u>	<u>50</u>
<u>MgF₂</u>	<u>1 1 0</u>	<u>50</u>
<u>None</u>	<u>1 1 1</u>	<u>0</u>

Table. S4 | Material code 2

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

(iii) In the abstract, we have rewritten a paragraph covering different metrics, consistently using a more widely applicable mathematical metric, the **deviation rate** [Ref. R2.17] to describe the performance of the optical hyperspectral camouflage.

(Page 2, lines 24-26)

In the optical band, the hyperspectral digital camouflage can simulate various vegetational spectra as primary colors, with a deviation rate of less than 0.2.

Supplement 5. Theoretical supplement for hyperspectral digital camouflage

Moreover, this study employs a more widely applicable mathematical metric, the deviation rate [R2.17], which is not limited to spectroscopy, to evaluate spectral accuracy.

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

[R2.17] Dinwoodie, I. H. Identifying a large deviation rate function. The Annals of Probability 21, 216-231 (1993).

(iv) GCD and SWD are proposed in this paper to link hyperspectral and digital camouflage. The generalized color difference (GCD) is a metric used to measure the spectral difference between two pixels, which can simultaneously consider both digital camouflage and hyperspectral classification. The spectral weight distance (SWD) is based on the principles of spectral distance (SD) and spatial color mixing in digital camouflage, describing the differences between two spectral vectors.

The additional references and detailed explanations of the quantities have been revised in Supplement 5, along with the inclusion of relevant references.

Supplement 5. Theoretical supplement for hyperspectral digital camouflage

In hyperspectral field, the absolute value differences are described using spectral distance[Ref. R2.18-R2.19] (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[Refs. R2.20-R2.21] (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 divergence[Ref. R2.22] (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.

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

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 rate[Ref. R2.23], which is not specific to spectroscopy, is also used to evaluate the spectra:

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

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 difference [Ref. R2.24], 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

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

The pattern of digital camouflage within a band is composed of primary colors specific to that band (Table S1). 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 similarity [Ref. R2.25]. 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.

Table. S1 | Multiband level-pixel coupling table.

<u>Multilayer structure</u>	<u>δ of sub-pixel (μm)</u>	<u>Optical</u>	<u>MWIR</u>	<u>LWIR</u>	<u>THz</u>	<u>X-band</u>
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

	<u>10</u>		<u>LM1</u>	<u>LL1</u>	<u>LT4</u>	<u>LX1,</u>
<u>YS</u>	<u>77</u>	<u>LH3</u>	<u>LM2</u>	<u>LL2</u>	<u>LT4</u>	<u>LX2,</u>
	<u>150</u>		<u>LM3</u>	<u>LL3</u>	<u>LT3</u>	<u>and LX3</u>

[R2.18] Jovanović, I. *et al.* Spectral distances of graphs. *Linear Algebra and its Applications* **436**, 1425-1435 (2012).

[R2.19] Konukoglu, E. *et al.* WESD--Weighted Spectral Distance for measuring shape dissimilarity. *IEEE transactions on pattern analysis and machine intelligence* **35**, 2284-2297 (2013).

[R2.20] Chakravarty, S. *et al.* Hyperspectral Image Classification using Spectral Angle Mapper. *2021 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE)*, 87-90 (2021).

[R2.21] Park, B. *et al.* Contaminant Classification of Poultry Hyperspectral Imagery using a Spectral Angle Mapper Algorithm. *Biosystems Engineering* **96**, 323-333 (2007).

[R2.22] Chang, C.-I. Spectral information divergence for hyperspectral image analysis. *IEEE 1999 International Geoscience and Remote Sensing Symposium. IGARSS'99 (Cat. No. 99CH36293)* **1**, 509-511 (1999).

[R2.23] Dinwoodie, I. H. Identifying a large deviation rate function. *The Annals of Probability* **21**, 216-231 (1993).

[R2.24] Xu, C. *et al.* The relationship between spatial color mixing with color and radiation similarity in digital camouflage study. *Infrared Physics & Technology* **130**, 104593 (2023).

[R2.25] Wang, Z. *et al.* Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing* **13**, 600-612 (2004).

(v) The reason for introducing the parameters $(\alpha_i, \beta_{i,j}, k, b)$ in the GCD calculation is based on the physical meaning of GCD, which represents the overall spectral difference between different ROIs. Since GCD must account for both digital camouflage and hyperspectral classification, the GCD values among the three ROIs should be as equal as possible.

The method for choosing these values follows an optimization principle, where we optimized the undetermined parameters $(\alpha_i, \beta_{i,j}, k, b)$ in this study. The exact computed values of α_i and $\beta_{i,j}$ are provided in the attachment, with $k = 48.657$ and $b = -2.375$. For the convenience of readers performing quick calculations, these parameters can be approximated as $\alpha_i = 0.5$, $\beta_{i,j} = 0$, $k = 50$, and $b = 0$.

The purpose of these adjustments is that, with the chosen values, the calculations effectively add a factor of 100 to SID while keeping SD unchanged. This is because the definition of SD is influenced by the number of hyperspectral channels, and this operation serves as a correction for the impact of spectral channel count. Readers can, of course, calculate and adjust these parameters according to their own hyperspectral camera model.

We have revised it in Supplement 5:

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 attachment, 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 $b = 0$.

8. Human body Thermal IR demonstration. we think this part is a little misleading regarding the statement “The device can lower the body’s radiation temperature from 36.8 °C to an average of approximately 25 °C”. The IR image was taken for a human wearing a jacket and holding the sample close to the jacket. The IR images (Fig. S7 B and C) indicate the human coat temperature to be 36 deg C. We believe the authors adjusted the emissivity value of the infrared camera such that the human coat temperature was 36, equal to human body temperature. But we do not think this is correct. The coat should have a lower temperature than the human body temperature.

Response:

We thank the reviewer for the comments and suggestions.

The coat indeed has the same temperature as the human body. The main reasons are as follows:

First, as observed through MWIR and LWIR infrared cameras, the clothing temperature (red frame in Fig. R2.8b and c) is slightly **higher than the radiation temperature of hand** (white frame in Fig. R2.8b and c).

Second, under solar heating, the temperature of **black clothing** can typically reach around **30-40 °C**, which is similar to the temperature of the human body at ~15 °C ambient temperature. This point has been verified in our previous work [Ref. R2.26, *Nano letters* **21**, 3879-3886(2021).], as shown by the **purple line in Fig. R2.9** (~15 °C ambient temperature, yellow line).

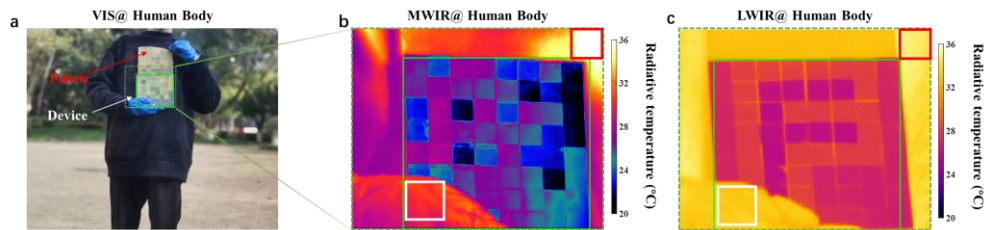


Fig. R2.8 | Thermal IR human body demonstration (March 3rd, 2024, ~15 °C). a. Human body demonstration in jungle environment. **b.** MWIR demonstration. **c.** LWIR demonstration.

[REDACTED]

Fig. R2.9 | Daytime thermal measurement results. The recorded data corresponds to the real-time temperature of the skin simulator covered with different textiles (red line, Janus textile in heating mode; blue line, Janus textile in cooling mode; purple line, black cotton; black line, white cotton; yellow line, ambient temperature). [Ref. R2.26, Luo, H. *et al.* Outdoor personal thermal management with simultaneous electricity generation. *Nano letters* 21, 3879-3886 (2021).]

Minor comments:

1. “Each GS, LGS, and YS pixel contains approximately 400 (20×20) rectangular sub-pixels”. Do you have different number of sub-pixels in pixels?

Response:

We thank the reviewer for the question.

The number of all sub-pixels in each pixel is consistent; every single pixel has 400 sub-pixels.

2. Note S2. It will be interesting to readers if the ranges of frequency/wavelength of the typical atmospheric windows not covered in this study are explicitly mentioned.

Response:

We thank the reviewer for the suggestion.

The bands not covered include the UV and the 60-200 GHz electromagnetic wave band.

We also have added explanations for all atmospheric windows in Supplement 2:

Supplement 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: (i) 0.3-0.4 μm (ultraviolet, UV), which is rarely considered due to the limitations of detectors; (ii) below 0.2 THz, 60-75 GHz (part of the V-band), 75-110 GHz (W-band), and 110-200 GHz (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.

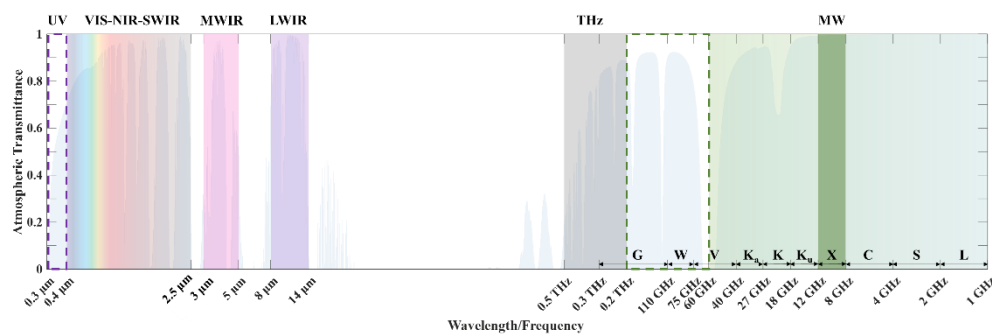


Fig. S2 | The overview of atmospheric windows.

3. What are the units of intensity in equations? Why there is no units for SD? What is C_N^2 in Eq.3?

Response

We thank the reviewer for the questions.

The intensities in the equations are all dimensionless.

The spectral distance (SD) has no unit because it is a relative metric used to compare the differences between two spectra. It is usually calculated using a mathematical method, such as

the Euclidean distance or other statistical distances. Since it represents the relative difference between two spectra rather than an absolute physical quantity, it does not require a unit.

C_N^2 refers to the number of combinations where two patterns are selected out of N spectral bands.

We have added the explanation in Supplement 5:

C_N^2 refers to the number of combinations where 2 patterns are selected out of N bands.

4. Reference/-s is recommended for the paragraph regarding the human vision and eye in Notes S3.

Response:

We thank the reviewer for the suggestions.

We have added references related to human vision and the eye in Supplement 3:

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 ~2.57[Ref. R2.27].

[R2.27] Zhou, Z. *et al.* A comprehensive multimodal eye recognition. *Signal, Image and Video Processing* 7, 619-631 (2013).

5. Fig. 2d shows t_1 , t_2 , etc. with no explanation.

Response:

We thank the reviewer for pointing this out.

The terms t_1 , t_2 , etc. represent the thicknesses of different layers in the fresh vegetation simulation (such as GS and LGS).

We have added some explanations for the terms t_1 , t_2 , etc., and revised the manuscript accordingly.

(Page 7, lines 130-132)

based on the same layer distribution, the thickness (t_1 , t_2 , etc.) in Fig. 2d are optimized spectrally

6. Fig. 2h shows spectra only between 8 and 12 GHz. Why there is no information about R/T for 5-8 GHz and 12-60 GHz? What is the meaning of "Average Transmittance" line?

Response:

We thank the reviewer for the questions.

We have supplemented the 5-60 GHz spectrum, as shown in Fig. R2.10. The blue, green, and red dashed lines show the MW reflectance of LX1-3, respectively.

The "Average Transmittance" line (black bold solid line) demonstrates the high transmittance of the upper layer pixels within the range of 5-60 GHz, indicating that the upper layer pixels do not affect the MW pattern.

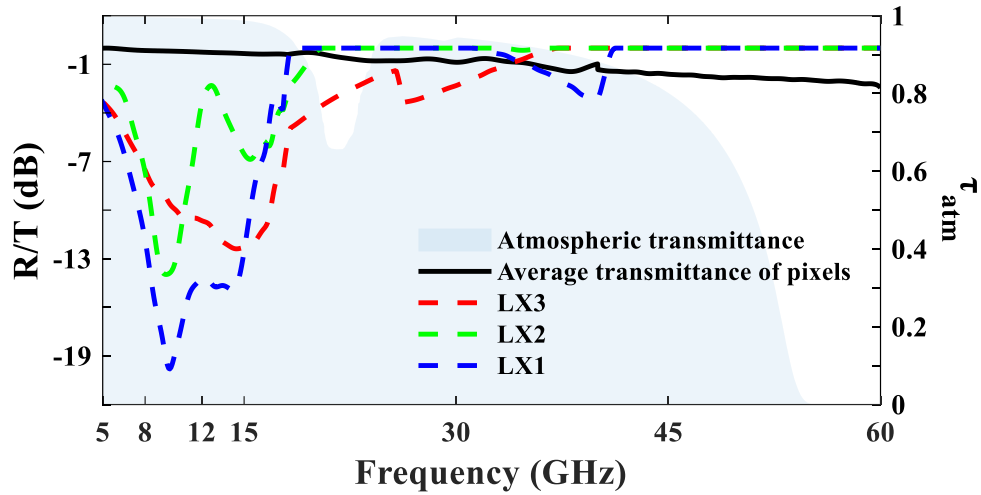


Fig. R2.10 | 5-60 GHz MW spectra.

7. “The LM4 spectrum is created by the total structural resonance between GS and LGS pixels, which is evident from the electric field distribution and resistive loss plots at approximately 4 μm wavelength (Fig. 2d).” In Fig. 2d there is no electric field for LGS.

Response:

We thank the reviewer for the question.

As shown in Fig. R2.11, GS and LGS have similar structures (different thicknesses of t_1 , t_2 , etc.) and electric field distributions, so the electric field analysis on LGS is not provided.

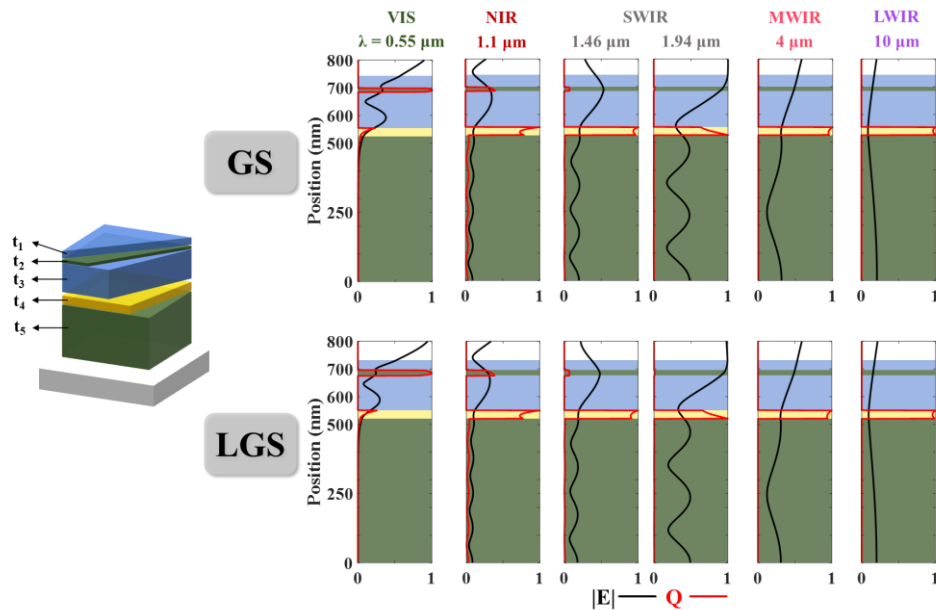


Fig. R2.11 | The illustration depicts the multilayer structures of GS and LGS, along with simulated electric field distribution ($|E|$) and resistive loss (Q) across wavelengths in the VIS, NIR, SWIR, MWIR, and LWIR bands.

We have revised the manuscript accordingly:

(Page 8, lines 151-152)

For GS/LGS, they have similar structures and exhibit comparable spectral performance.

8. In Note S10, the authors show that the device performance is similar at 350 degC. Is this heating process reversible, meaning that after heating and then cooling, will the performance of the optical device be identical to the original one?

Response:

We thank the reviewer for the questions.

This process is reversible, and the spectra after heating to 350 °C and cooling to room temperature, which still maintain the camouflage performance (Fig. R2.12).

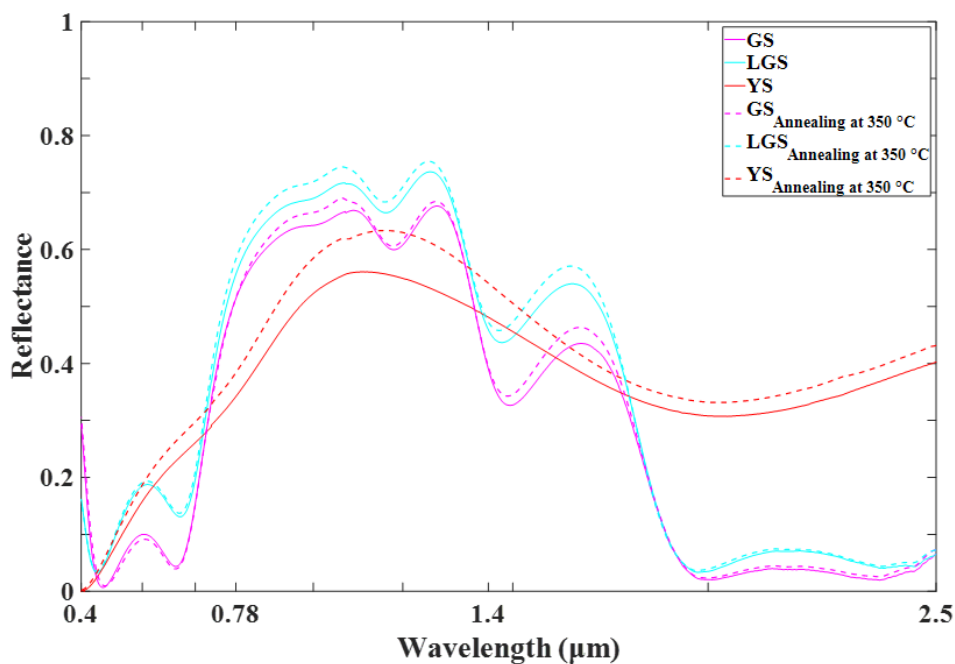


Fig. R2.12| High temperature annealing demonstration.

We have revised the manuscript accordingly:

(Supplement 15)

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.

The Reviewer #3's comments

Reviewer's general remarks:

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

Response:

We appreciate the reviewer's positive evaluation of our digital camouflage strategy encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands. We are very thankful to the reviewer for their helpful comments and suggestions. We have revised the manuscript accordingly. A point-by-point response has already been combined with the reply to the co-reviewer (Reviewer #2).

The Reviewer #4's comments

Reviewer's general remarks:

This work reports a broadband camouflage strategy across the visible, near-infrared, shortwave infrared, mid-wave infrared, long-wave infrared, terahertz, and microwave bands, which covers over 80% of the atmospheric windows. It addresses a lingering challenge in creating an adaptable camouflage solution for diverse surveillance threats. A novelty, I believe, is its seamless integration of optical (visible, near-infrared, and shortwave infrared) hyperspectral adjustment with multispectral intensity modulation. In the optical range, the camouflage replicates vegetational spectral features with high fidelity, while in the thermal infrared, terahertz, and microwave bands, it produces multilevel intensity camouflage to counter imaging systems working across those bands. While I find the manuscript somewhat interesting and recommendable for publication in Nature Communications, I believe that several major flaws need to be resolved in revision.

Response:

We appreciate the reviewer's positive evaluations of our digital camouflage strategy encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands. We are very thankful to the reviewer for helpful comments and suggestions. We have revised the manuscript according to the valuable comments of the reviewers. Below is a point-by-point response.

1. The text is challenging to read, which is due to a lack of logical flow between paragraphs. The authors should improve the narrative for better coherence. Additionally, the quality of the figures (I should say all the figures including data) needs improvement. Spacing, axis and legend labeling, and overall visual clarity should be improved. For example, Figures 2e, 2f, 2g, and 2h are difficult to interpret because it is unclear which plot corresponds to which dataset. Enhancing the quality of both the text and figures throughout the manuscript will promise its readability.

Response:

We thank the reviewer for the comments and suggestions.

We have redrawn Fig. 2e-2h and presented them as separate images (Fig. 3). We adjusted attributes such as spacing, axis, and legend labeling to improve readability.

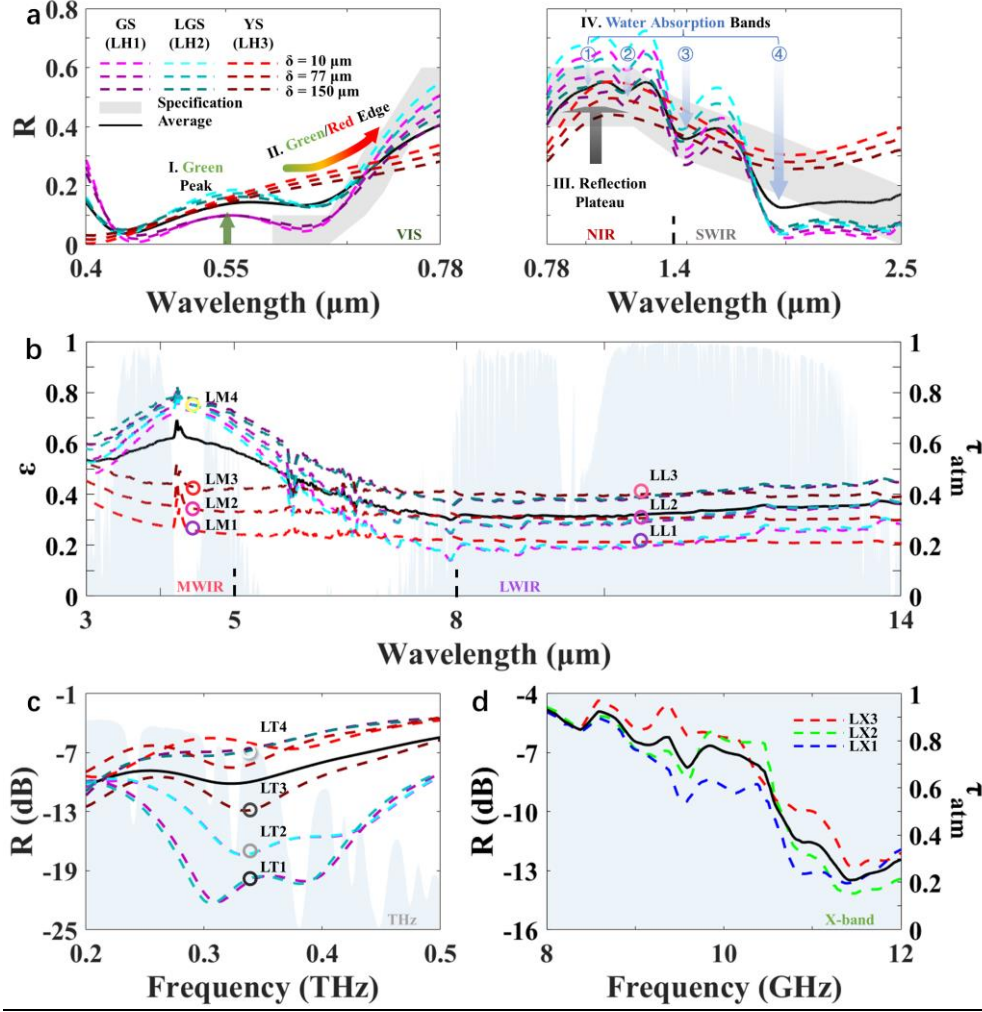


Fig. 3 | Multilevel reflectance, transmittance, and emissivity spectra of pixels. a. Experimental reflectance spectra of the three structures (GS, LGS, and YS) in the VIS, NIR, and SWIR bands. **b.** Experimental emissivity spectra of the three structures in the MWIR and LWIR bands, categorized into four levels (LM1-4) for the MWIR band and three levels (LL1-3) for the LWIR band. **c.** Experimental reflectance spectra of the three structures in the THz band, showing four levels (LT1-4). **d.** Experimental reflectance spectra of the whole device (including the structures and the MW-absorbing substrate) and average transmittance spectra of the microwave-absorbing substrate. The inset shows the zoomed-in X-band spectra and the corresponding three levels (LX1-3).

2. (i) The terms like SD, SAM, SID, SWD, and GCD may not be familiar to general readers. The authors should provide clearer definitions and explanations of these terms, highlighting their distinctions. (ii) Furthermore, the values mentioned in the abstract could sound unattractive. Replacing them with more widely understood metrics would make the work accessible to a broader audience. (iii) Similarly, the tables in Figure 3d are difficult to interpret, so the purpose and meaning of the numerical values should be clarified.

Response:

We thank the reviewer for the comments and suggestions.

(i) We have moved all the equations to Supplement 5 and added explanations for the quantities (e.g., SD, SAM, SID, SSIM, etc.):

Supplement 5. Theoretical supplement for hyperspectral digital camouflage

In hyperspectral field, the absolute value differences are described using spectral distance[Ref. R3.1-R3.2] (*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[Refs. R3.3-R3.4] (*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 divergence[Ref. R3.5] (*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 rate[Ref. R3.6], which is not specific to spectroscopy, is also used to evaluate the spectra:

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

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 difference[Ref. R3.7], 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

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

The pattern of digital camouflage within a band is composed of primary colors specific to that band (Table S1). 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 similarity [Ref. R3.8]. 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.

Table. S1 | Multiband level-pixel coupling table.

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

[R3.1] Jovanović, I. *et al.* Spectral distances of graphs. *Linear Algebra and its Applications* **436**, 1425-1435 (2012).

[R3.2] Konukoglu, E. *et al.* WESD--Weighted Spectral Distance for measuring shape dissimilarity. *IEEE transactions on pattern analysis and machine intelligence* **35**, 2284-2297 (2013).

[R3.3] Chakravarty, S. *et al.* Hyperspectral Image Classification using Spectral Angle Mapper. *2021 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE)*, 87-90 (2021).

[R3.4] Park, B. *et al.* Contaminant Classification of Poultry Hyperspectral Imagery using a Spectral Angle Mapper Algorithm. *Biosystems Engineering* **96**, 323-333 (2007).

[R3.5] Chang, C.-I. Spectral information divergence for hyperspectral image analysis. *IEEE 1999 International Geoscience and Remote Sensing Symposium. IGARSS'99 (Cat. No. 99CH36293)* **1**, 509-511 (1999).

[R3.6] Dinwoodie, I. H. Identifying a large deviation rate function. *The Annals of Probability* **21**, 216-231 (1993).

[R3.7] Xu, C. *et al.* The relationship between spatial color mixing with color and radiation similarity in digital camouflage study. *Infrared Physics & Technology* **130**, 104593 (2023).

[R3.8] Wang, Z. *et al.* Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing* **13**, 600-612 (2004).

(ii) We adopt a more widely applicable mathematical metric, **deviation rate** [Ref. R3.9], which is more friendly to the broader community and is not specific to spectroscopy, to evaluate the spectra:

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

Meanwhile, in the abstract, we have rewritten a paragraph covering different metrics, consistently using the deviation rate to describe the performance of optical hyperspectral camouflage.

(Page 2, lines 24-26)

In the optical band, the hyperspectral digital camouflage can simulate various vegetational spectra as primary colors, with deviation rate less than 0.2.

[R3.9] Dinwoodie, I. H. Identifying a large deviation rate function. *The Annals of Probability* **21**, 216-231 (1993).

(iii) The original spectral evaluation quantities (SD, SAM, SID, etc.) in Fig. 3d have been moved to Supplement 13:

The detailed spectral parameter comparison among the digital camouflage device, fabric reference, and paint reference is listed in Tables S6-S8 (the data is interpolated to intervals of 1 nm).

Table. S6 | Detailed spectral parameter comparison among green samples.

	<u>Device</u>	<u>Fabric</u>	<u>Paint</u>
<u>$SD(I_a, I_b)$</u>	<u>2.4789</u>	<u>17.4043</u>	<u>15.3712</u>
<u>$\cos[SAM(I_a, I_b)]$</u>	<u>99.04%</u>	<u>90.79%</u>	<u>88.03%</u>
<u>$SID(I_a, I_b)$</u>	<u>0.0370</u>	<u>0.4223</u>	<u>0.4324</u>
<u>$SID_{0.4-1\mu m}(I_a, I_b)$</u>	<u>0.0172</u>	<u>0.1684</u>	<u>0.1856</u>
<u>$SID_{1-2.5\mu m}(I_a, I_b)$</u>	<u>0.0198</u>	<u>0.2539</u>	<u>0.2469</u>

$\underline{SWD(I_a, I_b)}$	<u>1.2395</u>	<u>8.7022</u>	<u>7.6856</u>
$\underline{GCD(I_a, I_b)}$	<u>1.2655</u>	<u>12.4133</u>	<u>12.8170</u>
$\underline{DR(I_a, I_b)}$	<u>0.1825</u>	<u>1.0994</u>	<u>0.9681</u>

Table. S7 | Detailed spectral parameter comparison among light-green samples.

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

Table. S8 | Detailed spectral parameter comparison among yellow samples.

	<u>Device</u>	<u>Fabric</u>	<u>Paint</u>
$\underline{SD(I_a, I_b)}$	<u>2.1990</u>	<u>15.6074</u>	<u>18.3661</u>
$\underline{\cos[SAM(I_a, I_b)]}$	<u>99.25%</u>	<u>97.93%</u>	<u>91.05%</u>
$\underline{SID(I_a, I_b)}$	<u>0.0301</u>	<u>0.4265</u>	<u>0.5673</u>
$\underline{SID_{0.4-1\mu m}(I_a, I_b)}$	<u>0.0064</u>	<u>0.1229</u>	<u>0.1707</u>
$\underline{SID_{1-2.5\mu m}(I_a, I_b)}$	<u>0.0237</u>	<u>0.3035</u>	<u>0.3966</u>
$\underline{SWD(I_a, I_b)}$	<u>1.100</u>	<u>7.8037</u>	<u>9.1831</u>
$\underline{GCD(I_a, I_b)}$	<u>1.1147</u>	<u>4.5920</u>	<u>11.8695</u>
$\underline{DR(I_a, I_b)}$	<u>0.1498</u>	<u>1.0113</u>	<u>1.1600</u>

The **purpose and meaning** of the numerical values are clarified in Supplement 5:

Supplement 5. Theoretical supplement for hyperspectral digital camouflage

In hyperspectral field, the absolute value differences are described using spectral distance[Ref. R3.10-R3.11] (*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[Refs. R3.12-R3.13] (*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 divergence[Ref. R3.14] (*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 rate[Ref. R3.15], which is not specific to spectroscopy, is also used to evaluate the spectra:

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

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 difference[Ref. R3.16], 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

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

The pattern of digital camouflage within a band is composed of primary colors specific to that band (Table S1). 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 similarity[Ref. R3.17]. 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.

Table. S1 | Multiband level-pixel coupling table.

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

[R3.10] Jovanović, I. *et al.* Spectral distances of graphs. *Linear Algebra and its Applications* **436**, 1425-1435 (2012).

[R3.11] Konukoglu, E. *et al.* WESD--Weighted Spectral Distance for measuring shape dissimilarity. *IEEE transactions on pattern analysis and machine intelligence* **35**, 2284-2297 (2013).

[R3.12] Chakravarty, S. *et al.* Hyperspectral Image Classification using Spectral Angle Mapper. *2021 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON-ECE)*, 87-90 (2021).

- [R3.13] Park, B. *et al.* Contaminant Classification of Poultry Hyperspectral Imagery using a Spectral Angle Mapper Algorithm. *Biosystems Engineering* **96**, 323-333 (2007).
- [R3.14] Chang, C.-I. Spectral information divergence for hyperspectral image analysis. *IEEE 1999 International Geoscience and Remote Sensing Symposium. IGARSS'99 (Cat. No. 99CH36293)* **1**, 509-511 (1999).
- [R3.15] Dinwoodie, I. H. Identifying a large deviation rate function. *The Annals of Probability* **21**, 216-231 (1993).
- [R3.16] Xu, C. *et al.* The relationship between spatial color mixing with color and radiation similarity in digital camouflage study. *Infrared Physics & Technology* **130**, 104593 (2023).
- [R3.17] Wang, Z. *et al.* Image quality assessment: from error visibility to structural similarity. *IEEE transactions on image processing* **13**, 600-612 (2004).

3. (i) The manuscript frequently refers to “spatial” texture and “spatial” resolution, but these terms are not clearly explained. (ii) The authors should clarify what is meant by “spatial” and what specific efforts were made to mimic “spatial” texture and improve “spatial” resolution.

Response:

We thank the reviewer for the comments and suggestions.

(i) **“Spatial” texture** refers to the texture information features of an image. For example, Fig. R3.1b shows the spatial texture figure extracted from Fig. R3.1a using the gray-level co-occurrence matrix (GLCM) method.

“Spatial” resolution can be understood as the resolution of the camera. For instance, Fig. R1a is high resolution, while Fig. R3.1c is low resolution.

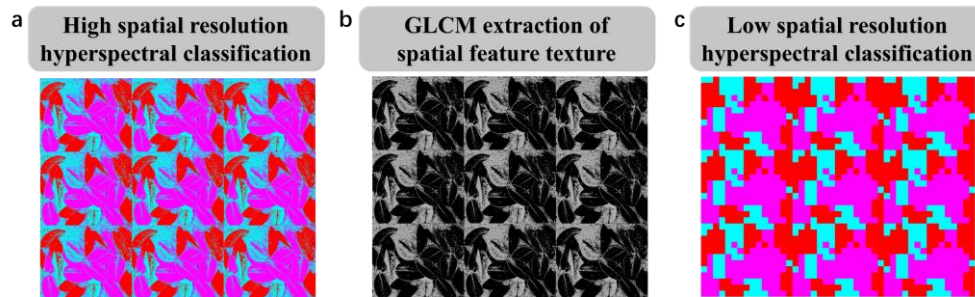


Fig. R3.1 | Spatial texture of images. a. The high spatial resolution hyperspectral classification image. b. The spatial texture. c. The low spatial resolution image.

We have revised the manuscript accordingly:

(Page 3, lines 50-54)

First, ever-improving imaging technologies with greater spatial resolution (e.g., a camera with higher clarity, from 720P to 1440P) can detect the texture and shape of targets, necessitating digital camouflage technology to simulate natural patterns (e.g., the shape of the edges and contours of grass or prominent local features of leaves in the background).

(ii) “Spatial” refers to a spatial domain formed by imaging.

We have added an algorithm for designing camouflage patterns that **mimic “spatial texture”** and explained how it counteracts high-spatial-resolution cameras:

(Page 6, lines 111-115)

The optical hyperspectral digital camouflage pattern, composed of primary color pixels, replicates to the texture of vegetation in the hyperspectral image within the optical band (Fig. 1a). Therefore, optical hyperspectral camouflage pattern (spanning VIS, NIR, and SWIR bands in Fig. 1b) can be designed by integrating hyperspectral classification, background texture detection, pixelation, and patch templates (see Supplement 6).

Supplement 6. Digital camouflage pattern design method

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 Fig. S4:

(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 pattern.

(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) (Table S2). In Fig. S4, 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 Table S2, 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.

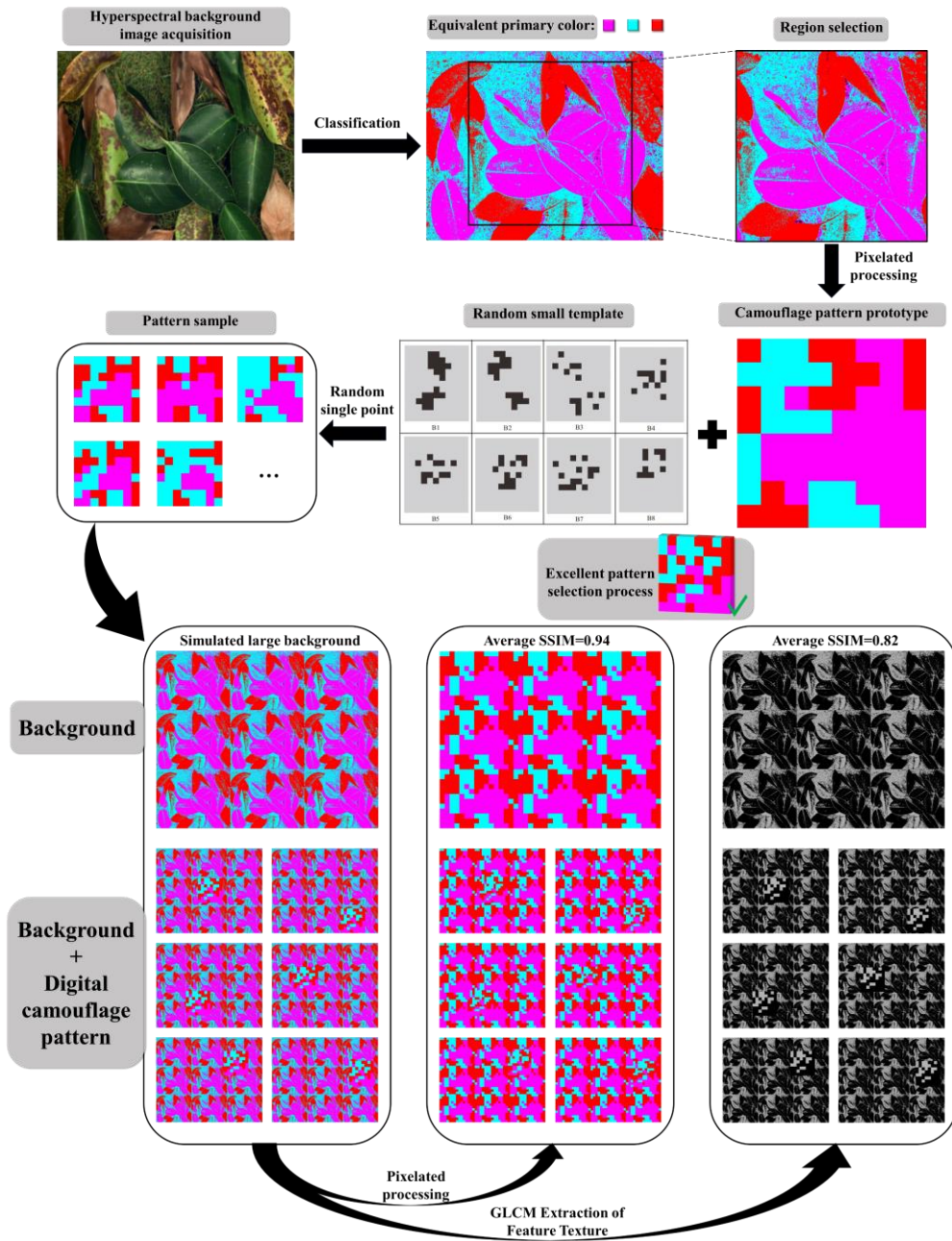


Fig. S4 | Digital camouflage pattern design process.

Table. S2 | Time taken to find targets in simulated scenes.

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

Improving “spatial resolution” is related to the detector and the imaging work field, and it is not within the scope of this work’s discussion on “camouflage”.

4. Figure 2d shows the electric field distribution and resistive loss within the multilayers at the target wavelengths. The authors should provide a more detailed discussion of these results, including the physics behind them.

Response:

We thank the reviewer for the comments and suggestions.

We have provided a more detailed discussion of **electric field distribution and resistive loss within the multilayers**, and revised the manuscript accordingly:

(Page 8, lines 151-158)

For GS/LGS, they have similar structures and exhibit comparable spectral performance (a detailed physical analysis is shown in Supplement 11): (i) The green peak is precisely aligned at $0.55\ \mu\text{m}$, formed by the F-P resonance and antireflection effects of the four-layer ZnS/Ge/ZnS/Ti structure. (ii) The red edge and NIR plateau ($\sim 1.1\ \mu\text{m}$) meet military specifications, which is formed by the high reflectance of Ti layer. (iii) The four water absorption bands in the NIR/SWIR exhibit increasing absorption from shortwave to longwave, resulting from all layers' resonance.

Supplement 11. Simulations of optical hyperspectra and thermal IR-terahertz bands

Using GS as an example (similar for LGS, LYS, RS, and BGS), its electric field (Fig. S10a) and loss (Fig. S10b) 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 $550\ \text{nm}$, and the first-order resonance occurs after $550\ \text{nm}$, resulting in the relative high reflection green peak at $550\ \text{nm}$. (ii) At longer wavelengths, the F-P mode is no longer dominant. As the loss of Ge decreases (Fig. S10c), 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 $1300\ \text{nm}$, 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.

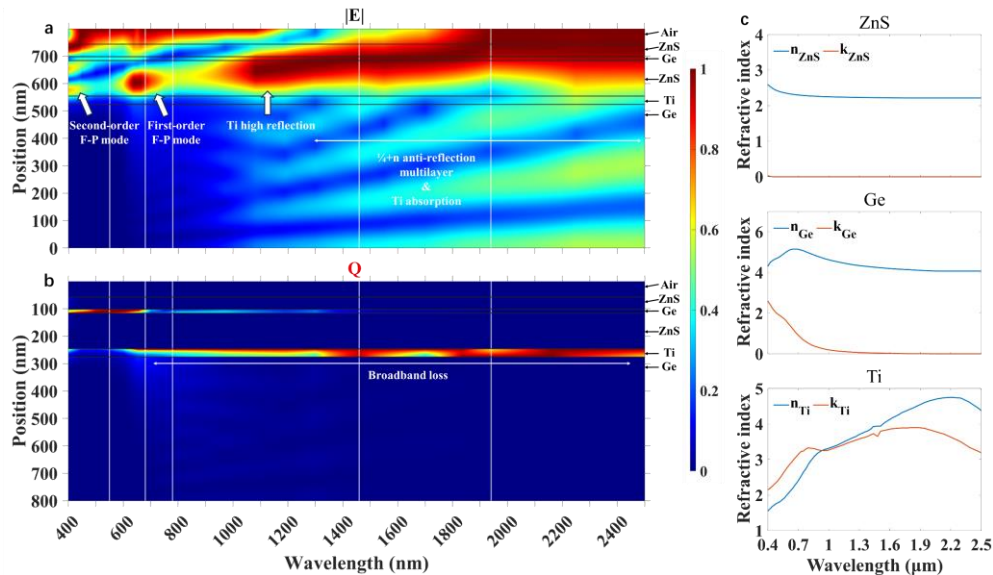


Fig. S10 | GS optical hyperspectral simulated a. electric field distribution ($|E|$) and b. resistive loss (Q). c. Material refractive index.

5. The authors should explain the selection rules of ZnS, Ge, and Ti in the designed multilayers. Additionally, the manuscript can benefit from a thorough description of the machine learning model, including how it was trained and validated.

Response:

We thank the reviewer for the comments and suggestions.

As shown in Fig. R3.2, our design algorithm first establishes an initial sample in the material library, then trains the Hamiltonian function using the FM method. Afterward, simulated annealing iterations are continuously performed. The optimal two-dimensional vector obtained reveals **the best distribution and approximate thickness of ZnS, Ge, and Ti**. Finally, the thickness is finely optimized using the Nelder-Mead algorithm, resulting in an excellent structure.

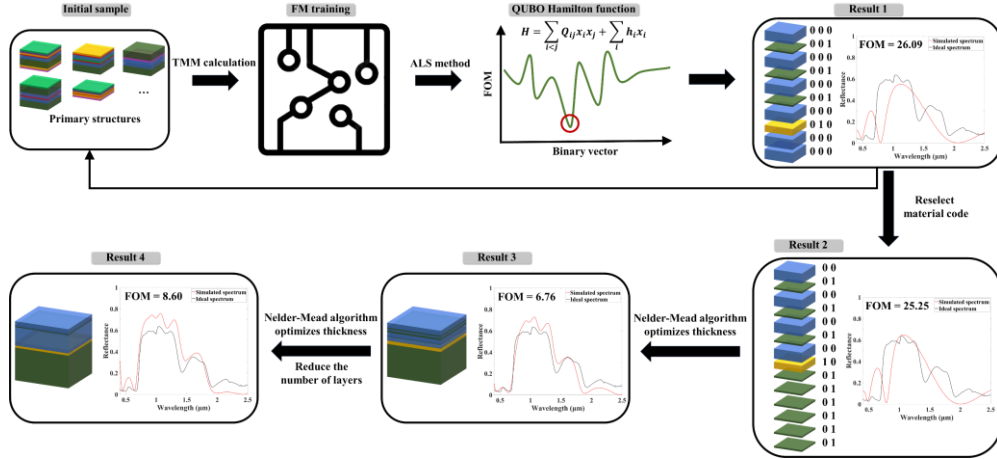


Fig. R3.2 | Multilayer structure design method

Its detailed training process is described in Supplement 8, but we have not conducted a detailed performance validation:

Supplement 8. Multilayer structure design method

The multilayer structures are designed using the QUBO model and employing the factorization machine (FM) model. As shown in Fig. S7, 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 Table S3, 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 Table S4, 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.

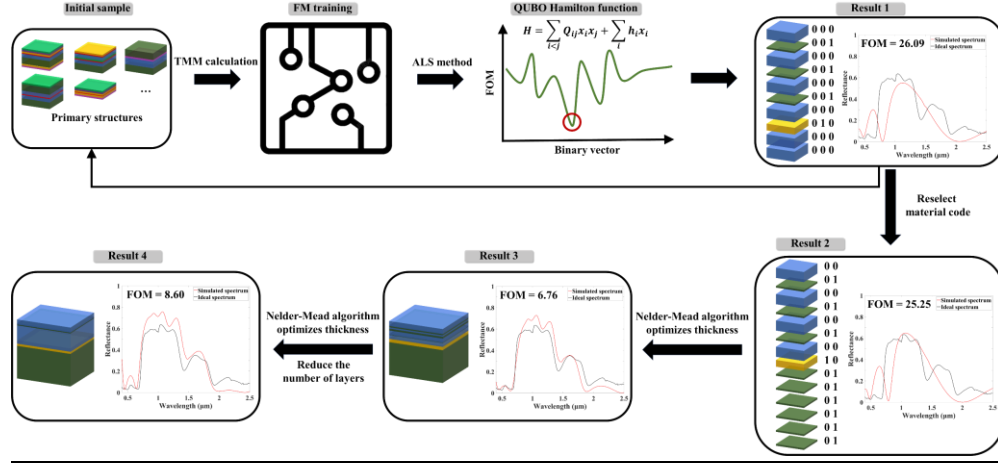


Fig. S7 | Multilayer structure design method

Table. S3 | Material code 1

<u>Material</u>	<u>Binary code</u>	<u>Thickness (nm)</u>
<u>ZnS</u>	<u>0 0 0</u>	<u>50</u>
<u>Ge</u>	<u>0 0 1</u>	<u>5</u>
<u>Ti</u>	<u>0 1 0</u>	<u>30</u>
<u>Au</u>	<u>0 1 1</u>	<u>5</u>
<u>Ag</u>	<u>1 0 0</u>	<u>10</u>
<u>SiO₂</u>	<u>1 0 1</u>	<u>50</u>
<u>MgF₂</u>	<u>1 1 0</u>	<u>50</u>
<u>None</u>	<u>1 1 1</u>	<u>0</u>

Table. S4 | Material code 2

<u>Material</u>	<u>Binary code</u>	<u>Thickness (nm)</u>
-----------------	--------------------	-----------------------

<u>ZnS</u>	<u>0 0</u>	<u>50</u>
<u>Ge</u>	<u>0 1</u>	<u>5</u>
<u>Ti</u>	<u>1 0</u>	<u>30</u>
<u>None</u>	<u>1 1</u>	<u>0</u>

6. (i) *What specific spectra of natural vegetation were used as targets for the multilayer design?* (ii) *The target spectra should be shown in the spectra in Figures 2e, 2f, 2g, and 2h, which help readers recognize how closely the multilayers replicate the desired natural creatures.*

Response:

We thank the reviewer for the questions and suggestions.

(i) In this manuscript, we used the spectra of **fresh green, fresh light-green, and withered yellow leaves (*Cinnamomum camphora*)** as the basic ROIs, which serve as the targets for the multilayer design. The target spectra are shown in Supplement 7:

Supplement 7. Reference spectra

In the optical band (Fig. S5a), the three types of ROIs—fresh green vegetation (G), fresh light-green vegetation (LG), and withered yellow vegetation (Y)—exhibit distinct characteristic responses in the green peak, red edge, NIR plateau, and water absorption bands. In the thermal IR band (Fig. S5b), the emissivity of Y in the MWIR is about 0.85, differing from that of G and LG, 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 (Fig. S5d). Combined with the reflection spectra in Fig. S5c, the actual environmental reflection spectra become more complex, resulting in a 4-level pattern in the THz band.

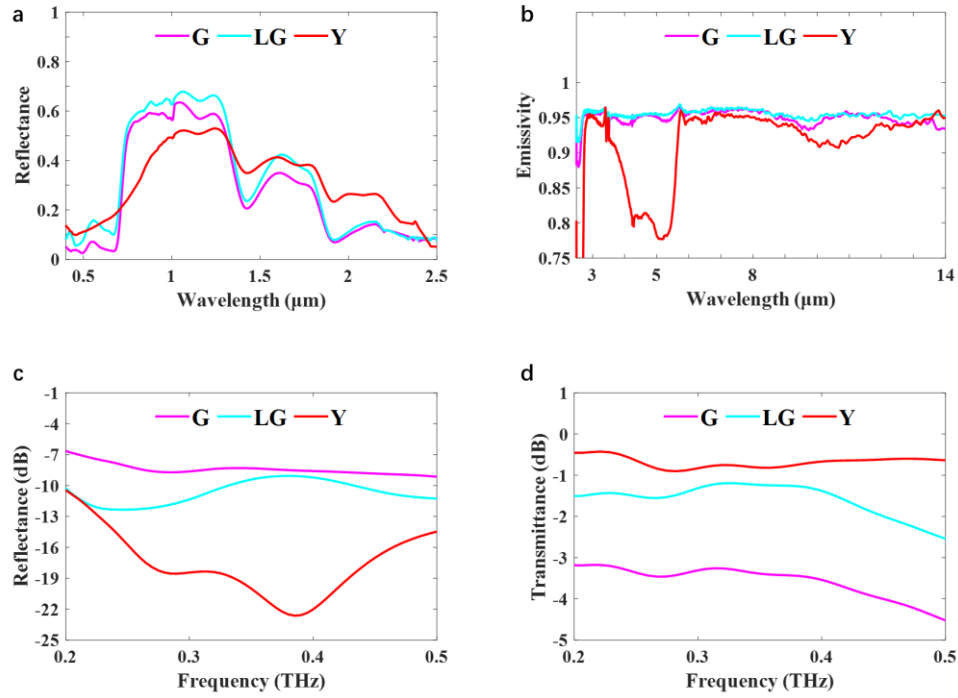
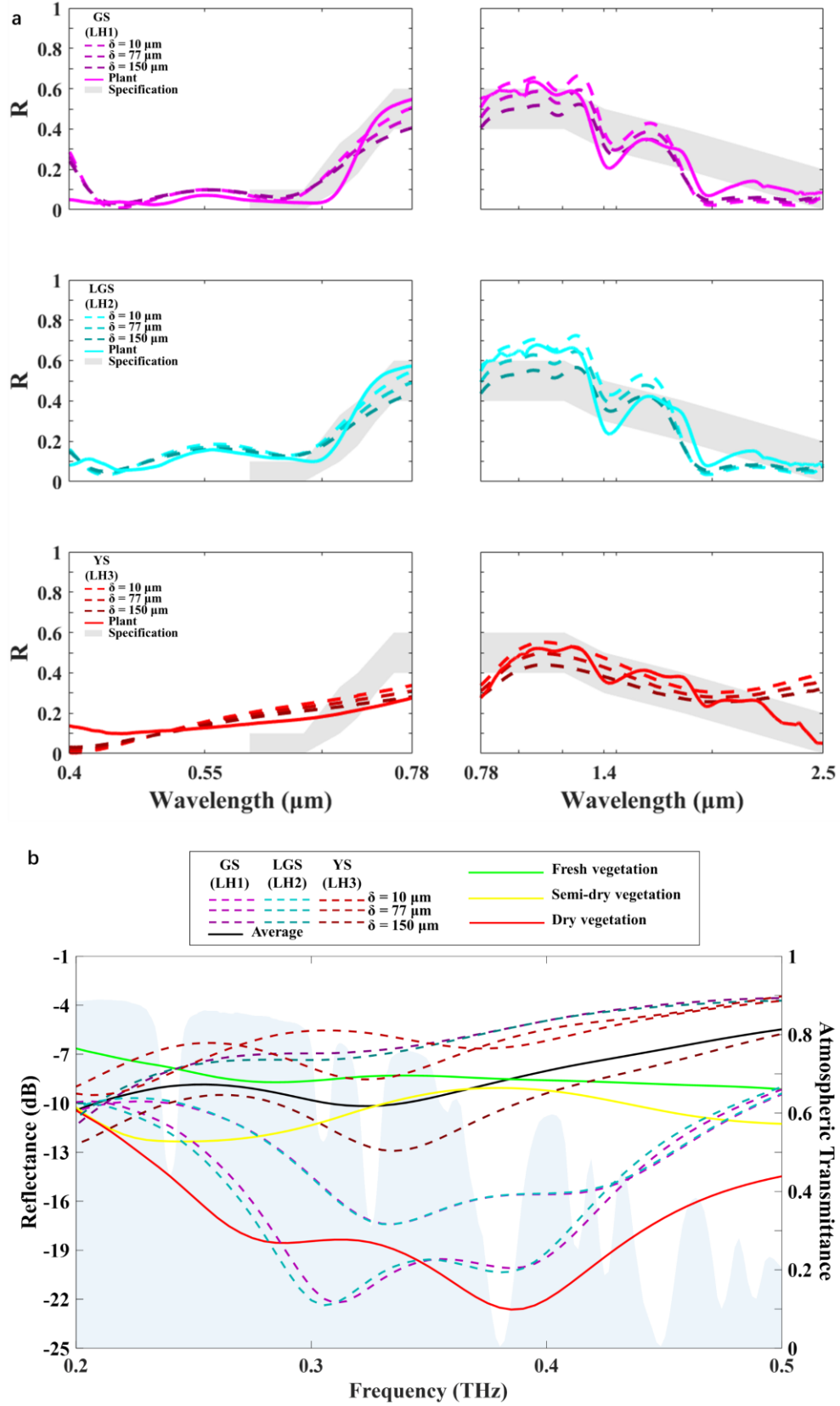


Fig. S5 | Reference spectra of vegetations. a. Optical reflectance. **b.** Thermal infrared emissivity. **c.** Terahertz reflectance and **d.** Terahertz transmittance.

(ii) We move the **target spectra** to Supplement 7, instead of showing them in Figures 2e, 2f, 2g, and 2h.

In the optical band, our device performs hyperspectral camouflage, so spectral comparison is required. For the thermal infrared-terahertz-microwave tri-bands, our device performs intensity camouflage. Intensity integration is used, so spectral comparison is not necessary (the relevant spectra are still provided in Supplement 7).

Supplement 7. Reference spectra



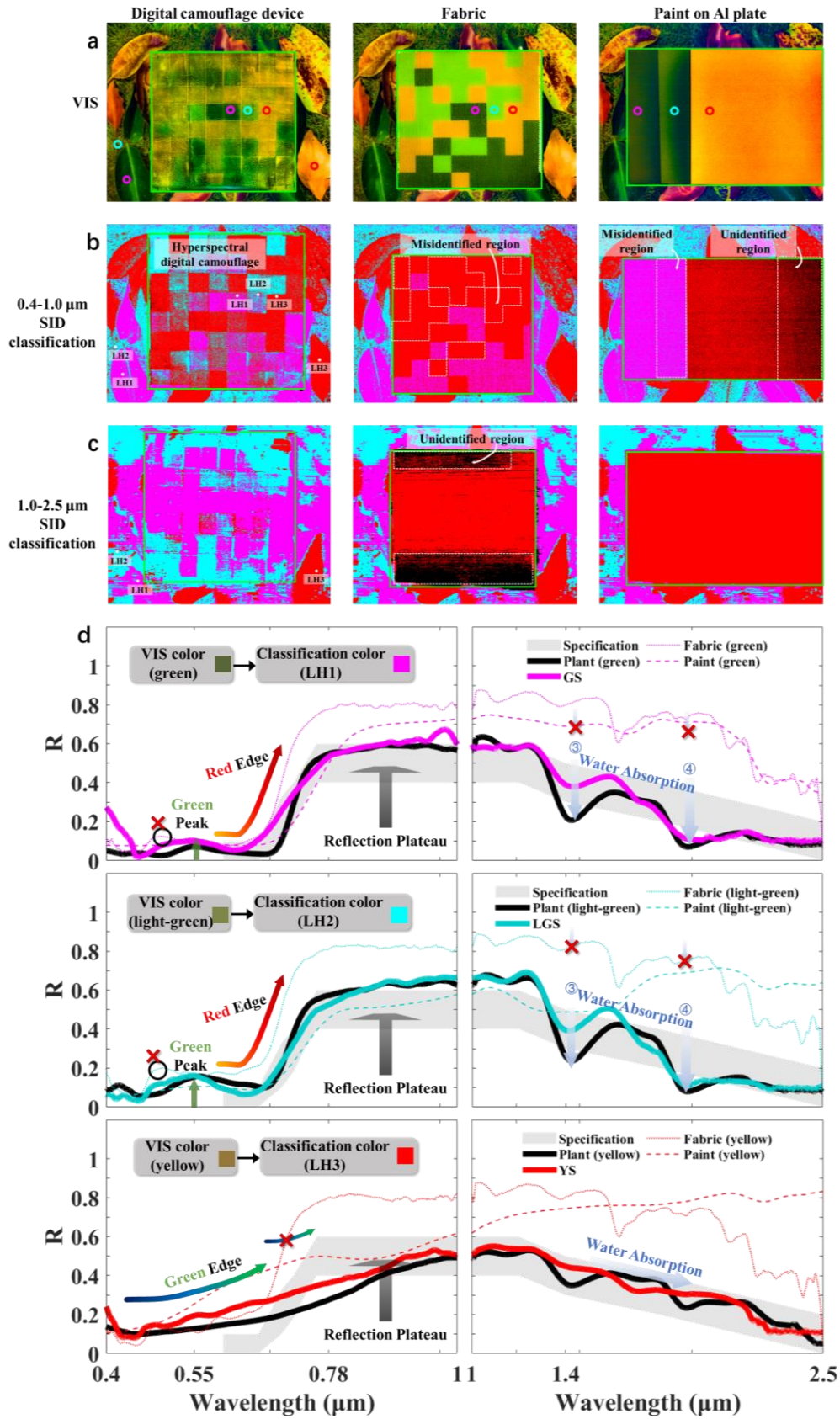


Fig. 4 | Hyperspectral digital camouflage. **a.** A simulated jungle scenario created in an experimental black box, displaying VIS images of the device, fabric reference, and paint reference. **b.** SID classification images in the 0.4-1.0 μm range, reflecting basic spectral features in the VIS/NIR spectrum. **c.** SID classification images in the 1.0-2.5 μm range, highlighting

water features. **d.** Spectral diagrams illustrating three types of vegetation (I_a) and various camouflage samples (the device and references, I_b).

7. For the MWIR and THz bands, the authors fabricated four samples instead of three. Please clarify the rationale for introducing an additional sample for these bands.

Response:

We thank the reviewer for the comment.

Digital camouflage requires at least three distinct levels of samples, while a four- or five-level effect provides even better adaptability [Ref. R3.18]. Therefore, we set up basic 3-level samples (fresh green vegetation (G), fresh light-green vegetation (LG), and withered yellow vegetation (Y)) in the optical, LWIR, and MW bands.

In contrast, in the MWIR band, withered vegetation exhibits relatively low emissivity (~ 0.85 , Fig. R3.3a), creating a more complex background (**4-level** MWIR radiance in Fig. R3.3b) than in the LWIR band (**3-level** LWIR radiance in Fig. R3.3c). Thus, we introduced an additional sample in MWIR to enhance its adaptability to more complex backgrounds.

In the THz band, the total leaf reflectance exhibits a highly complex multi-level response, forming a complex background. As a reference, the total spectra after a single transmission through leaves (Fig. R3.4, one leaf on top of another) clearly separate into **4-levels**. Thus, we have introduced an additional sample in the THz band as well.

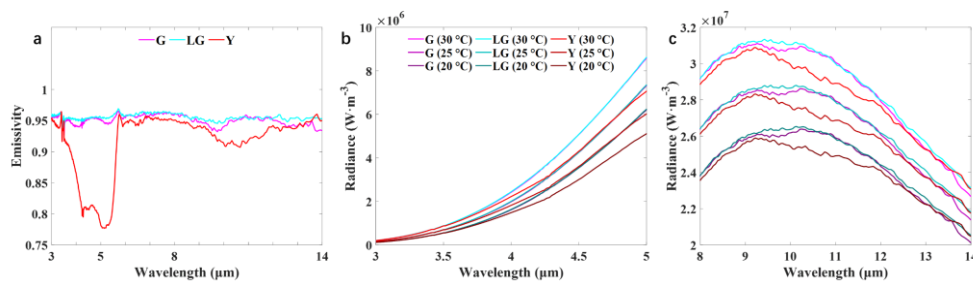


Fig. R3.3 | Thermal infrared spectra of vegetation **a.** Referenced vegetation emissivity spectra. **b.** MWIR and **c.** LWIR radiance at ambient temperature (20-30 °C).

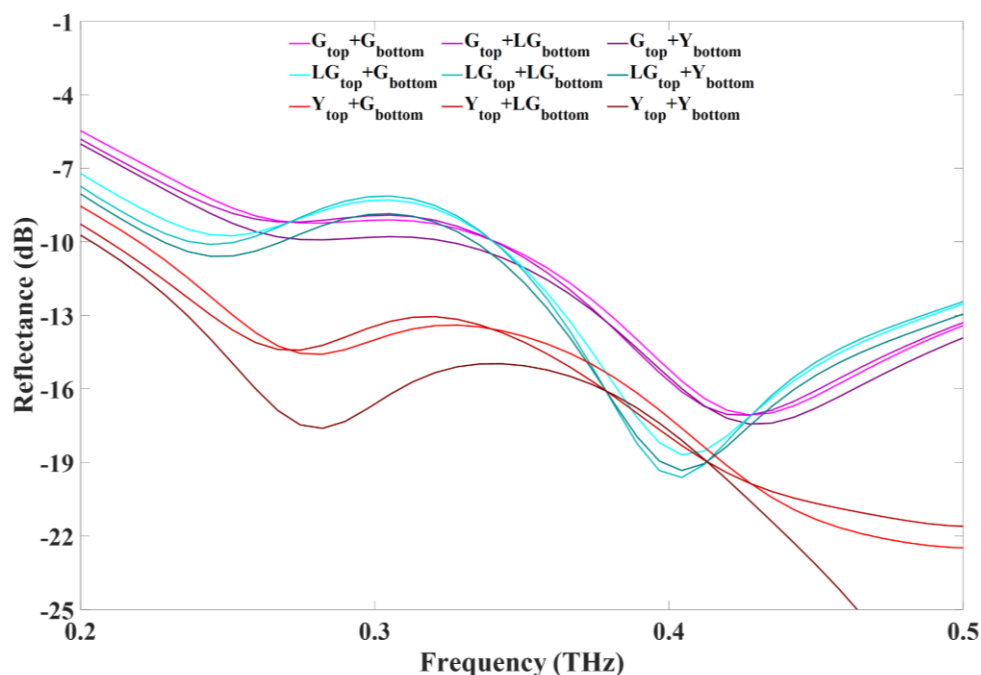


Fig. R3.4 | The THz total reflection spectra after a single transmission through leaves.

We have revised the manuscript accordingly:

(Page 11, lines 225-226)

The MWIR pattern presents an additional level due to the emissivity difference of withered vegetation (see Supplement 7).

(Page 12, lines 234-235)

The THz pattern presents an additional level due to the transmission of vegetation spectra (see Supplement 7).

Supplement 7. Reference spectra

In the optical band (Fig. S5a), the three types of ROIs—fresh green vegetation (G), fresh light-green vegetation (LG), and withered yellow vegetation (Y)—exhibit distinct characteristic responses in the green peak, red edge, NIR plateau, and water absorption bands. In the thermal IR band (Fig. S5b), the emissivity of Y in the MWIR is about 0.85, differing from that of G and LG, 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 (Fig. S5d). Combined with the reflection spectra in Fig. S5c, the actual environmental reflection spectra become more complex, resulting in a 4-level pattern in the THz band.

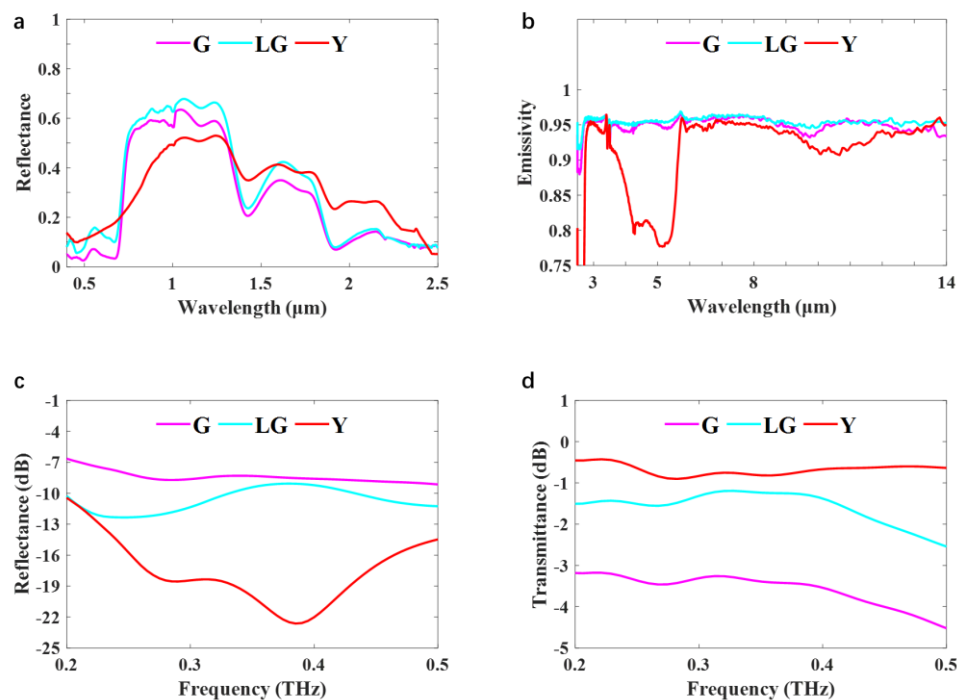


Fig. S5 | Reference spectra of vegetations. a. Optical reflectance. b. Thermal infrared emissivity. c. Terahertz reflectance and d. transmittance.

[R3.18] Xue, F. *et al.* Design of digital camouflage by recursive overlapping of pattern templates. *Neurocomputing* **172**, 262-270 (2016).

8. In Figure 3a, the multilayer devices appear partly transparent in the visible range. Please provide their transmittance spectra. It would be helpful to discuss the visual appearance of the devices, particularly how the combination of transmission and reflection colors seems to the naked eye.

Response:

We thank the reviewer for the comments and suggestions.

The multilayer device (Fig. R3.5b) is completely opaque in the visible range. For the sub-pixel (Fig. R3.5a), the Ge/Ti-containing multilayer structure (Fig. R3.5c) blocks all visible transmission. In the interspacing of the sub-pixel, the PI and MW absorbing material prevent any transmission.

Additionally, we have considered the combination of PI reflectance and the multilayer structure (Fig. R3.6). The PI reflectance is low (~ 0.1 , Fig. R3.7), and its proportion in our sub-pixels is minimal (1.99%, 14.81%, and 27.75%), having almost no effect on the overall color (the dashed lines in Fig. R3.6 are nearly identical).

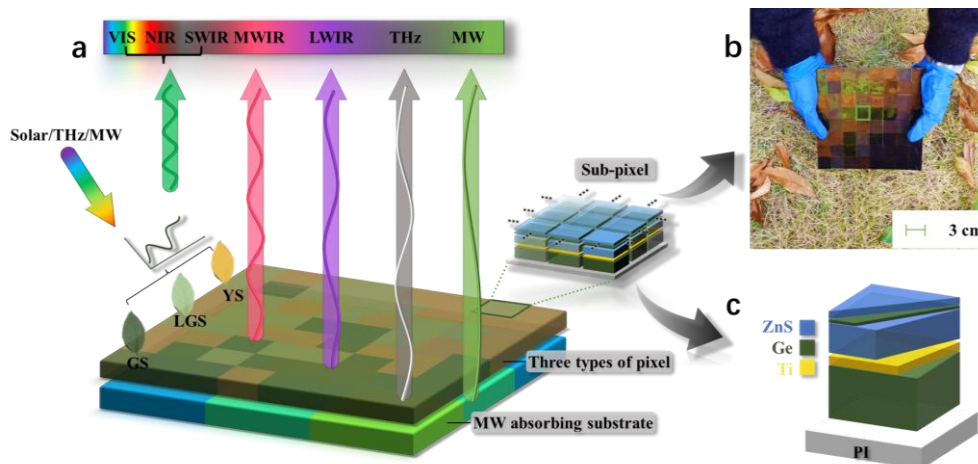


Fig. R3.5 | The pixel structures. **a.** Illustration of the various components and basic functions of the device. **b.** VIS image of the device captured using an ordinary camera. **c.** Multilayer structure.

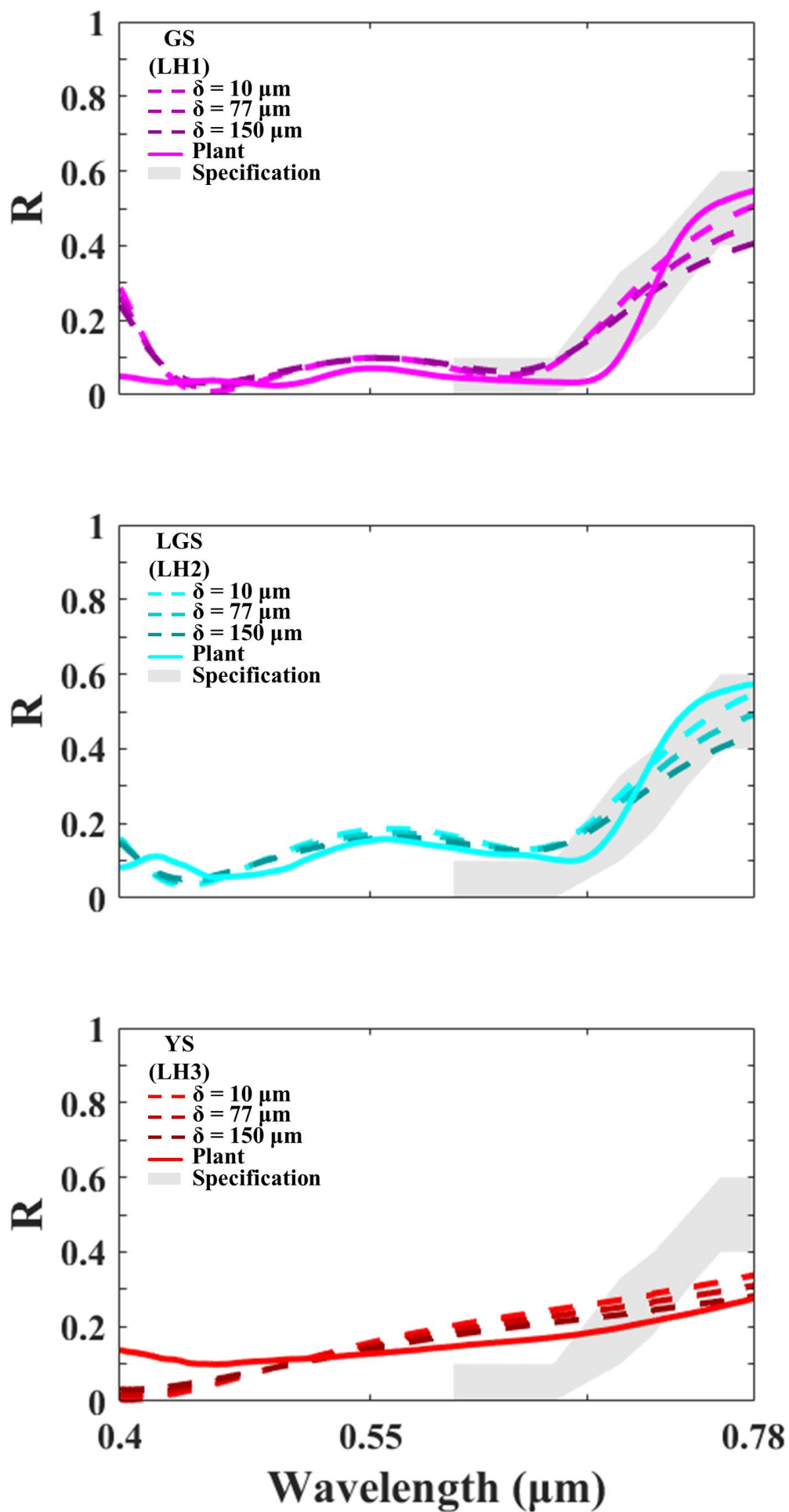


Fig. R3.6 | The spectra of pixel structures.

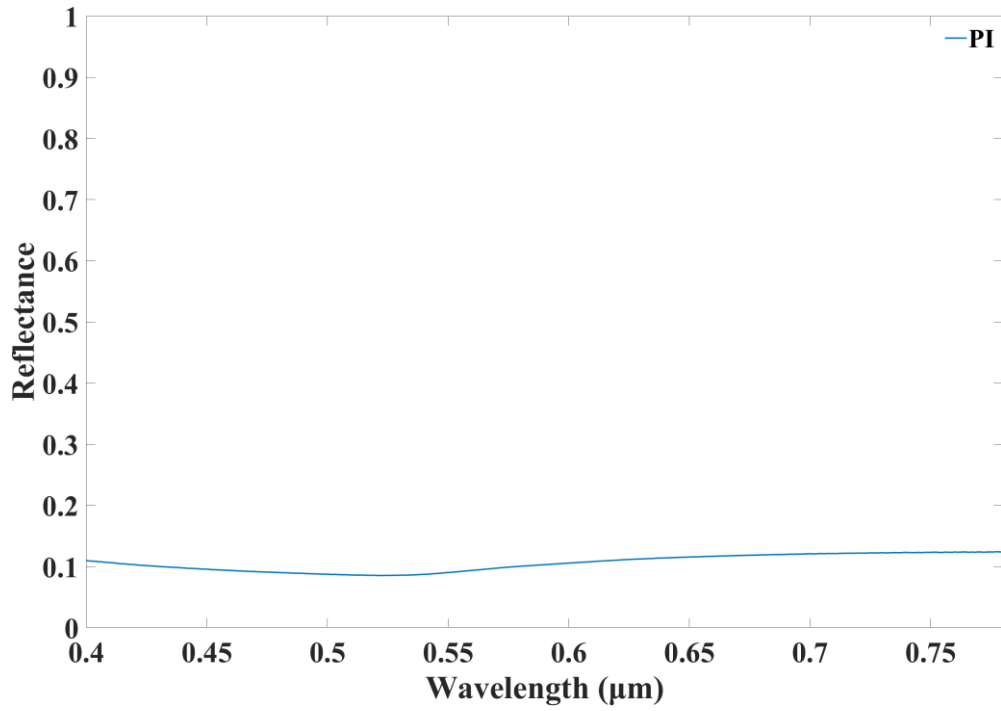


Fig. R3.7 | The reflectance spectrum of PI.

9. In Figure 4c, while the multilayer devices successfully conceal the underlying metallic object, none of the pixels seem to match the background. The authors should point out this discrepancy and discuss potential improvements.

Response:

We thank the reviewer for the comments and suggestions.

At short imaging distance (Fig. R3.8a), the THz digital camouflage pattern is clearly distinguishable. This is because the imaging distance is smaller than the maximum object distance (detailed calculations in Supplement 3[Refs. R1-2]), so the pattern's texture remains sharp and spatial color mixing has not yet occurred.

In THz band, to make a potential improvement, we provide simulated images at the maximum object distance (Fig. R3.8b). Comparing Fig. R3.8a, at the maximum object distance, the camouflage effect of the pattern is enhanced due to the spatial color mixing effect, blending with the background.

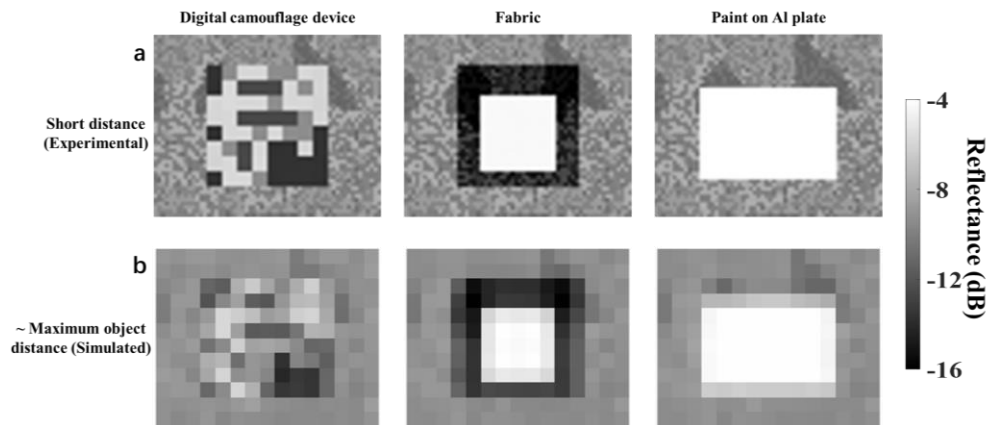


Fig. R3.8 | Comparison of THz images at different distances: **a.** Experimental THz images at a short distance. **b.** Simulated THz images at the maximum object distance.

We have revised the manuscript accordingly:

(Page 12, lines 239-247)

Additionally, it should be noted that in Fig. 5a and Fig. 5c, camouflage patterns do not blend well with the background. As mentioned earlier, passive camouflage cannot perfectly adapt to all background environments (factors such as temperature and moisture can affect the background's reflectance or emissivity response). The patterns still maintain camouflage effectiveness, although they require greater distance than perfect pattern, to escape detection by the sensor (see Supplement 3 for maximum object distance calculation, Supplement 4 for lock-on range calculation). Furthermore, there are potential improvements, such as decoupling and independently designing patterns for the thermal IR and THz bands (see Supplement 10 and 11), which would allow them to perfectly align with the background.

Supplement 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[Ref. R3.19]. 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 by[Ref. R3.20]:

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

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.

[R3.19] Zhou, Z. *et al.* A comprehensive multimodal eye recognition. *Signal, Image and Video Processing* **7**, 619-631 (2013).

[R3.20] Xu, C. *et al.* The relationship between spatial color mixing with color and radiation similarity in digital camouflage study. *Infrared Physics & Technology* **130**, 104593 (2023).

10. The manuscript should explain in detail how intensity modulation in the thermal infrared and terahertz bands is achieved by adjusting the interspacing of the pixels.

Response:

We thank the reviewer for the suggestion.

We simulate the sub-pixels (Fig. R3.9) in GS, LGS, and YS and compare the results with the experimental data (Fig. R3.10).

For thermal IR band, the larger the sub-pixel interspacing (δ in Fig. R3.9b), the higher the thermal infrared emissivity. For THz band, the reflectance is jointly controlled by the sub-pixel interspacing, the metal thickness in GS/LGS/YS.

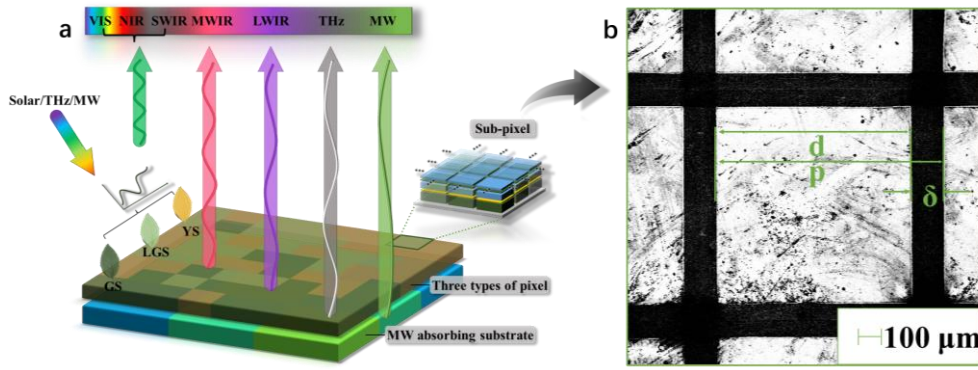


Fig. R3.9 | The pixel structures. **a.** Illustration of the various components and basic functions of the device. **b.** Partial SEM overhead view of the device showing the effects of laser etching.

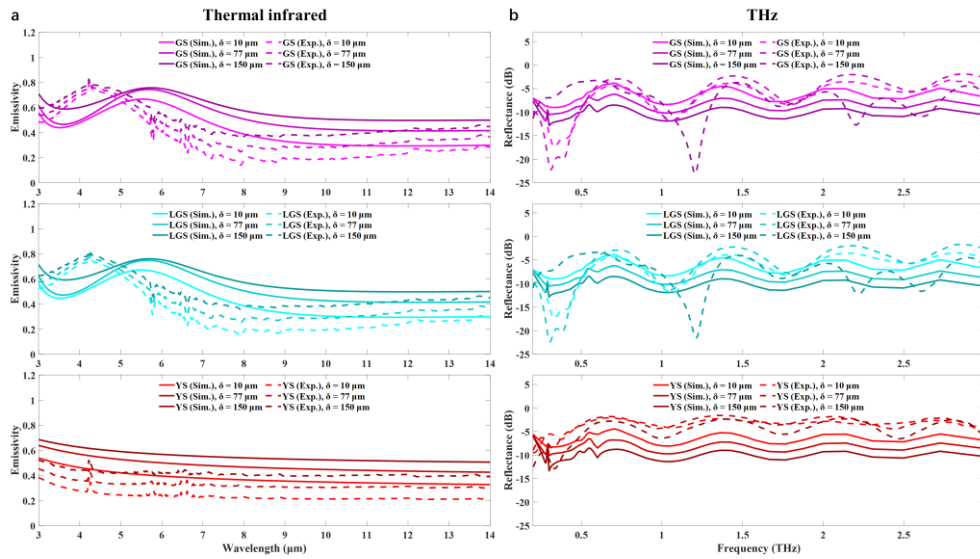


Fig. R3.10 | Comparison between simulation and experimental results for a. the thermal IR band and b. the THz band.

We have revised the manuscript accordingly:

Supplement 11. Simulations of thermal infrared and terahertz bands

We simulate the sub-pixels in GS, LGS, and YS and compare the results with the experimental data (Fig. S11). As shown in Fig. S11a, 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 (Fig. S11b), 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.

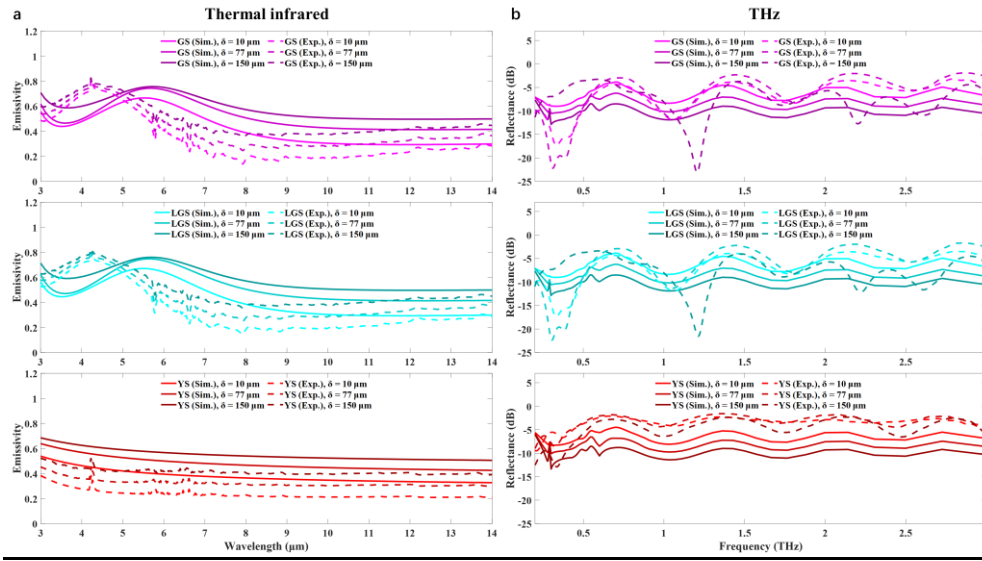


Fig. S11 | Comparison between simulation and experimental results for a. the thermal IR band and b. the THz band.

The Reviewer #2's comments

Reviewer's general remarks:

Rongxuan Zhu et al. made suitable corrections to their manuscript "Digital camouflage encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands". However, not all questions and comments were fully addressed in the response letter. Additionally, we have identified new points of confusion in the revised manuscript that should be clarified by the authors before the manuscript can be considered for publication. So, our recommendation is minor revision required.

Response:

We appreciate the reviewer's positive evaluation of our corrections. We are grateful for the reviewer's helpful comments and suggestions. In response, we have revised the manuscript accordingly. Below is a point-by-point response.

Major comments:

1. Deviation rate. Starting from the abstract, authors claim that with a proposed design they achieve deviation rates which vary from 0.1343 to 0.1825. Why are these values considered acceptable? Additional discussion (examples) will be helpful.

Response:

We thank the reviewer for the valuable comment.

Crucially, the effectiveness of hyperspectral camouflage is determined by whether the spectral signature of the device falls within the natural variation observed in the target background environment (e.g., vegetation). While a universally defined threshold for an "acceptable" deviation rate does not exist in the literature, we demonstrate the acceptability of our values by comparing them to the inherent spectral variability found within natural vegetation itself.

Specifically, we measured the spectral deviation between different points on a single, natural leaf (Fig. R1) under identical conditions. This measurement revealed deviation rates reaching up to 0.1954. This value is higher than the deviation rate (0.1343-0.1825) achieved by our digital camouflage device relative to the target vegetation spectra.

Therefore, the deviation rates of our camouflage device (0.1343–0.1825) are smaller than the natural spectral variations observed within a single leaf. This strongly suggests that the device's spectral signature blends effectively within the range of variability naturally present in the vegetation background it aims to mimic.

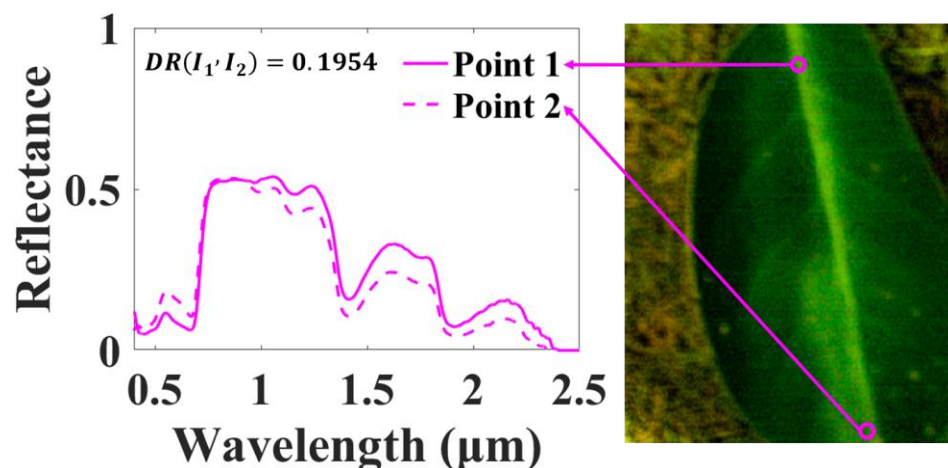


Fig. R1 | Spectral comparison between two points on the same leaf.

We have revised the manuscript accordingly:

(Page 2, lines 26)

with deviation rate less than 0.2 (can be regarded as the same type of plant)

(Page 11, lines 221-223)

the deviation rate between the digital camouflage device and the background vegetation is less than 0.2 (can be regarded as the same type of plant, see detailed discussion in Supplement 5)

We have also added discussion in Supplement 5:

Supplement 5. Theoretical supplement for hyperspectral digital camouflage

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, Fig. S3).

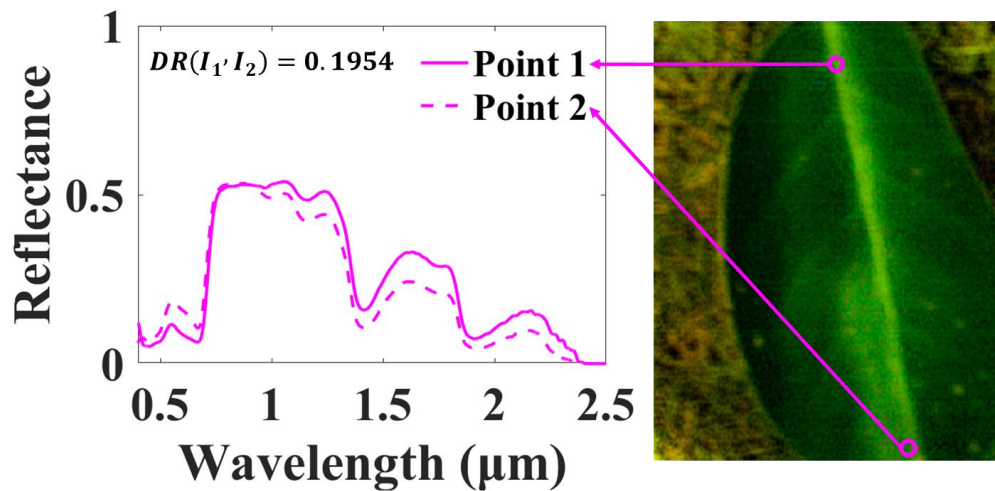


Fig. S3 | Spectral comparison between two points on the same leaf.

2. *Optimization. In the “Strategy of the digital camouflage” authors mention that camouflage patters are “not fully optimized”. In the “Discussion”, that performance can be improved “by pattern design or structure optimization”. These points are unclear, since the manuscript contains both pattern design method (Suppl 6) and structure design method (Suppl 8). It is clear that optimization is very challenging. In the “Discussion” and “Strategy of the digital camouflage”, more examples of possible improvement strategies and limitations of the current optimization methods are required for clarification.*

Response:

We thank the reviewer for the detailed and helpful suggestion.

The limitations of the current optimization method arise from the complexity of the background environment (Fig. R2). In such complex environments across multiple spectral bands (optical-thermal infrared-terahertz-microwave), fully independent multispectral pattern design results in numerous possible combinations of target spectra (Table. R1, where the total number equals the product of the number of levels in each band). This multiplicative effect across multiple bands (a total of 432 spectral combinations are listed in Table. R1) creates prohibitive demands on structure design complexity.

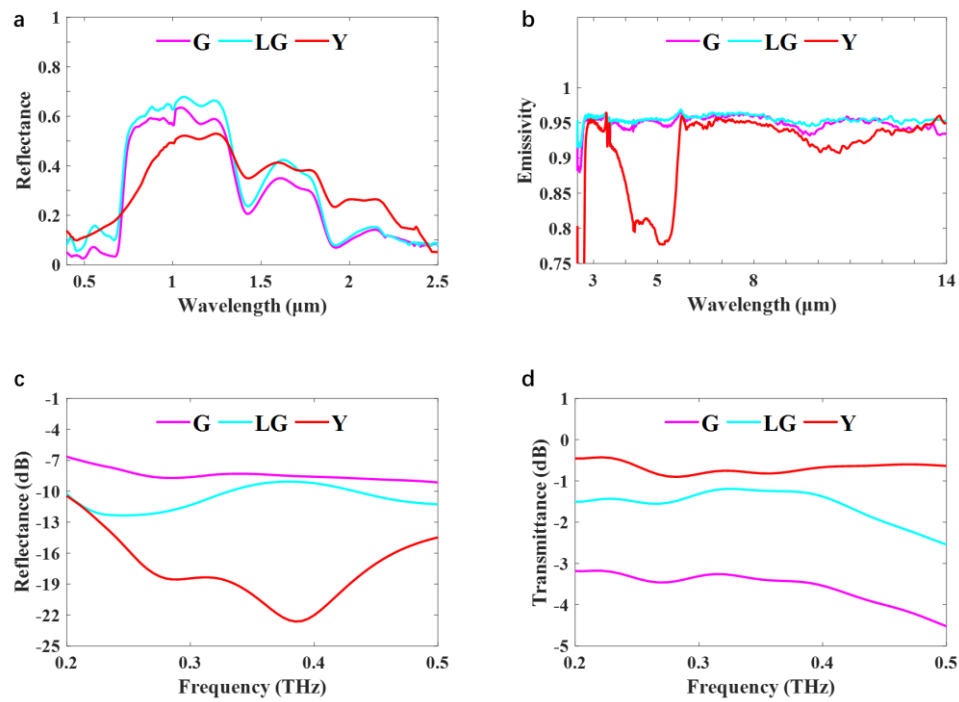


Fig. R2 | Reference spectra of vegetations. a. Optical reflectance. **b.** Thermal infrared emissivity. **c.** Terahertz reflectance and **d.** transmittance.

Table. R1 | Complex levels in real environments.

	Signal source	Number of levels in real vegetational background	The number of levels extracted in this paper
Optical hyperspectra	Reflection	Multiple	3

Thermal infrared	Temperature and emission		4-level for MWIR, 3-level for LWIR
Terahertz	Multiple reflections		4
Microwave	Reflection		3

Possible improvement strategies: As previously discussed in the limitations of the current optimization method, fully independent multispectral pattern design can make structural design extremely challenging. However, it is possible to reduce the coupling among different spectral bands as much as possible, thereby increasing the design flexibility for multispectral patterns.

We demonstrate two decoupling examples targeting specific spectral bands:

1. Thermal Infrared (IR) Band: The energy signals received by the thermal IR camera depend on the surface emissivity and temperature of the target. In Fig. R3a, 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 Fig. R3b and R3c, 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.

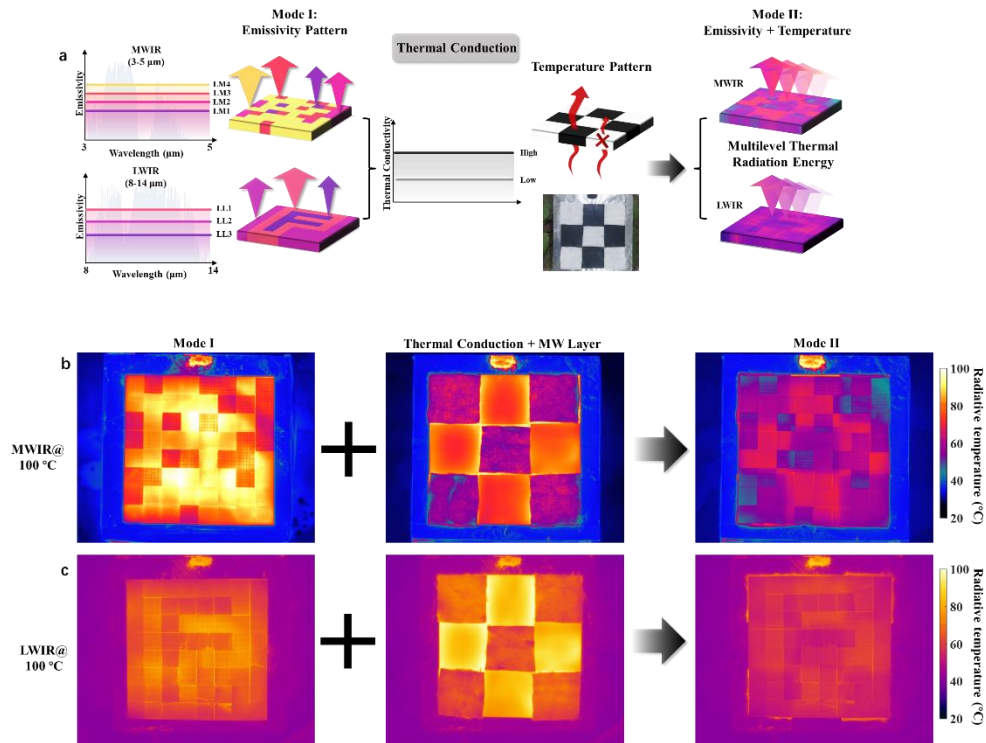


Fig. R3 | Thermal IR dual-mode of the device. a. The principle of the thermal IR dual-mode. **b.** MWIR demonstration. **c.** LWIR demonstration.

2. Microwave (MW) Band: Coupling in the MW band can be minimized by strategically employing different types of microwave-absorbing materials.

We have also added clarification accordingly:

Strategy of the digital camouflage

(Page 6-7, lines 122-128)

(limitations of the current pattern optimization methods) Due to the greater variability of signals in these bands (see Supplement 7 for reference vegetational spectra and complex levels in real environment), obtaining accurate and effective background textures is challenging.
(possible improvement strategies) To further improve and achieve optimal camouflage performance, the digital camouflage patterns should be independently designed according to the distinct signals in each band. This requires that the patterns for each band remain independent and decoupled from one another. For example, in Fig. 1c, the LWIR band pattern is designed in the shape of the letter “F” to preliminarily demonstrate the decoupling performance of the device.

Discussion

(Page 14, lines 274-283)

(possible improvement strategies) Thirdly, the coupling among the device's multispectral patterns can be eliminated, allowing each band's pattern to be designed more independently. In this work, a strategy is employed to further decouple the digital camouflage: in the thermal IR band, the radiation energy patterns are formed by controlling the average emissivity through sub-pixels with different duty cycles, which is equivalent to the emissivity pattern. Another temperature pattern can be generated by incorporating an insulating layer that utilizes materials with different thermal conductivities (see Supplement 10). The radiation energy patterns are modulated by varying the emissivity and the temperature without affecting the patterns of other bands.
(limitations of the current optimization methods) In the case of complete decoupling with m levels of patterns for each of n spectral bands, a total of m^n structural designs would be required, which poses a significant challenge for structural optimization.

3. IR and THz performance distance. Lines 239-247 and supplements explain why camouflage is distinguishable from the background in Fig.5a and c. However, it remains unclear why Fig.5a is shown as a main result even though there are Fig.S14 b and c, where camouflage is similar to background. In response to the reviewers, authors provide simulated THz images at a longer object distance. If it is impossible to get experimental images at longer distances, simulations for both short and longer distances should be included either in main or supplementary figures to clarify the difference between camouflage and background in the experimental images. Distance values should be included as it is done for the IR images.

Response:

We thank the reviewer for the valuable suggestions.

We have provided experimental images captured in the MWIR and LWIR bands at 0.5 m (short distance, Fig. 5a and 5c) and 10 m (longer distance, Fig. 5b and 5d) in the main text, along with corresponding explanations:

(Page 12, lines 233-238)

At longer distances (10 m, approximately equal to the maximum object distance; see Supplement 3 for the calculation of the maximum object distance and Supplement 14 for detailed thermal IR experiments), the digital camouflage device exhibits a blending performance with the background, effectively camouflaging a 100 °C target to appear close to ambient temperature (Fig. 5b and 5d), whereas the fabric and paint references remain exposed against it.

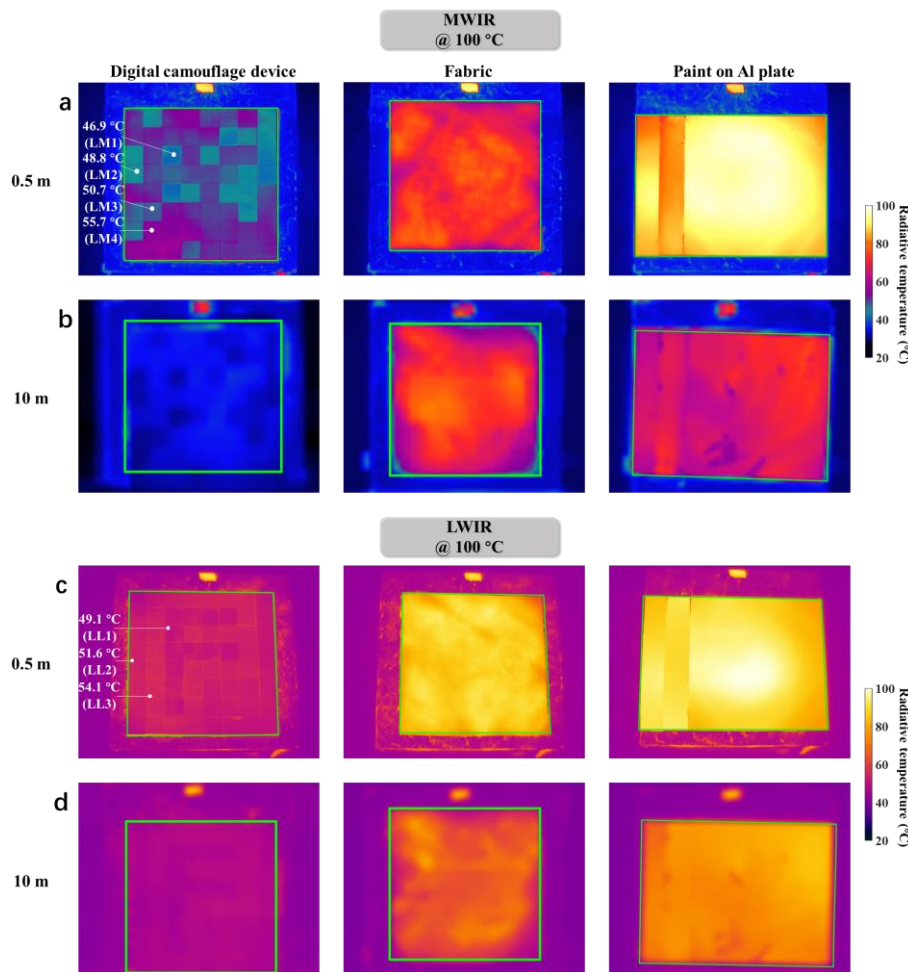


Fig. 5 | MWIR/LWIR digital camouflage. A thermal infrared comparison of the digital camouflage performance between the device and two references (fabric and paint on Al plate).

MWIR images captured at distances of **a.** 0.5 m and **b.** 10 m, LWIR images captured at distances of **c.** 0.5 m and **d.** 10 m. For the MWIR and LWIR bands, the samples are placed on a hot plate at 100 °C. The corresponding optical images of the device and the references are shown in Fig. 4a.

We have also provided experimental images captured in the THz and MW bands at 0.1 m (short distance, Fig. 6a and 6c) and simulation images at 0.4 m (longer distance, Fig. 6b and 6d, due to experimental limitations that prevent long distance imaging, simulation images are provided instead) in the main text, along with corresponding explanations:

(Page 12, lines 247-250)

At longer distances (0.4 m, approximately equal to the maximum object distance), the digital camouflage device also exhibits a blending performance with the background (Fig. 6b and 6d, due to experimental limitations that prevent long distance imaging, simulation images are provided instead).

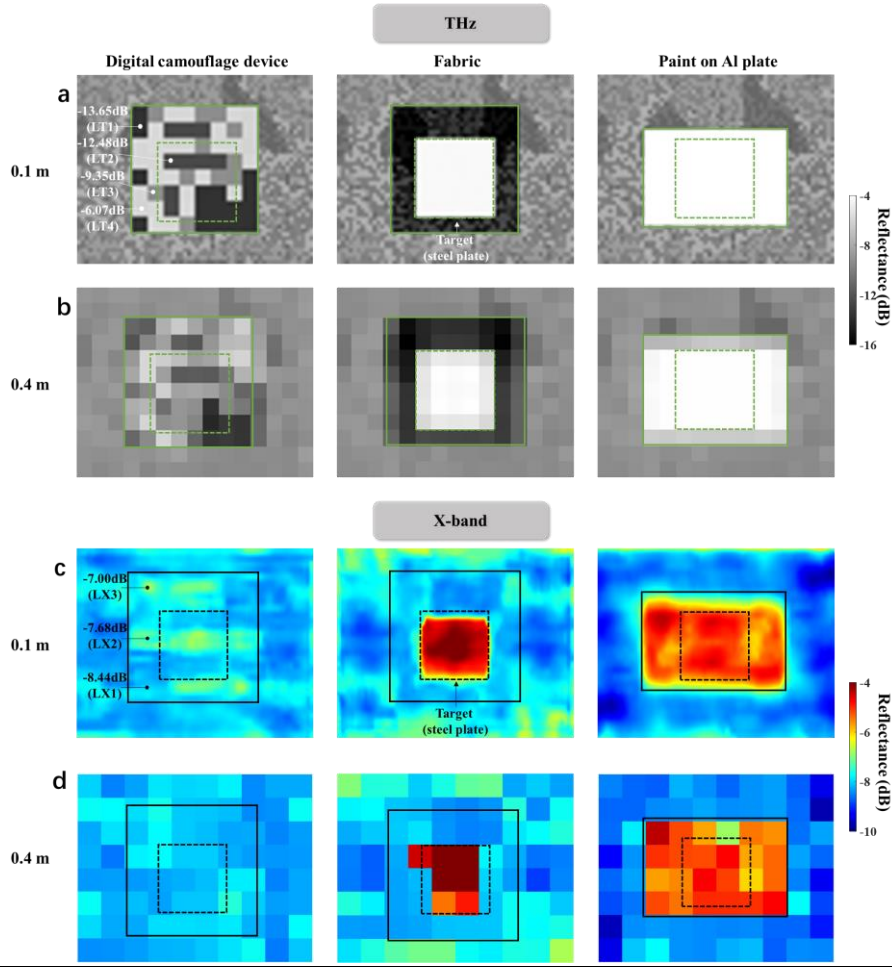


Fig. 6 | THz/X-band digital camouflage. A THz/MW comparison of the digital camouflage performance between the device and two references (fabric and paint on Al plate). A steel plate is placed under the samples as a target. **a.** THz experimental images captured at distances of 0.1 m, **b.** THz simulation images captured at distances of 0.4 m, **c.** X-band experimental images captured at distances of 0.1 m, **d.** X-band simulation images captured at distances of 0.4 m. The THz digital camouflage mimics water characteristics. The X-band digital camouflage is presented under SAR imaging, along with MW absorption camouflage. The corresponding optical images of the device and the references are shown in Fig. 4a.

Minor comments:

1. Line 97. CMOS, CCD and SAR should be written in full first.

Response:

We have added the full names of CMOS and CCD:

(Page 5, lines 98-99) (e.g., complementary metal oxide semiconductor (CMOS), charge-coupled device (CCD), and SAR arrays)

The full name of SAR, synthetic aperture radar, has already been provided earlier (Page 4, line 75).

2. Line 131. “the thickness (t1, t2, etc.) in Fig. 2d are optimized spectrally according to Supplement 7” should be paraphrased. It is not clear what is the meaning of spectral optimization and Supplement 7 does not provide any optimization information.

Response:

We have revised this sentence to make its meaning clearer:

(Page 7, lines 136-137) The thicknesses (t1, t2, etc.) in Fig. 2d were further optimized based on the plant spectra in Supplement 7 using the method described in Supplement 8.

3. Line 139. Erase “approximately”.

Response:

We have erased “approximately” (Page 7, lines 145).

4. Line 155-156. “and the decreasing intrinsic loss of Ge decreases.” should be paraphrased.

Response:

We have paraphrased this sentence:

(Page 8, lines 161-162) and the decreasing intrinsic loss of Ge

5. Line 157-158. “resulting from all layers’ the resonances of all layers.” should be paraphrased.

Response:

We have paraphrased this sentence:

(Page 8, lines 163) resulting from the resonances of all layers.

6. Line 182. SSIM should be written in full first.

Response:

We have added the full names of SSIM:

(Page 9, lines 187) structure similarity index measure (SSIM)

7. Line 192. SID should be written in full first.

Response:

We have added the full names of SID:

(Page 10, lines 198) spectral information divergence (SID)

8. Supplement 7. “*showingleading*” and “*bebecome*” should be modified.

Response:

We have revised these two points: “leading” and “become”

The Reviewer #3's comments

Reviewer's general remarks:

I co-reviewed this manuscript with one of the reviewers who provided the listed reports. This is part of the Nature Communications initiative to facilitate training in peer review and to provide appropriate recognition for Early Career Researchers who co-review manuscripts.

Response:

We appreciate the reviewer's positive evaluation of our digital camouflage strategy encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands. We are very thankful to the reviewer for their helpful comments and suggestions. We have revised the manuscript accordingly. A point-by-point response has already been combined with the reply to the co-reviewer (Reviewer #2).

The Reviewer #4's comments

Reviewer's general remarks:

Overall, the authors have faithfully addressed all the concerns raised by the reviewers. I hope the authors will pay more attention to organizing and clarifying the plots in the figures before publication.

Response:

We appreciate the reviewer's positive evaluations of our digital camouflage strategy encompassing optical hyperspectra and thermal infrared-terahertz-microwave tri-bands. We have revised the manuscript according to the valuable comments of the reviewers. We have reviewed the plots in the figures according to the reviewer's comments.