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Optimal LED Spectral Multiplexing ∀ NIR2RGB Translation.

① In general, ∀ night-video surveillance - auxillary NIR LEDs - 850 nm - 940 nm - used ∀ illumination.
↓
captures monochromatic images.
→ lacks visual color, texture tends to disappear.
→ No issues regarding brightness, noise do not exist.

② In this paper - ?
- Examined the imaging mechanisms of single-chip silicon-based RGB cameras under NIR illuminat^n.
- Proposed to retrieve the optimal LED multiplexing via deep learning.

③ Improve the img. quality ⇒ Add more illuminat^n ⇒ Increase the exposure time ⇒ IMPACT: Motion blur.

④ NIR LEDs - take advantage of the sensitivity of the camera's silicon sensor around the NIR band.

⑤ In this paper,
- Proposed to retrieve the optimal LED multiplexing to reasonably maximize the distinguishability of the different materials in the NIR band, & finally to achieve stable NIR2RGB restoration.

⑥ Main highlights of this work:

- Robustify the NIR2RGB translation by engineering on the illumination multiplexing of existing NIR LEDs.

- Put forward 2 optimiz^n schemes ∀ retrieving the optimal LED spectral multiplexing.

(a) Maximizing the no. of distinguishable colors based on the variance of typical reflectance spectra.

(b) Minimizing NIR2RGB translational error directly.

⇓

the optimal LED combination should correspond to the smallest NIR2RGB image reconstruction error.

↓ how?

Through deep learning, we directly minimize the reconstruct^n loss of NIR2RGB, and get the LED spectral multiplexing that might be physically realized by lightening a set of LEDs.

⑦ It is the first work on optimal LED spectral selection for NIR2RGB translation.

(c) Dataset released - Hyperspectral Images (HSI)

↓

IDH (Indoor - Darklight - Hyperspectral imgs)

↓

simulates night surveillance imaging.

⑧ RELATED WORKS.

i) Low light image enhancements.

- Previous models tend to fail in darker environments.
- We introduced NIR LED illuminations to avoid SNR issue.

ii) Colorization.

- Gray scale to RGB = only chrominance info traced ∀
  - luminance already present.
- In contrast, ∀ NIR2RGB translation, have to recover chrominance & luminance from an input with domain gap.

iii) NIR2RGB.

- NIR light captured by silicon based sensors.
- [22] Patricia et. al., puts forward NIR images coloriz^n method based on CNN & GANs. The model learns 3 channels independently, and thus the convergence can be faster.

-

- [24] Jinhui et. al., tries to enhance weak RGB signals with the assistance of a bright image captured under deep red flash illumination. (680 nm

⑨ METHODOLOGY.

- To achieve stability and effectiveness ∀ NIR2RGB translation.
- Have to : optimize models' translation capability.
  : Find an optimal LED spectral Multiplexing (LSM) to get NIR images.

(a) Optimal LED Spectral Multiplexing (LSM) Selectⁿ Module :

- It is necessary to design the selection modules for the optimal LSM searching.

(i) RGB Variance Maximization (RVM)

- For the reflectance spectra of many objects, the corresponding RGB intensities are very close, so the captured image looks grayish.

- If selectⁿ module can make pixels of specific material & color carry more informatⁿ, gives robustness ∀ NIR2RGB translation. — that can be shaped by sufficiently large intensity variance of RGB channels.

↓

With this idea, we need to determine the source of the colors as the typical spectral curves (TSC)

↓ comparing 2 schemes

> using standard ColorCheck to generate TSC.

> clustering all spectra in the training set to obtain TSC.

↓

choosing ColorCheck

- $I_i = \int_{NIR} (T_{i,w} \cdot L_w \cdot C_w)\, dw + N_i \quad , i \in N$

here, L_W - NIR LED Spectrum (NLS)
C_w - Camera spectral sensitivity (CSS)
T_{iw} - spectral curve of i^{th} color in Color Check.
N_i - overall noise to system.

⇓

So,
TSC, CSS - are fixed
⇒ I is determined by LED spectrum (L_w).

⇓

∀ each LSM, there is a response I of N typical colors.

↓

Calculate the variance of RGB 3-channel intensity of each color.

⇓

Now,
if we do direct summat^n of variance from different colors - leads to loss of info ⇒ making it harder ∀ the model to restore more colors.

⇓

So, set threshold 'k' to count the no. of colors whose variance reaches 'k' in each LSM.

$$\text{MEAN}(I_{var}), \quad I_{var} = \begin{cases} lsm & , var \geq k \\ 0 & , others \end{cases}$$

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(ii) Target Loss Minimization (TLM):

- Inorder to select the optimal LSM, NIR imgs ∀ each HSIs are synthesized under all LSM at the first of the corresponding dataset.

⇓

Let,

$C_j (j = 1, 2 \ldots, J)$ - j-th LSM of training dataset

∀ t-th HSI, j^{th} LSM, the synthesized img → (NIR synthesized img) →

$$Y_{j,t} = C_j X_t$$

↓

So, for each scene in the dataset, by stacking all the NIR images with every LSM, the selectⁿ network gets the i/p:

$$y_t = \text{stack}(Y_{1t}, \ldots Y_{jt}, \ldots Y_{Jt})$$

- According to the imaging principle, synthesizing images can be seen as adding the corresponding intensity of RGB channels from NIR images.

↓

So, after stacking, y_t; the optimal LSM selection is equivalent to the NIR images selectⁿ in y_t. ↘

NIR img channels separated to 3 channels branches ↘

Given as inputs ∀ our selection module V.

V size → $J \times 1 \times O_i$; $O_i = 1$ - no. of o/p in i-th channel.

⇒ Output of V:

$$Y_t = \text{stack}(V * y_t(R), V * y_t(G), V * y_t(B))$$

$$Y_t = \text{stack}\left(V * y_t(R),\ V * y_t(G),\ V * y_t(B) \right)$$

$$L_s(V) = \frac{1}{T} \sum_{t=1}^{T} \| Y_t(V) - \hat{Y}_t \|^2 \quad \text{s.t. } V \geq 0$$

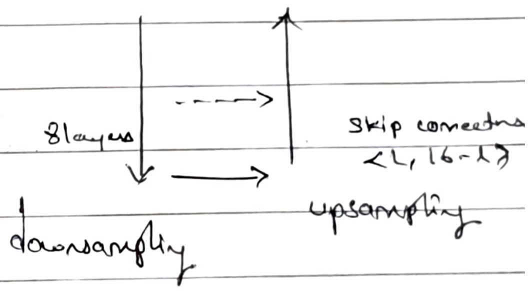
Selected NIR img

corresponding optimal multiplexing NIR img

(b) RGB Translation Module.

- To learn the non-linear mapping from NIR-to-RGB, a translational model is built based on conditional GANs.

G - U-Net 16 layers



D - Classifier NxN patch on o/p img. - Patch GAN

L1 loss

<real or not>

(c) Learning Strategy.

- Our model has
  - Select^n module.
  - Translat^n module.

- During training process, RVM results i/p to RGB translat^n module as an optimal LSM choice.

- As ∀ TLM,

large set of LSMs & HSIs are given.

⇓ whereby

multiple NIR imgs can be synthesized from the HSIs with different LSMs.

↓ then

put the NIR img set into the network to search ∀ the optimal LSM and its corresponding NIR imgs ∀ RGB translatⁿ.

SAY,

- α - indicates RGB translatⁿ module parameters.

- For G in GANs - objective :
  - > L_1 distance bwn the o/p of G & ground truth.
  - > MSE of D's o/p with correct judgement.

$$L_t(\alpha) = \frac{1}{T} \sum_{t=1}^{T} \| D(G_t(Y_t, \alpha)) - 1 \|^2 + \lambda \, L_1(G_t(Y_t, \alpha), Z_t)$$

where G_t - t-th o/p.

Y_t - corresponding selected NIR img from the LSM selectⁿ module.

Z_t - corresponding ground truth

λ - predefined parameter.

- The joint training of entire network is to minimize: $L = L_s(V) + \tau \, L_t(\alpha)$

τ - pre-defined parameter.

(10) EXPERIMENT.

(a) Set up & Protocols:

- DATASETS → $\boxed{HSI}$ λ: 420nm to 10^3nm

↓ stacked

420 - 700 nm RGB

700 - 10^3 - NIR img synthesis

Main sources ↓

ICVL, TokyoTech, ~~HSA~~ IDH.

→ $\boxed{NLS}$ NIR LED Spectrum

- measure the spectrum of 14 narrow band LEDs (λ: 700 - 10^3 nm)
- our optimal ~~LED~~ LSM is the combinatn of these LEDs.
- In visible light band, ↓
  white light LED (Panasonic Premium X)
  ∀ RGB img restorn

→ $\boxed{CSS}$

- the response curves of 3 cameras is measured after removing the IR cut-filter.
- CSSs are diff. ∀ 3 cameras as Si modules diff.

- DATA PROCESSING →
- Metrics →
  - PSNR, SSIM, RMSE
  - Delta-E