

Unsupervised Lightweight 3D Convolutional Network for Enhanced Infrared Imaging in Wearable Devices

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Problems & Ideas

- Problems of Enhanced Infrared Imaging in Wearable Devices:
 - Imaging performance challenges: imaging results suffer from lack of contrast, dark areas, high noise, and blurred edges;
 - Lack of high quality paired infrared images;
 - Low power consumption and sustainability requirements: lightweight model that can be integrated into a variety of embedded platforms.
- Ideas: Infrared image enhancement is conceptualized as generating high dynamic range infrared images from the corresponding temperature sequences during thermal equilibrium.

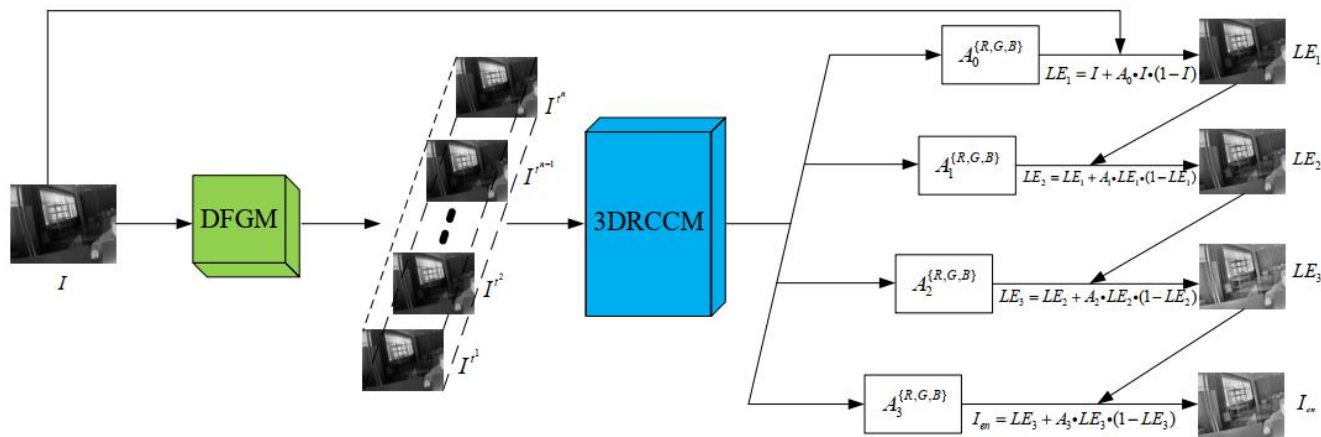


Fig.1 The overall framework of UL3DCN, which primarily consists of two key components: the Dynamic Filter Generation Module (DFGM) and the 3D Rubik's Cube Correlation Module (3DRCCM)

Main Contributions

- Contributions:
 - A novel unsupervised lightweight 3D convolutional neural network(UL3DCN) can effectively enhance imaging in wearable infrared imaging devices;
 - The Dynamic Filter Generation Module (DFGM) simulates infrared image sequences, effectively extending infrared image from the spatial to the spatio-temporal domain;
 - The 3D Rubik's Cube Correlation Module (3DRCCM), which accurately estimates the higher-order curves required for pixel-level adjustments and dynamic range enhancement of infrared images.



Table 1 Comparison experiments of related methods, with ‘.’ sign representing none. ‘↓’ indicates that the lower the value, the better the indicator, ‘↑’ indicates that the higher the value, the better the indicator.

| Category | Method | Year | MSE↓ | PSRN(dB)↑ | SSIM↑ | BRISQUE↓ | NIQE↓ | Params(M) |
|---------------|-----------------|--------------|---------------|--------------|---------------|--------------|--------------|-----------|
| Traditional | GHE [23] | - | 0.210 | 12.312 | 0.633 | 32.356 | 10.463 | - |
| | CLAHE [28] | 1994 | 0.229 | 12.533 | 0.746 | 31.421 | 9.436 | - |
| | BPDFHE [32] | 2013 | 0.222 | 11.492 | 0.693 | 31.374 | 9.684 | - |
| | DUAL [43] | 2019 | 0.214 | 13.237 | 0.804 | 31.646 | 9.423 | - |
| | MSR [44] | 2014 | 0.262 | 11.364 | 0.260 | 37.179 | 11.563 | - |
| Deep Learning | RetinexNet [40] | 2018 | 0.131 | 17.449 | 0.866 | 31.752 | 10.794 | 2.12M |
| | IE-CGAN [36] | 2018 | 0.107 | 19.014 | 0.871 | 30.862 | 9.316 | 0.32M |
| | DeepUPE [45] | 2019 | 0.144 | 15.483 | 0.828 | 31.843 | 9.7231 | 2.28M |
| | IAT [46] | 2022 | 0.153 | 16.415 | 0.891 | 31.584 | 9.694 | 0.42M |
| | Zero-DCE [19] | 2020 | - | - | - | 31.137 | 9.422 | 0.63M |
| | SCI [47] | 2022 | 0.103 | 19.699 | 0.943 | 32.316 | 9.488 | 0.43M |
| | SwinIR [48] | 2022 | 0.126 | 18.294 | 0.863 | 31.471 | 9.867 | 98.1M |
| Ours | 2024 | 0.087 | 22.283 | 0.964 | 30.669 | 9.284 | 1.23M | |

Comparison of experimental results and indicators: left: enhanced infrared image; right: experimental comparison indicators