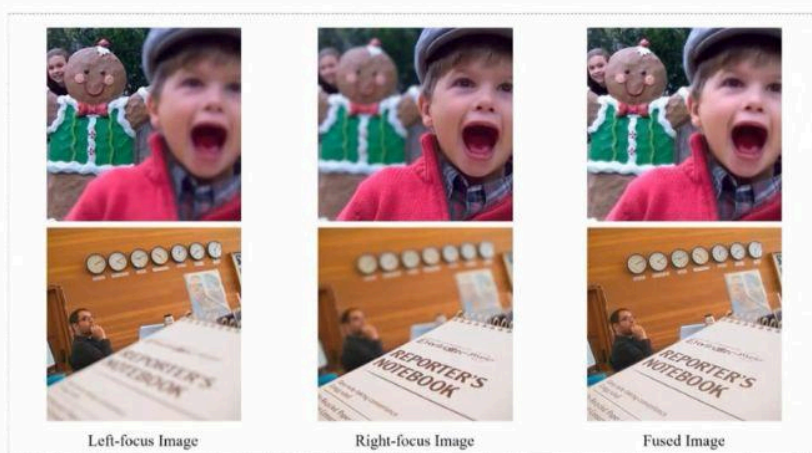
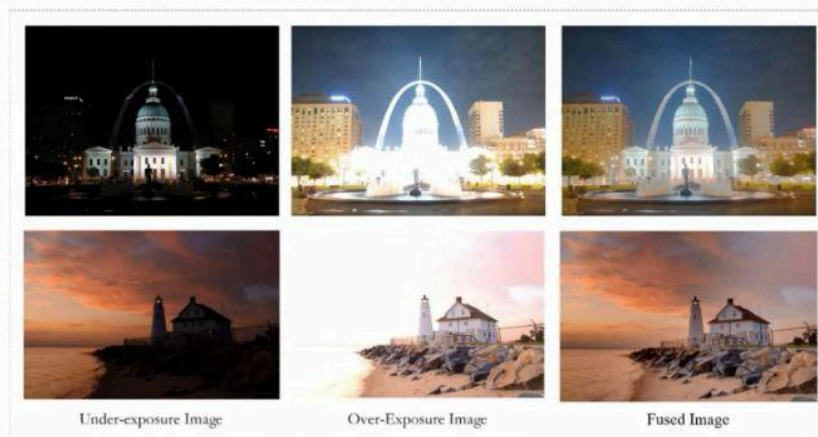


# Image Fusion

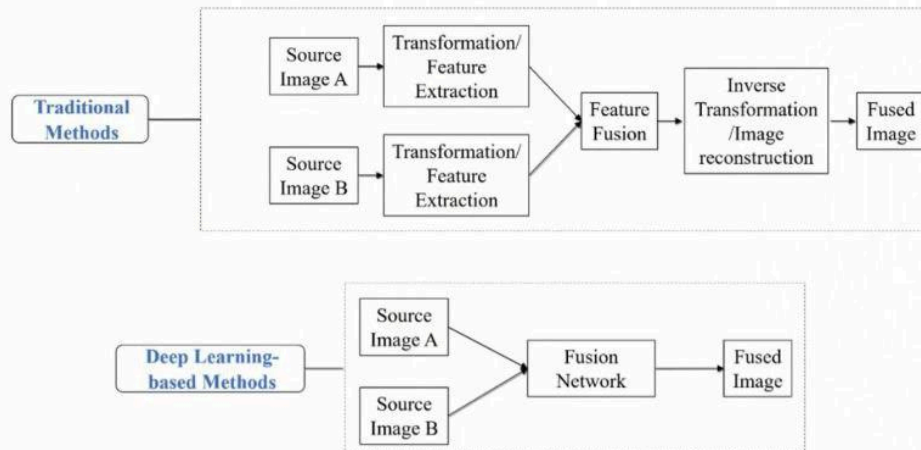
- **Definition:** A technique where multiple images are combined into a single image to enhance overall information or quality.
- **Purpose:** To create a composite image with more detailed or comprehensive information than any single input image.
- **Types of Image Fusion:**
  - **Pixel-level fusion:**
    - Merges pixel values from different images.
    - Techniques include averaging, PCA, and wavelet transforms.
  - **Feature-level fusion:**
    - Combines extracted features (e.g., edges, textures, shapes).
    - Focuses on combining relevant features from the images.
  - **Decision-level fusion:**
    - Merges decisions made on each image (e.g., classifications or object detections).
- **Goal:**
  - Improve clarity, information content, or visualization in the combined image.
  - Useful when working with images taken under different conditions or sensors.
- **RGB-IR Image Fusion:**
  - process of combining **RGB** images with **Infrared (IR)** images to create a new image that enhances both visible and infrared information.
  - This fusion technique leverages the strengths of both image types for applications where both visible and thermal details are required.





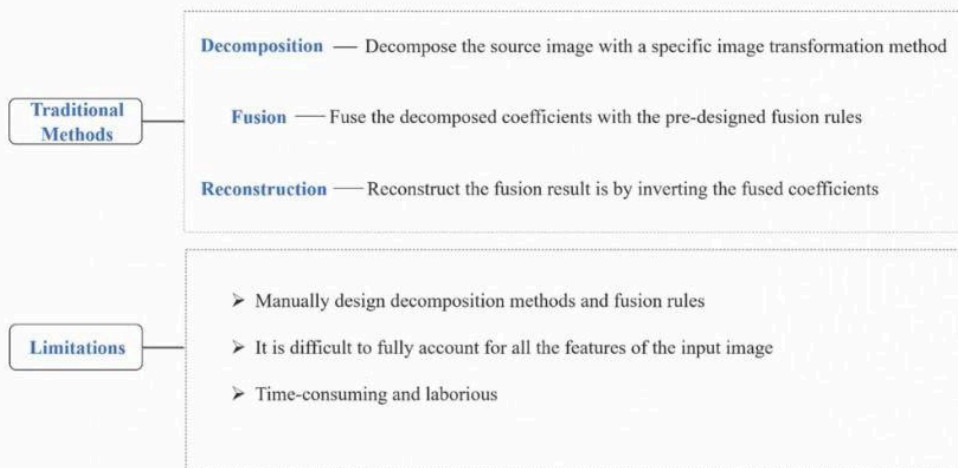
46:49

## Literature Review



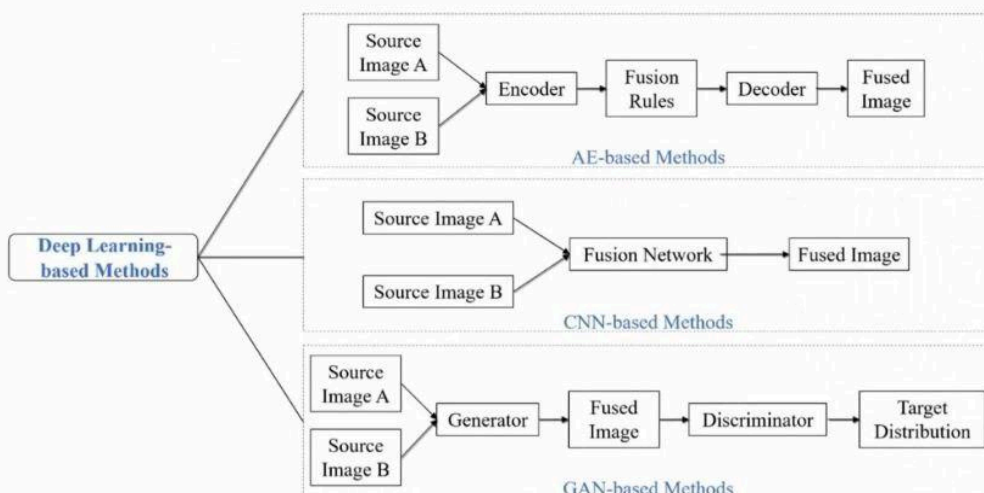
45:08

## Literature Review



43:47

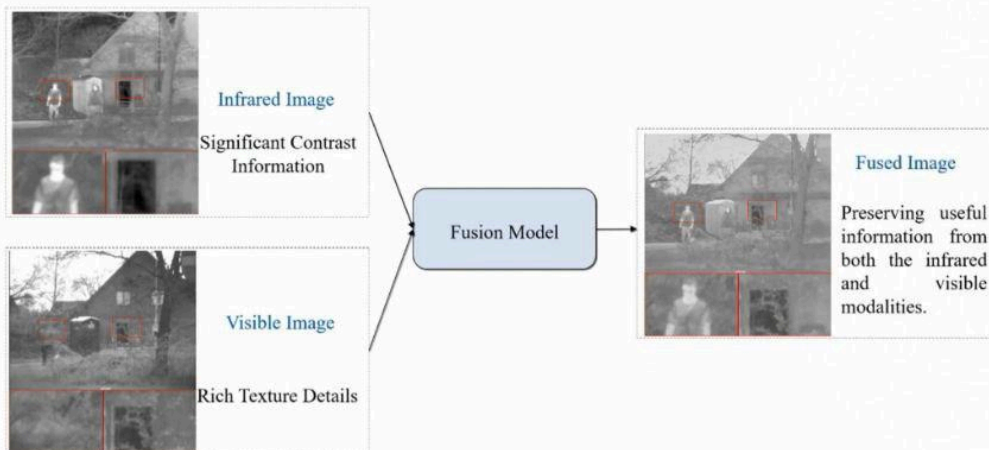
## Literature Review





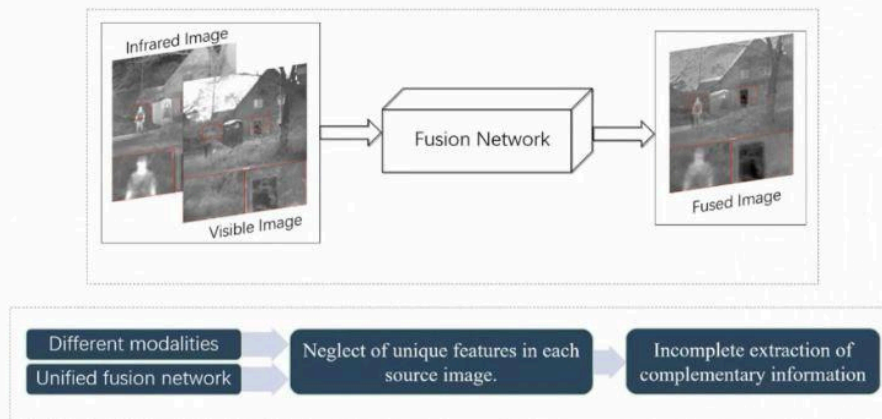
41:08

## Research Background



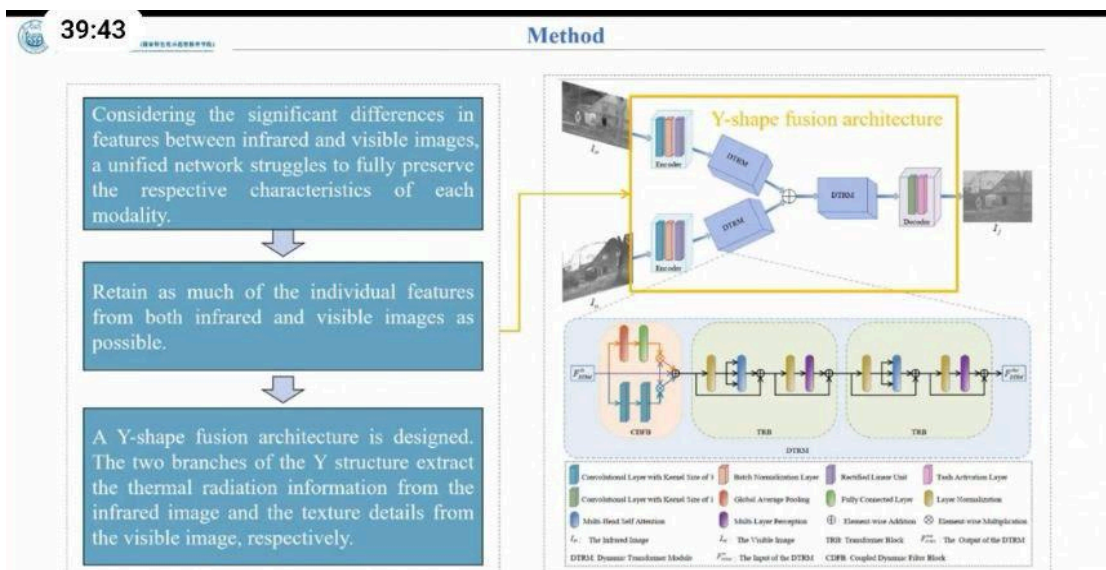
39:59

## Research Background



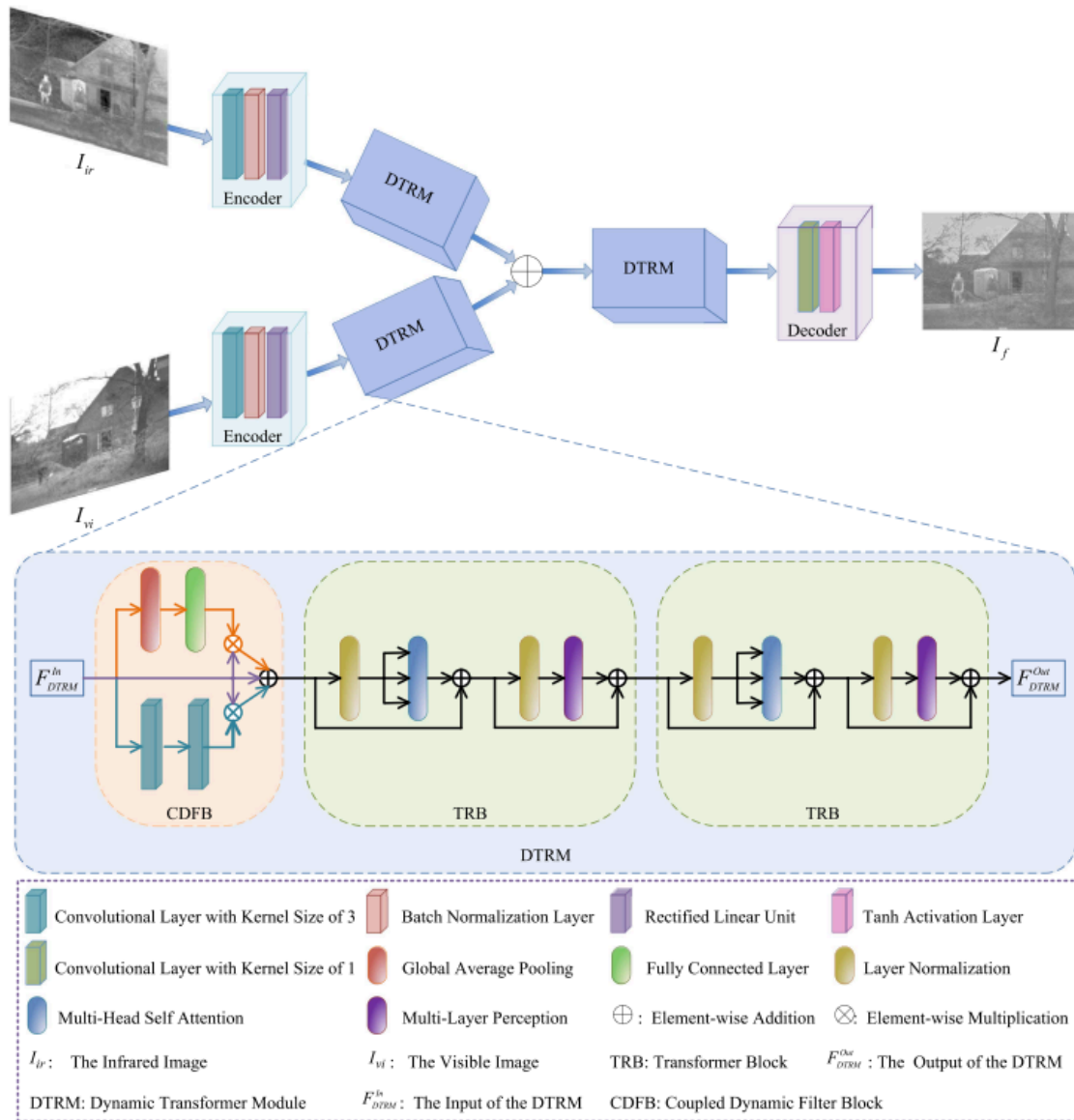
# Y-shape Dynamic Transformer (YDTR)

- **Goal:** Develop a novel infrared and visible image fusion method
- **Objective:** Generate a composite image that combines:
  - Salient target in the infrared image.
  - Texture details from the visible image.
- **Problem with existing methods:** Current deep learning based methods rely on convolutional operations, which limit global feature preservation.
- **Proposed solution:**
  - YDTR uses a dynamic Transformer module (DTRM) to capture both local features and significant context information
- **YDTR architecture** consists of:
  - **Two Y-shaped branches:** One branch extracts thermal information from the IR image, and the other extracts texture details from the visible image.
  - Each branch uses an **encoder** to capture shallow features and a **dynamic Transformer module (DTRM)** to model long-range relationships.
  - The **main path** combines these features through a DTRM and a decoder to reduce dimensions and integrate the information.
- **Loss function:** Combines two terms to enhance fusion quality:
  - Structural similarity (SSIM)
  - Spatial frequency (SF)
- **Extension:** YDTR can be extended to handle:
  - Infrared and RGB-visible images.
  - Multi-focus images.
- **Generalization:** The method demonstrates strong generalization capability without requiring fine-tuning.



IR images - Thermal radiation information

RGB images - texture details





If only structural loss is employed to guide network training, it's challenging to retain rich scene details.

Preserve as many important details from the source images as possible.

A spatial-frequency loss is designed.

$$L = L_{SSIM}(I_f, I_s) + L_{SF}(I_f, I_s)$$

$$L_{SSIM}(I_f, I_s) = 1 - SSIM(I_f, I_s)$$

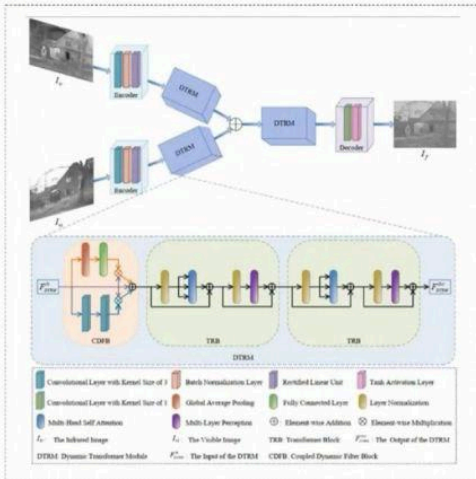
$$SSIM(I_f, I_s) = \frac{(2\mu_s\mu_f + C_1)(2\sigma_{sf} + C_2)}{(\mu_s^2 + \mu_f^2 + C_1)(\sigma_s^2 + \sigma_f^2 + C_2)}$$

$$L_{SF}(I_f, I_s) = \|SF(I_f) - SF(I_s)\|_2$$

$$SF = 1 - \sqrt{Hor^2 + Ver^2}$$

$$Hor = \sqrt{\frac{1}{HW} \sum_{i=1}^H \sum_{j=2}^W |I(i, j) - I(i, j-1)|^2}$$

$$Ver = \sqrt{\frac{1}{HW} \sum_{i=1}^H \sum_{j=2}^W |I(i, j) - I(i-1, j)|^2}$$



The design of the **Y-shape fusion architecture** allows for the comprehensive extraction of complementary features from multi-modal images.

The design of **the dynamic transformer** facilitates the extraction of global complementary information from the input images.

Loss Functions Incorporating Structural Similarity and Spatial Frequency.

Experimental results have validated the effectiveness of the method and its practical application value.

COMPARISON WITH STATE-OF-THE-ART IMAGE FUSION ALGORITHMS

Methods	End-to-End	Convolutional Operation	Transformer	Y-shape	SSIM Loss	SF Loss	Unsupervised	Generalization Ability
CNN [25]	×	✓	×	×	×	×	×	×
AUIF [26]	×	✓	×	×	✓	×	✓	×
DenseFuse [18]	×	✓	×	×	✓	×	✓	×
FusionGAN [19]	✓	✓	×	×	×	×	✓	×
AttentionFGAN [2]	✓	✓	×	✓	×	×	✓	×
GANMcC [24]	✓	✓	×	×	×	×	✓	✓
MgAN-Fuse [27]	✓	✓	×	×	×	×	✓	×
U2Fusion [20]	✓	✓	×	×	✓	×	✓	×
RFN-Nest [23]	✓	✓	×	×	✓	×	×	✓
MFE-EAG [28]	✓	✓	×	×	✓	×	×	✓
CSF [29]	×	✓	×	×	✓	×	✓	×
IFT [30]	×	✓	✓	×	✓	×	✓	×
DNDT [31]	✓	✓	✓	×	✓	×	✓	×
PPT Fusion [32]	×	×	✓	×	×	×	×	×
TGFuse [33]	✓	✓	✓	×	✓	×	✓	×
YDTR	✓	✓	✓	✓	✓	✓	✓	✓

# DL-Based Fusion

## Methods:

- **CNN-based Methods:** Liu et al. [25] introduced CNNs for infrared and visible image fusion, using a Siamese network for activity level measurement. Following this, methods like **DenseFuse** [18] and **FusionGAN** [19] leveraged dense connections and GANs to enhance fusion quality.
- **Attention Mechanisms:** FusionGAN was enhanced with a **multi-scale attention mechanism** [2] to focus on discriminative regions.
- **Multi-classification and Attention:** Methods like **GANMcC** [24] and **MgAN-Fuse** [27] incorporated **multi-classification constraints** and **multi-grained attention modules** for improved fusion.

## Challenges:

- **Limited Long-Range Context:** Convolutional operations capture local features but fail to model global context, leading to a loss of significant global features.
- **Feature Extraction Approach:** Many methods use single or parallel networks without tailoring to the specific characteristics of infrared and visible images.

## Transformer in Image Fusion:

- The **Transformer** architecture [37], introduced for NLP, addresses CNN's limited receptive field. The **Vision Transformer (ViT)** [41] applies this to image classification, improving global feature handling.
- **Transformer-based Fusion Methods:**
  - **Multi-Scale Fusion** [30] uses a two-stage training approach.
  - **DenseNet-Transformer** [31] combines DenseNet for encoding and dual-Transformers for fusion.
  - **Patch Pyramid Transformer (PPT)** [32] uses a patch Transformer for sequence transformation and a Pyramid Transformer for feature extraction.

## Proposed Approach:

- The paper proposes a **hybrid CNN-Transformer fusion method** to preserve both **local and global features**. This approach overcomes the limitations of existing DL-based methods, enhancing the overall fusion quality for infrared and visible images.