

# Elongated Object Detection and Segmentation

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**Version 2.1**

# Visual Detection of Elongated Objects

- **Introduction**
- Role of UAVs in elongated object detection
- Line segmentation
- Powerline detection and segmentation
- Pipeline detection and segmentation

# Introduction

Main goals of this presentation are:

- Provide the role of the UAVs in the problem of the elongated object detection.
- Present the most recent techniques used to locate and recognize elongated objects, specifically line, power lines and pipelines.

# Visual detection of elongated objects

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# Role of UAVs in elongated object detection



- UAVs can perform economic and faster asset inspection than the classic methods [LYU2019][SIN2019].
- For the visual inspection UAVs utilize RGB cameras, thermal camera and LiDAR sensors [LYU2019].
- UAVs external pipeline inspection constitutes a preferable replacement to in-pipe robots [AMI2016].

# Applications on industrial environment



Applications of automatic linear elongated object detection by UAVs :

- Pipeline external inspection on industrial environment [LYU2019.]
- Autonomous tracking of pipelines and navigation of UAV in industrial environment [LYU2019].
- Powerline visual inspection on electricity transmission and distribution networks. [VAN2018]

# Pipeline inspection

5 types of pipeline failures to be inspected.

Causes	Distribution (%)
Mechanical failures	42
3 <sup>rd</sup> party activity	24
Corrosion	18
Operational error	10
Natural Hazards	6

Table 1: Possible pipeline failures [SIN2019][JAK2014]

Mechanical failures and corrosion are the 2 causes of failure which is aimed to be detected through UAV inspection.

# Pipeline inspection

- Mechanical failures: open insulation , misplaced insulation, rapture, puncture and leak. [SIN2019]
- Corrosion: internal and external.
  - Causes of external corrosion: worn-off, open or misplaced insulation, manufacturing defects and location close to extreme environments. [SIN2019][JAK2014]
  - Causes of internal corrosion: chemicals such as, chloride, carbon dioxide, hydrogen sulfide, oxygen, and microbiological activity. [SIN2019][JAK2014]



# Pipeline inspection



Corrosion damage [SIN2019].



Mechanical failure [SIN2019].

# Powerline inspection

Powerline inspection tasks:

- Inspection and mapping of powerlines and its components (conductors and pylons). Main faults to be detected: damaged poles and crossarms and missing toppads [VAN2018].
- Monitoring for vegetation encroachment consists of: detection and classification of vegetation near the powerlines, estimation of height and distance from the powerlines [VAN2018].

# Powerline inspection

Powerline inspection tasks:

- Icing detection on the powerline and measurement of the icing thickness parameter [VAN2018]
- Disaster monitoring. Fast and accurate damage assessments on the powerlines to recover the power grid. [VAN2018]



# Visual detection of elongated objects



**Elongated object detection:** localization of instances of elongated structured objects inside an image.

- Powerline detection, referring to line detection.
- Pipeline detection, referring to linear structured object detection, such as cylinder.

Both object can be characterized as elongated linear objects because they extend in one direction (along one axis).



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# Line Segmentation

Edge Drawing Lines (EDLines):

- **Input:** RGB image
- **Output:** set of sharp, continuous, connected, chains of edge pixels, called edge segments.
- Fast, precise results and robustness to noise.
- Implementation steps:
  - Edge Drawing: produces an edge segment consisted of a chain of pixels corresponding to the edge.
  - Line Detection: uses the “Least Squares Line Fittings” method to extract lines from the edges.
  - Line Validation: uses the Helmholtz Principle

# Line segmentation

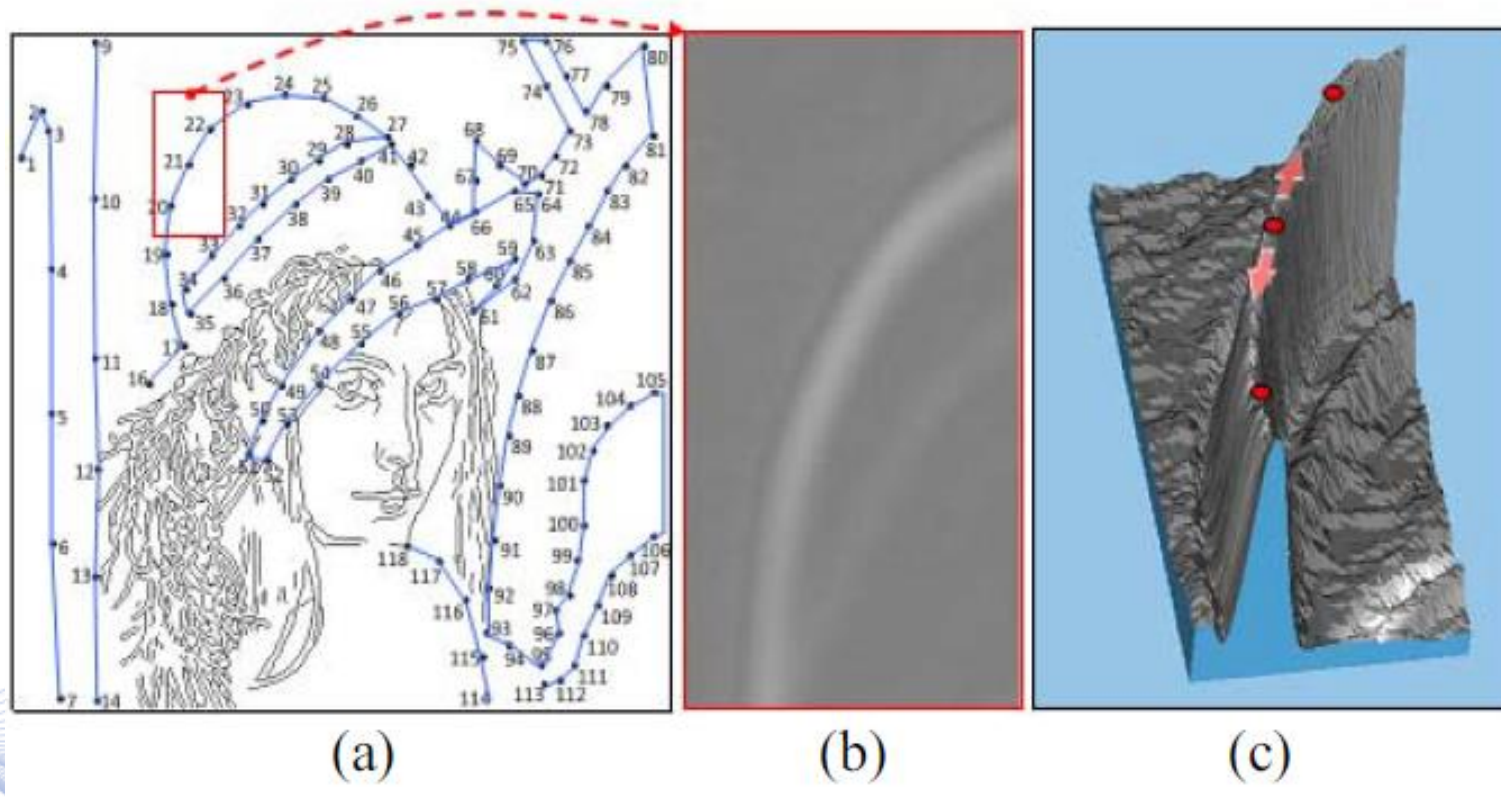


Image 3: (a) Edge map of Lena's photos. (b) Part of the gradient map of the input image. (c) The 3D illustration of (b). [YET2015]

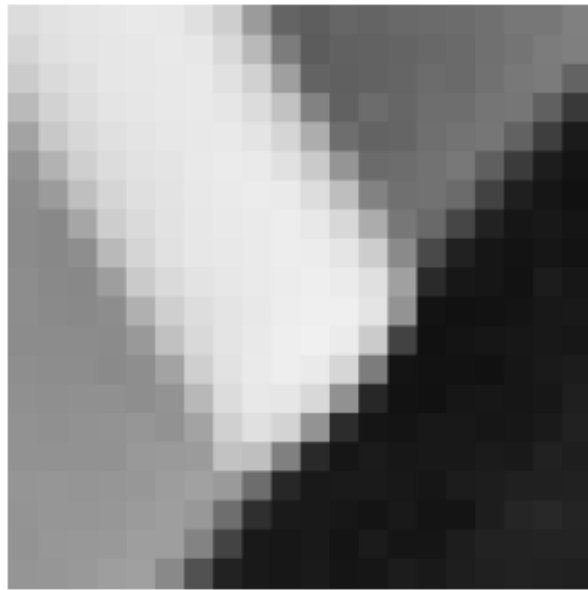
# Line segmentation

## Line Segments Detector (LSD):

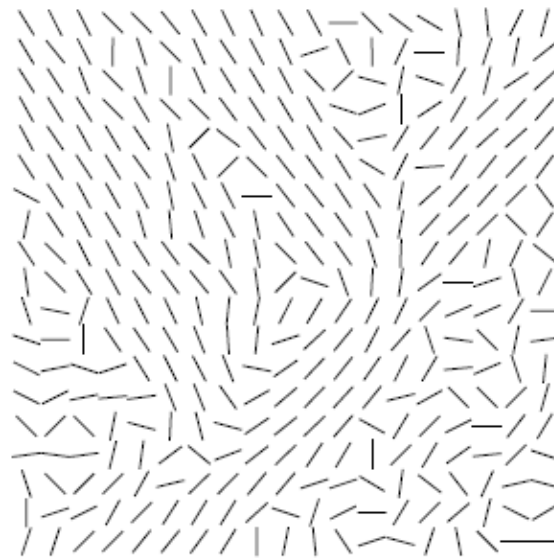
- **Input:** Grayscale image
- **Output:** List of detected line segments
- Steps of LSD:
  - Produce level-line field
  - Line Support Regions (Region growing)
  - Associate a rectangle to each region
  - Helmholtz principle to consider  $\epsilon$ -meaningful each reactnagel
- LSD is an automatic image analysis tool hence no parameter tuning is required. The values of the internal parameters of the algorithm are properly tuned to work on all images [VON2012].



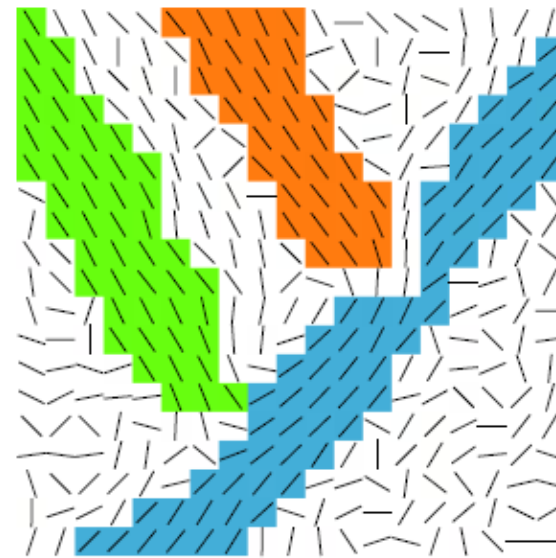
# Line segmentation



Image



Level-line Field



Line Support Regions

Image: Illustration of the vector field and the region growing steps for the line detection using the LSD algorithm [VON2012].

# Line segmentation

- Hough Transform has many variants and extensions, e.g. “Randomized Hough Transform”, “Elliptical Gaussian Kernel Hough Transform”, “Progressive Hough Transform” [YET2015] , etc..
- The parameters of these techniques must be adjusted manually as they cannot be determined automatically.
- An edge map produced from edge detectors, such as Cunny, is required for the Hough Transform
- The run times of these methods are long.

# Line segmentation

Comparison of Edge Drawing Lines (EDLines), Line Segmentation Detector (LSD) and Hough Transform [YET2015].



EDLines (82.11-0.79-1024x768)



LSD (89.92-1.11-1024x768)



Hough (88.00-2.18-1024x768)



EDLines (75.89-0.77-1024x768)



LSD (76.22-1.14-1024x768)



Hough (20.00-2.22-1024x768)

Image 4: Comparison results from [YET2015] (Accuracy (%), Time (seconds), Size (row x column))

# Deep line segmentation

Deep Hough Transform for semantic line detection [ZHA2021].

- **Input:** RGB image
- Combination of feature learning capabilities of CNN with the Hough Transform technique.
- Real-time efficient solution for semantic line detection.

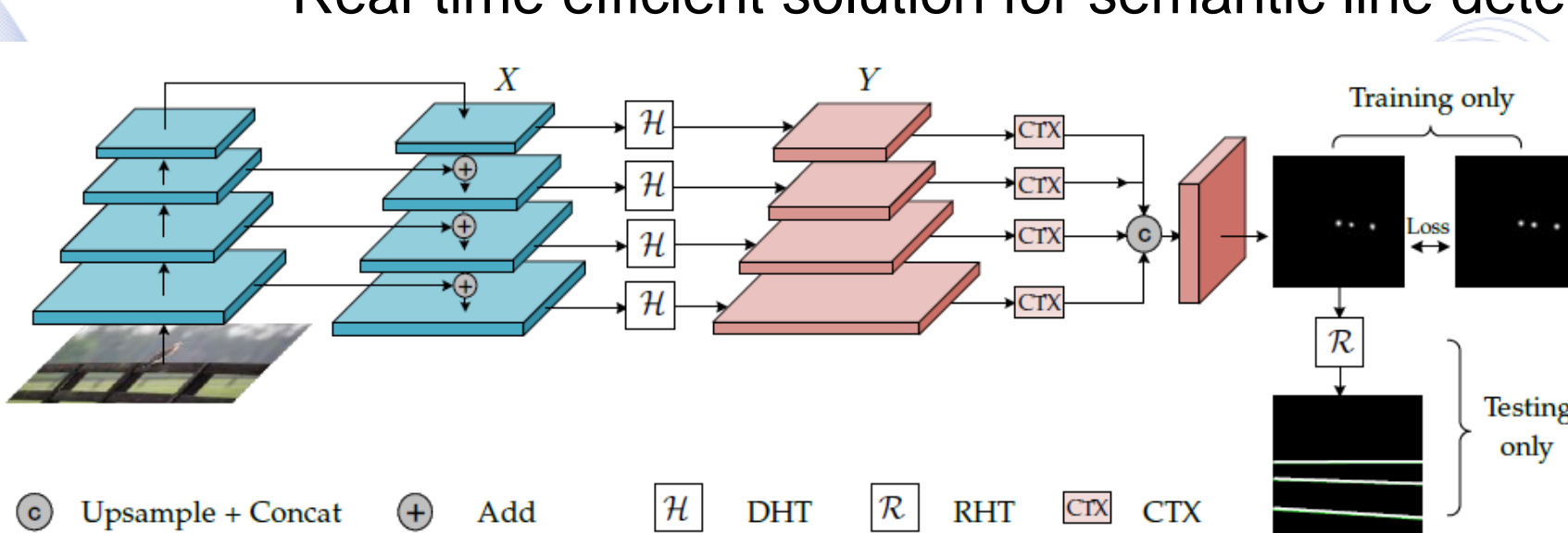


Image 5: Pipeline of the method proposed in [ZHA2021]. (DHT: Deep Hough Transform, RHT: Reverse Hough Transform, CTX: Context-aware line detection)

Upsample + Concat   
 Add   
 DHT   
 RHT   
 CTX



# Deep line segmentation

## Deep Hough Transform [ZHA2021]

- **Input:**  $\mathbf{X} \in \mathbb{R}^{C \times H \times W}$  (features from a Deep CNN encoder network)
- **Output:**  $\mathbf{Y} \in \mathbb{R}^{C \times \Theta \times R}$  transformed features.
- Along an arbitrary line  $l$  features are aggregated from all the pixels to the parametric space  $Y$ :

$$\mathbf{Y}(\hat{\theta}_l, \hat{r}_l) = \sum_{i \in l} \mathbf{X}(i).$$

# Deep line segmentation

## Context-aware line detector [ZHA2021]

- FPN encoder containing multiple  $3 \times 3$  convolutional layers (two at each stage).
- Through the convolutional layers contextual line features are aggregated which then are interpolated matching the resolution of features from the different stages and finally they get concatenated together.

The final pointwise predictions are produced through a  $1 \times 1$  convolutional layer applied to the concatenated feature maps.

# Deep Line Segmentation

- The **Loss Function** used is the cross-entropy and it is calculated in the parametric space [ZHA2021].

$$L = - \sum_i \{ \hat{G}_i \cdot \log(P_i) + (1 - \hat{G}_i) \cdot \log(1 - P_i) \}$$

- For the **Reverse mapping** the predicted map is binarized through a threshold then the centroids (parameter of detected lines) of each connected area are calculated. The detected lines are mapped to the image space with  $P^{-1}(\cdot)$ .



# Deep line segmentation



Image 6: Detection results from the Deep Hough Transform [ZHA2021].



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# Powerline segmentation

End-to-end convolutional architecture for pixelwise power line detection.

- Encoder-decoder CNN with information fusion
- Attention sub-brand creates high-resolution attention mask from the deep feature
- **Output:** a score for each pixel (by thresholding the low score pixel are suppressed and the final detection result is created).

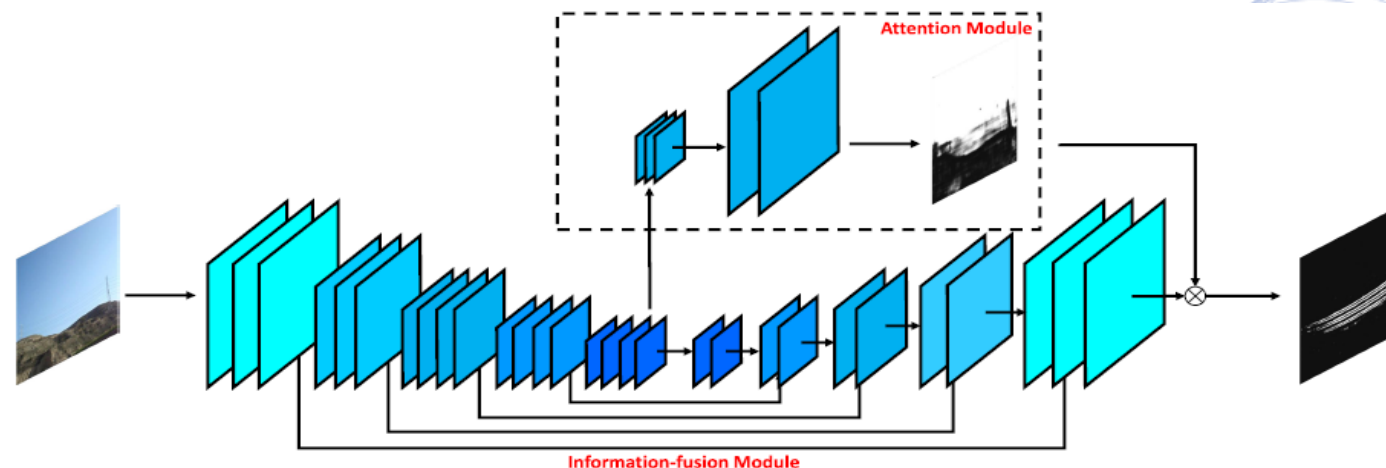


Image 7: Architecture of the attentional power line detection [LIY2019].

# Powerline segmentation

For the pixelwise detection of a powerline it is needed:

- Semantic information for the identification of the powerlines.
- The localization information for detecting the position of the powerline.

# Powerline segmentation

## Information Fusion Module [LIY2019]

- **Output:** Probability score map.
- The convolution layers and the upsampling provides semantic information.
- Lateral connections from the shallow to the same scale corresponding deep layers provides the needed localization information.

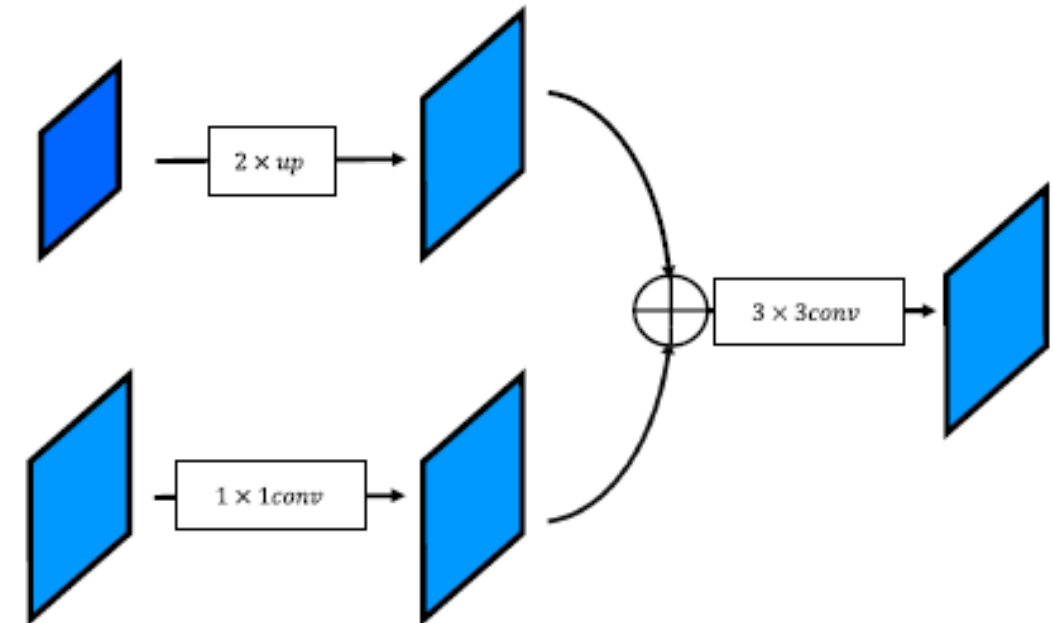


Image 8: Information fusion module in [LIY2019].



# Powerline segmentation

## Attention Module [LIY2019]

- **Goal:** Prevent misinterpretation of the background noise and focus on the powerlines.
- **Input:** Feature map from the last layer of the encoder.
- Upsampling and Convolution layers before and after the upsampling produce the attention map of the encoder-decoder structure. The size of the attention map is the same as the output.
- The attention map is elementwise multiplied with the output fused image from the encoding-decoding structure.

$$Y(x) = A(x) \odot I(x).$$

# Powerline segmentation

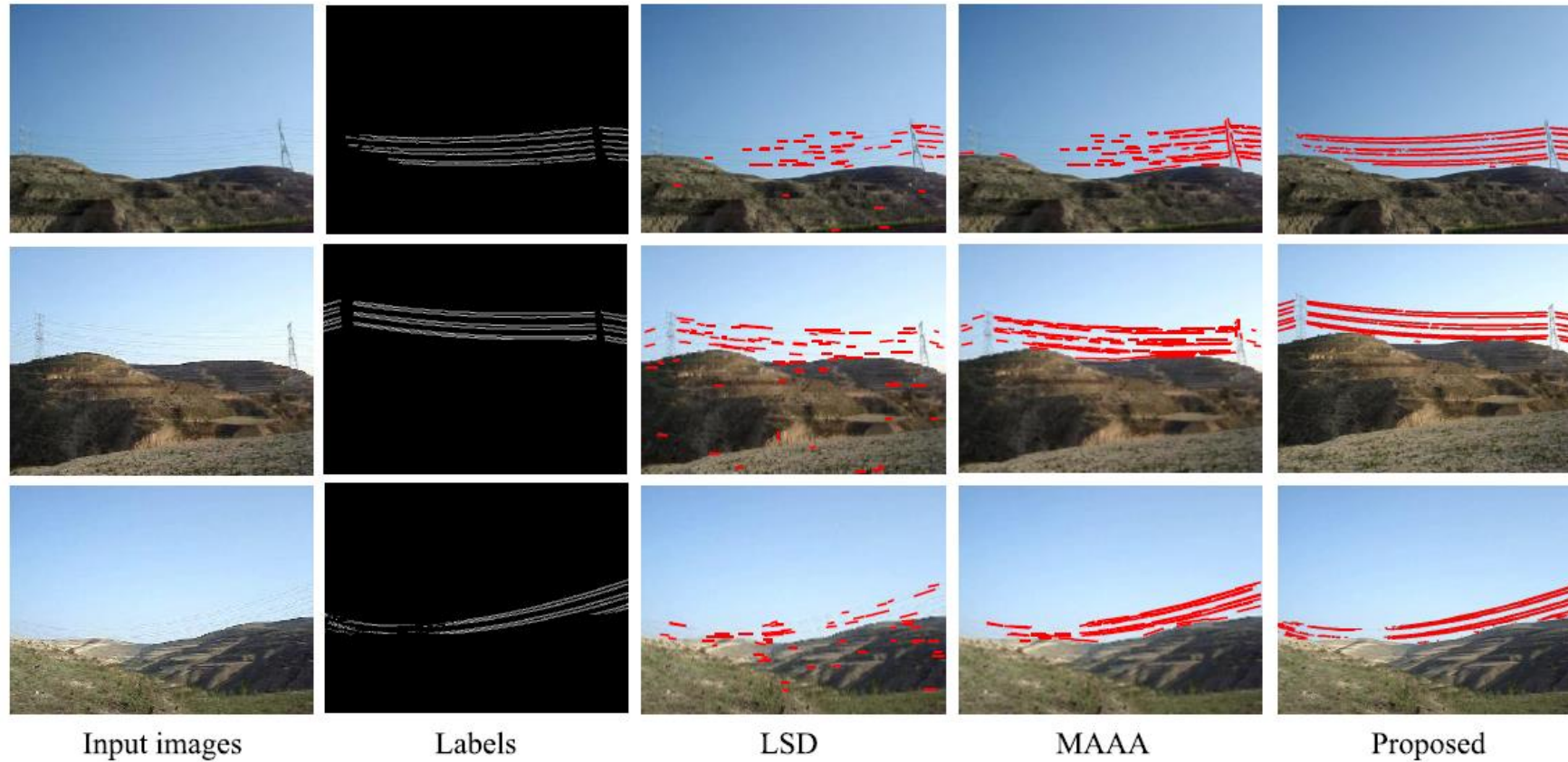


Image 9: Results from the comparison of the attentional powerline detection with LSD and MAAA [LIY2019].

# Powerline segmentation

Domain Adaptation (**DA**) for powerline segmentation in aerial images [KAL2023].

- **Synthetic Dataset:** RGB images with their corresponding segmentation maps captured in two Unity-created virtual environments.
- **Domain Adaptation:** bridge the domain discrepancy between the two datasets, a source (synthetic) dataset  $\mathcal{D}_S = \{(x_i^S, y_i^S)\}_{i=1}^{N_S}$  and a target (real) dataset  $\mathcal{D}_T = \{(x_i^T, y_i^T)\}_{i=1}^{N_T}$ , where  $x^S, x^T \in \mathbb{R}^{H \times W \times 3}$  is a RGB image, and  $y^S, y^T \in \mathbb{R}^{H \times W}$  is the segmentation map associated with  $x^S, x^T$  accordingly.



# Powerline segmentation

- Fourier-based image translation was employed by swapping the spectrum amplitude of a synthetic image with that of a random real image.
- Fourier **DA** utilized as a separate step and doesn't at all require any training to achieve domain alignment, instead relying on a simple Fourier Transform and its inverse.

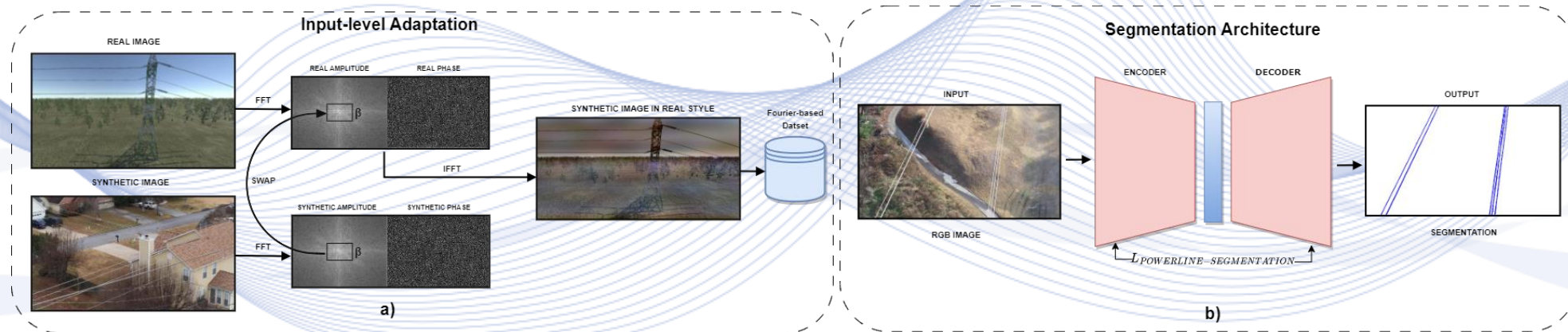


Image 12: The proposed framework for power line segmentation consists of two components: a) an input-level domain adaptation module that employs a Fourier-based image translation strategy, b) a high-performance semantic segmentation architecture trained with a power line segmentation loss.



# Powerline segmentation

- DeeplabV3+ was used since it can enhance the accuracy and smooth the boundaries and incorporates a number of strategies, like skip connections, dilated convolution, global context, strong backbone, etc.
- The segmentation architecture was trained using a proposed power line segmentation learning objective:

$$L_{total} = \lambda_1 \cdot L_{focal} + \lambda_2 \cdot L_{dice}.$$

# Powerline segmentation

- A comparison was conducted with existing SOTA method on TTPLA dataset where the proposed DA powerline segmentation method [KAL2023] outperforms the recently presented PLGAN [RAB2022] architecture by +3,82%

Method	Backbone Network	Image Resolution	TTPLA (Real dataset) Test set mIOU
PLGAN [RAB2022]	ResNet-6	512x512	53.30%
DA powerline segmentation [KAL2023]	ResNet-6	512x512	<b>57.12%</b>

# Powerline detection

Tiny-Yolov3 model for power line detection [HYU2022].

- **Input:** RGB image
- **Prediction:** Bounding boxes for detection of continuous object.
- A line is labelled using several continuous boxes of constant size. The shape of the power line (U-shaped curve, straight line etc.) is broken to small straight fragments.
- Lines close to each other are labelled by the same bounding boxes.

# Powerline detection



Power line ground truth Rols [HYU2022].



# Powerline detection

In tiny-Yolov3:

- Real-time implementation capabilities.
- It consist of seven convolution layers and six max-pooling layers.
- For the feature extraction  $1 \times 1$  and  $3 \times 3$  convolution layers were used.
- The continuous bounding boxes are predicted in two scales.
  - one  $13 \times 13$  feature map
  - concatenation of upsampled  $13 \times 13$  and  $26 \times 26$  feature maps

# Powerline detection

Evaluation metrics:

- **Precision, recall** and **Intersection over Union (IoU)**.

$$p(t) = \frac{\sum_{ij} n_{ij} z_{ij}}{\sum_{ij} n_{ij}}, \quad r(t) = \frac{\sum_{ij} n_{ij} z_{ij}}{M}$$

$$J(\mathcal{A}, \mathcal{B}) = \frac{|\mathcal{A} \cap \mathcal{B}|}{|\mathcal{A} \cup \mathcal{B}|}.$$

- Because of duplicate detection one ground truth has multiple IoUs, hence a true positive is counted when the sum of IoUs in one ground truth is over 0.5.

# Powerline detection

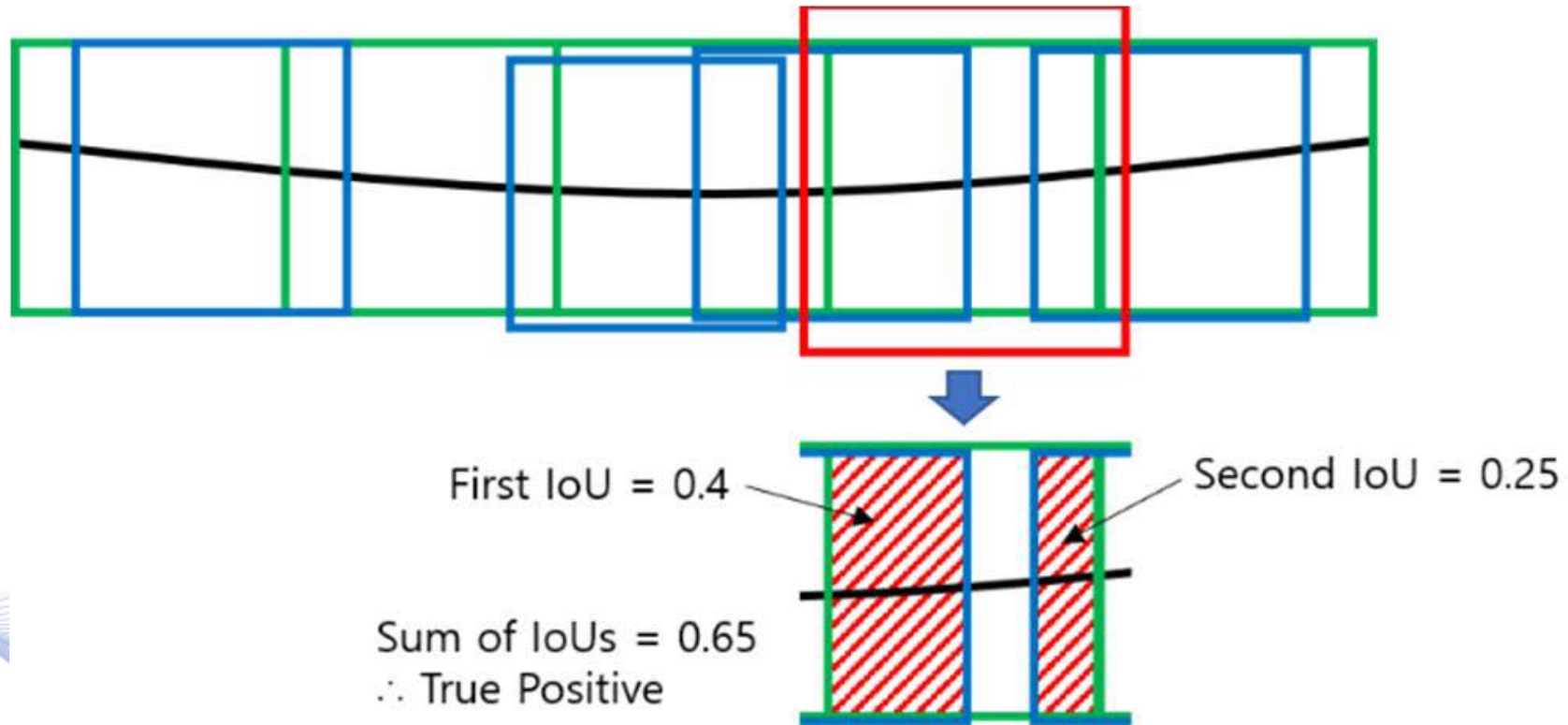


Image 11: Example of a case of a true positive in [HYU2022]

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- **Pipeline detection and segmentation**



# Pipeline detection and segmentation



Different sensors can be used for the pipeline detection.

- Visual sensors. The pipeline detection problem in computer vision is treated as a semantic segmentation problem [GUE2020].
- LIDAR-based detection is typically treated as a pipeline segmentation problem [GUE2020].
- Infrared thermal images has been used for automatic fault diagnosis on hot water pipelines [HAN2022].

For this presentation only computer vision and infrared thermal image are discussed.

# Pipeline segmentation

Automatic fault diagnosis method for hot water pipes on infrared images [HAN2022] .

- Infrared images were used because the distribution of surface temperature of the insulation is a good indicator that the layer is damaged.
- The algorithm comprises of two parts: image segmentation and fault diagnosis.

**Goal** of image segmentation part is to decrease as much as possible the influence of the background.

# Pipeline segmentation

Image segmentation contains gray processing, binarization and mathematical morphological processing.

- The gray processing extracts only the red component of the RGB input image.
- The gray image is divided to ROI (region of interest) and background:

$$g(x, y) = \begin{cases} 1 & f(x, y) > T \\ 0 & f(x, y) \leq T \end{cases}$$

- With Otsu's technique the optimal threshold can be determined by minimizing between-class variance and within-class variance

# Pipeline segmentation

- By labelling the connected components in the binary image small background regions are eliminated.
- The used Morphological filter comprise of firstly a closing and afterwards an opening, clearing the small connected components in the image.
- Finally the resulted binary image is multiplied with each channel of the input image resulting to the pipe infrared image.

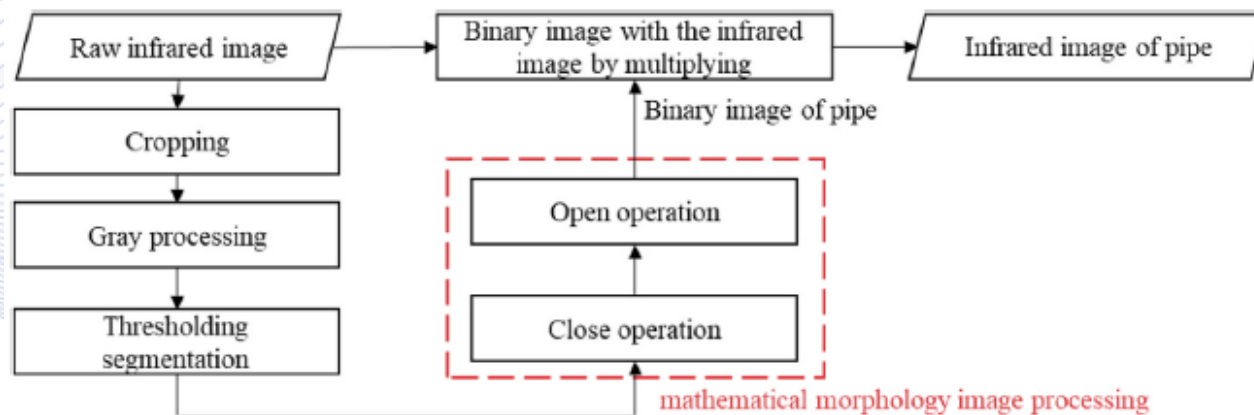


Image 18: Infrared image segmentation flowchart [HAN2022]



# Pipeline segmentation

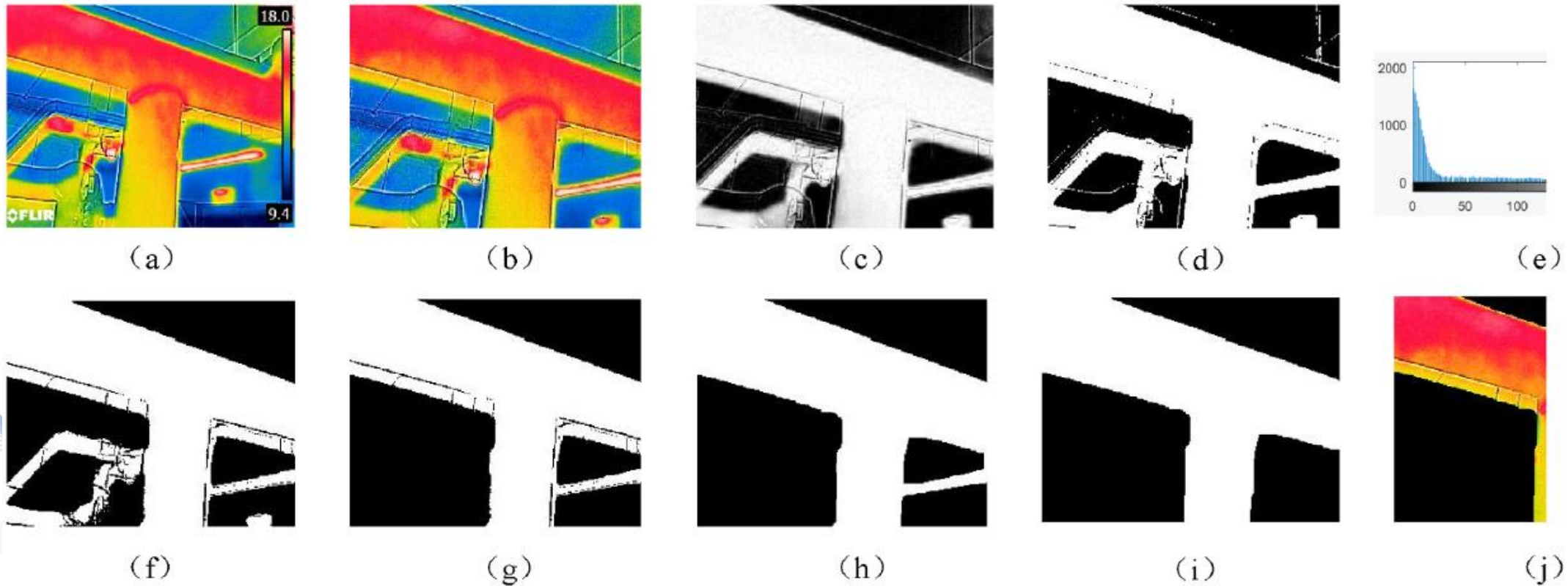


Image 19: Image segmentation results: (a) initial image, (b) cropped image, (c) grayscale image (d) Otsu's technique segmentation, (e) histogram of the red component image, (f) the segmentation result (the right peak method), (g) the largest connected component of (f), (h) output of closing, (i) output of opening (binary image of the pipe), and (j) the final segmented infrared image of the pipe. [HAN2022]

# Pipeline segmentation

## Classic semantic segmentation [GUE2020]

- Two step process: image processing for feature extraction, feature level classification.
- In dataset learned classes must be specified before training.
- The result of classification is used as input for the training of the classifier.



Image 15: Classic semantic segmentation architecture [GUE2020].

# Pipeline segmentation

## **Deep learning approach of the segmentation problem [GUE2020]**

- At the scale of inference, image level probabilistic detection and pixel level classification can be produced.
- Provides localization using centroids and/or bounding boxes.
- Pixel level labelling can be achieved by using fully convolutional network (FCN).

# Pipeline segmentation

FCN16 model with AlexNet for pipeline segmentation [GUE2020].

- The AlexNet functioned as the semantic segmentation model.
- In this model deep features are extracted through convolutional and max pooling layers.
- High level information is lost during the propagation of the data through the layers. Hence a fusion of the data from multiple layers is needed by upsampling through deconvolution data from deep layers.



# Pipeline segmentation

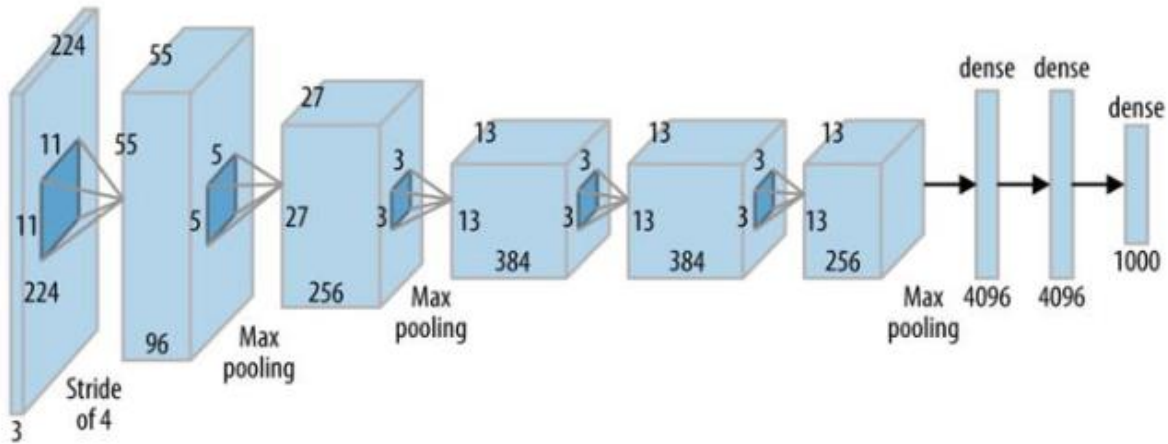


Image 16: AlexNet architecture [GUE2020]

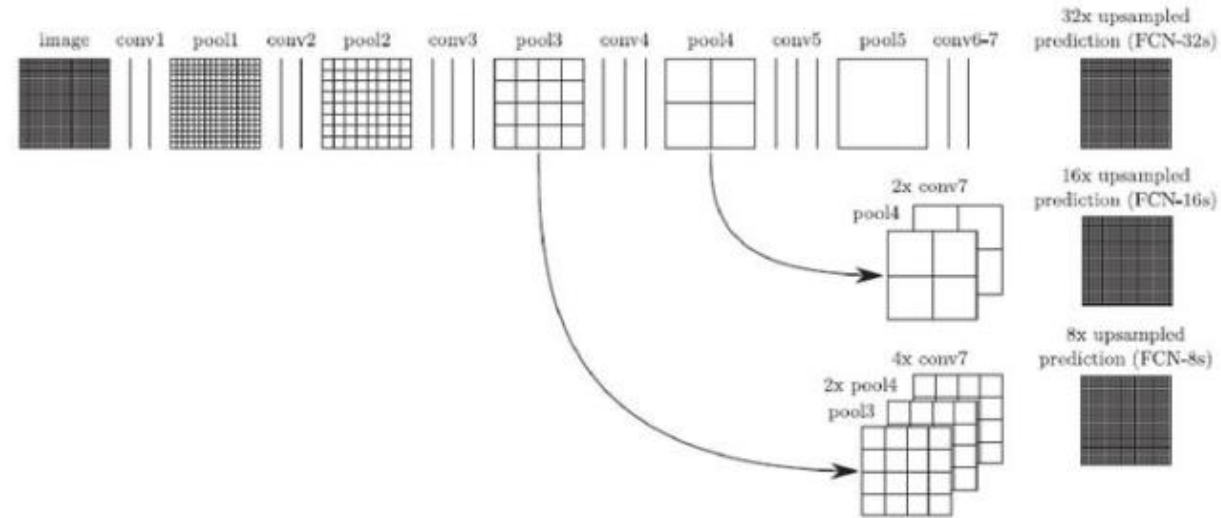
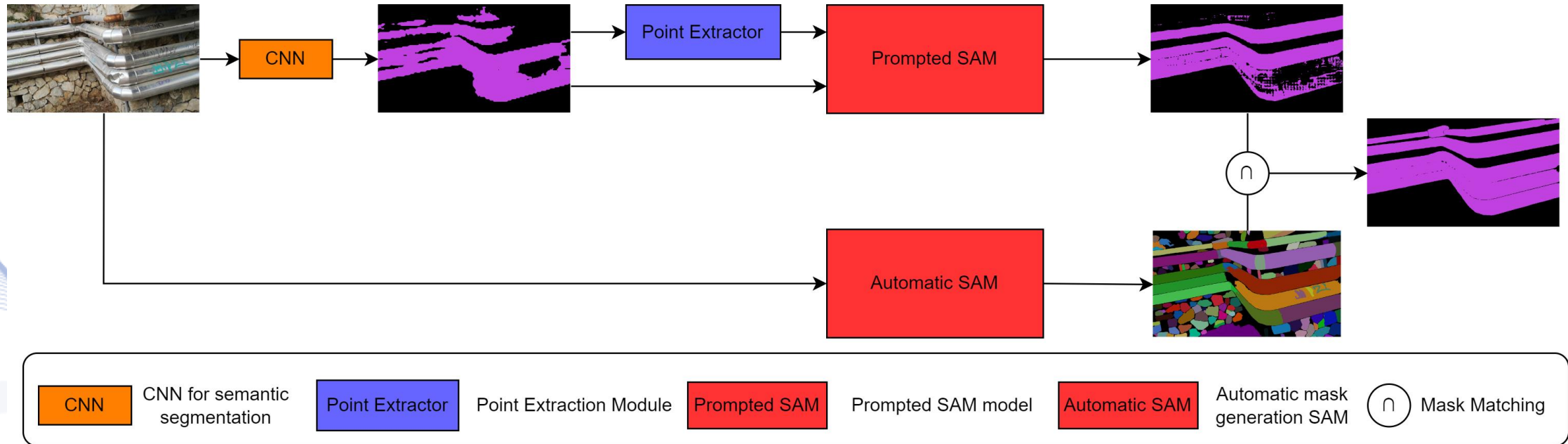


Image 17: FCN32, FCN16 and FCN8 architectures to use data from deep layers and fuse deep features and spatial information [GUE2020].

# Pipeline segmentation

- Cooperation of a CNN segmentation model [PAP2021] and Segment Anything Model [KIR2023].
- The CNN model produces masks of the pipes.
- A prompted SAM goal is used to refine the segmentation masks produced by CNN model.
- SAM also runs on automatic mode to produce masks for all objects.
- The final segmentation mask is produced by fusing the two intermediate outputs.

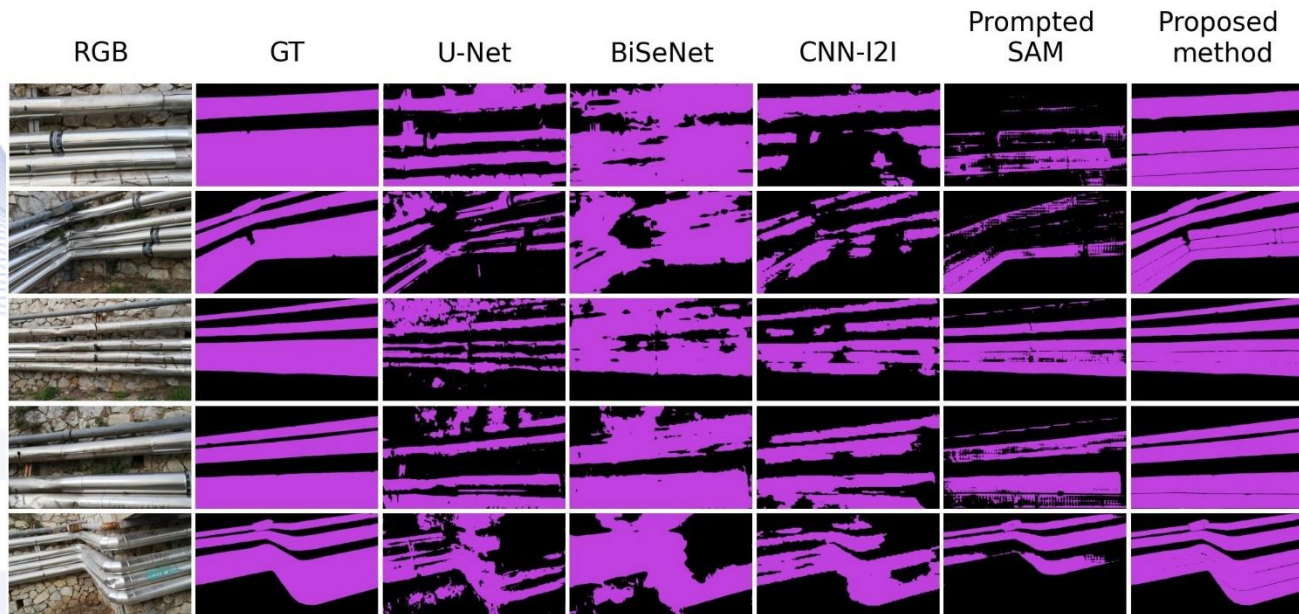
# Pipeline segmentation





# Pipeline segmentation

- The performance of the model was evaluated using the Intersection-over-Union (IoU) metric.



	IoU (%)			
	non-pipe	pipe	mIoU	mPA(%)
U-Net [7]	52.0	46.1	49.0	66.0
BiSeNet [8]	54.2	65.4	59.8	75.4
I2I-CNN [9]	68.5	63.7	66.1	79.7
prompted SAM	78.9	79.3	79.1	88.3
Proposed System	<b>89.0</b>	<b>90.9</b>	<b>89.9</b>	<b>94.8</b>

D. Psarras, C. Papaioannidis, V. Mygdalis, and I. Pitas, "A Unified DNN-Based System for Industrial Pipeline Segmentation", submitted as conference paper.



# Pipeline segmentation



Image 18: Pipe image segmentation.

# Pipeline detection

Yolov4 Neural Network (single stage detector, twenty-four convolution layers and two fully connected layers) for pipeline detection [YAG2022].

- **Input:** RGB image
- **Prediction:** Bounding Box that contains the pipe and a confidence score of the box. (x, y, h, w and confidence score)
- The confidence score represents the confidence of the model that the box contains an object and accurately predicts it, is given by:

$$\text{Pr}(\text{Object}) * J(\mathcal{A}, \mathcal{B})$$

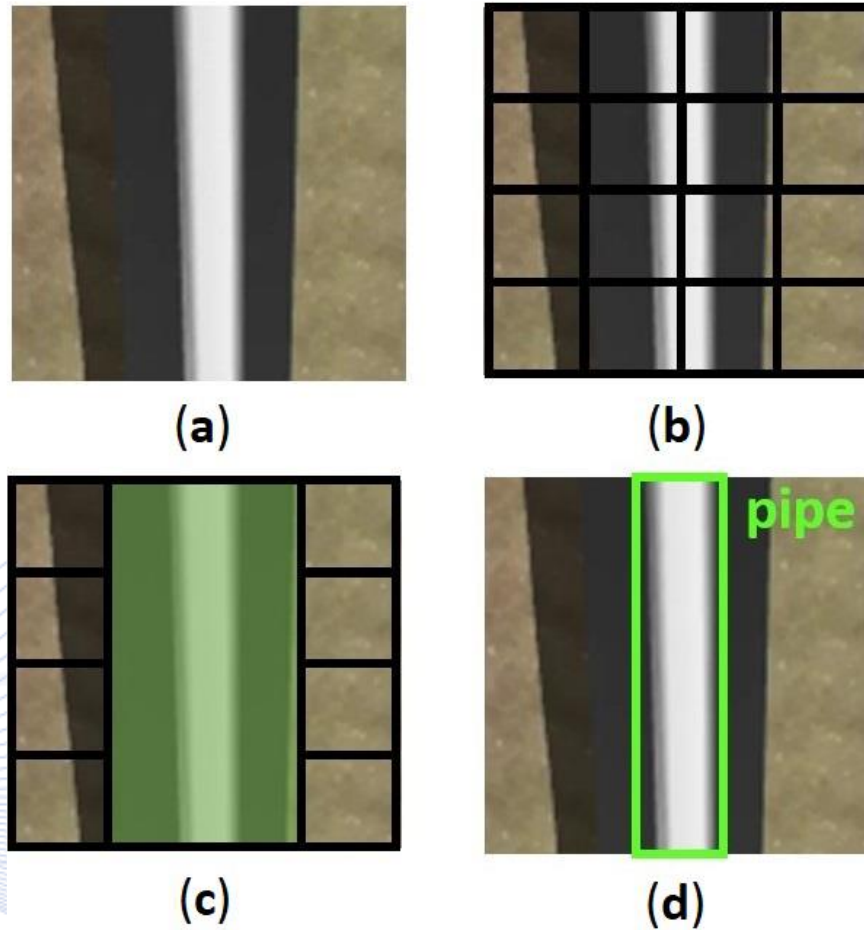
# Pipeline detection

In Yolov4:

- The input image is divided to an  $S \times S$  grid
- Each grid cell predicts a number of bounding boxes along with their respective confidence.
- The grid cells which contain an object predicts additionally one set of conditional class probabilities  $\Pr(\text{Class}|\text{Object})$ .
- A number of bounding boxes with their confidence and a class probability map are predicted and by multiplying them together the class-specific confidence score of the boxes is obtained.



# Pipeline Detection



YOLO object detection: a) input image of pipe; b) image division to grid cells; c) merged boxes that contain the pipeline; d) generated bounding box [YAG2022].



# Pipeline detection

The hyperparameters of the Yolo CNN used:

Optimizer	SGD (lr=0.01 learning rate)
Epochs	200
Batch size	16
Patience	100
Image size	448×448
Weight decay	0.0004

# Pipeline detection

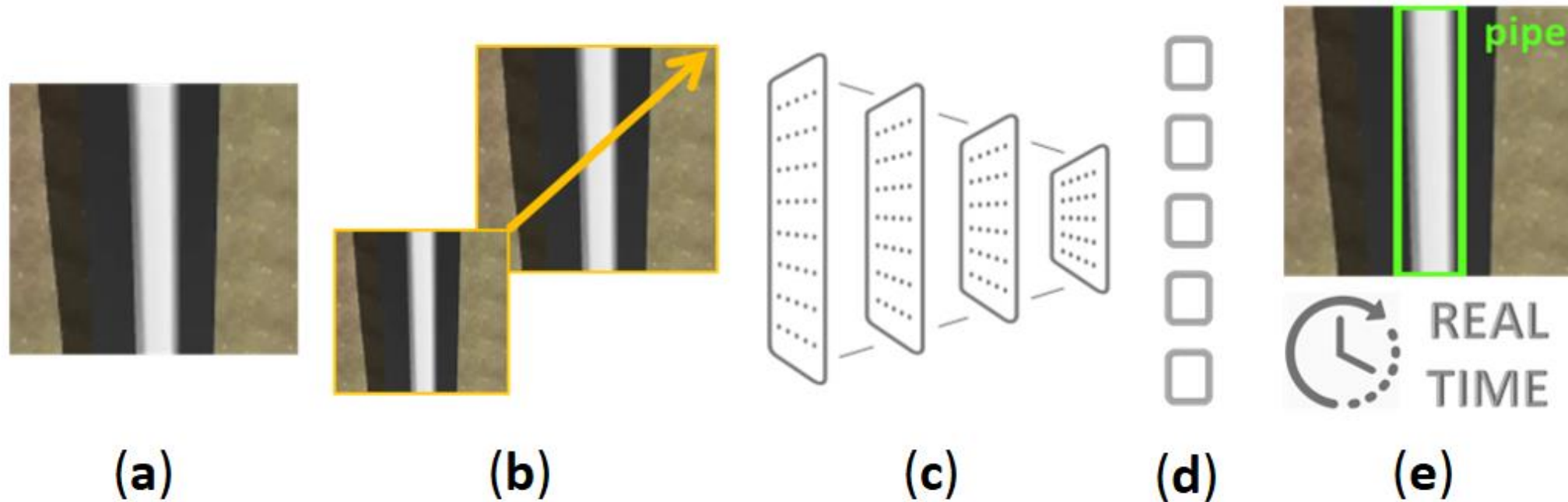


Image 14: (a) input image of pipe, (b) resizing of the input image and ground truth, (b) convolution and fully connected layers, (c) pooling process, (d) flattened output matrix, (e) real time object detection [YAG2022].

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# Q & A

**Thank you very much for your attention!**

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