COMBINING CGAN AND MIL FOR HOTSPOT SEGMENTATION IN BONE SCINTIGRAPHY

Hang XU, Shijie GENG, Yu QIAO*, Kuan XU, Yueyang GU

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上海交通大學
SHANGHAI JIAO TONG UNIVERSITY

Authors





Hang XU | Shijie GENG | Yu QIAO* | Kuan XU | Yueyang GU

Intelligence Learning Laboratory, Department of Automation,
Shanghai Jiao Tong University
P. R. China

⋆ Corresponding author: Yu QIAO (qiaoyu@sjtu.edu.cn)

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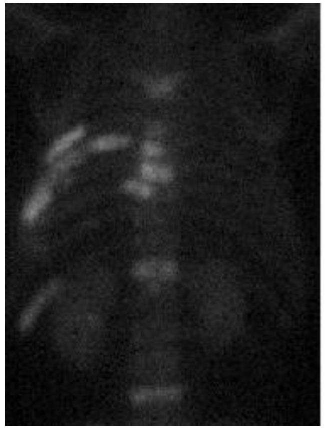
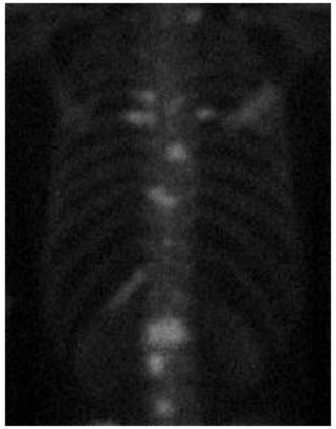
Introduction

- **Hotspot segmentation**
  - a key technique in bone scintigraphy
  - help diagnose cancer and tumor metastases
  - utilize machine learning methods in recent years
  - faced challenging problems
    - multiple targets
    - automatic implementation
    - lack of datasets





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Motivation

- Desired appropriate initialization for common segmentation method Level Set
  - patch-level classifier could obtain initialization
- Challenge of training classifier due to lack of datasets
  - utilize semi-supervised learning such as multiple instance learning (MIL)
- Desired appropriate features for MIL
  - location, texture, contrast features
- Desired image with separated regions for location information
  - apply conditional generative adversarial networks (cGAN)

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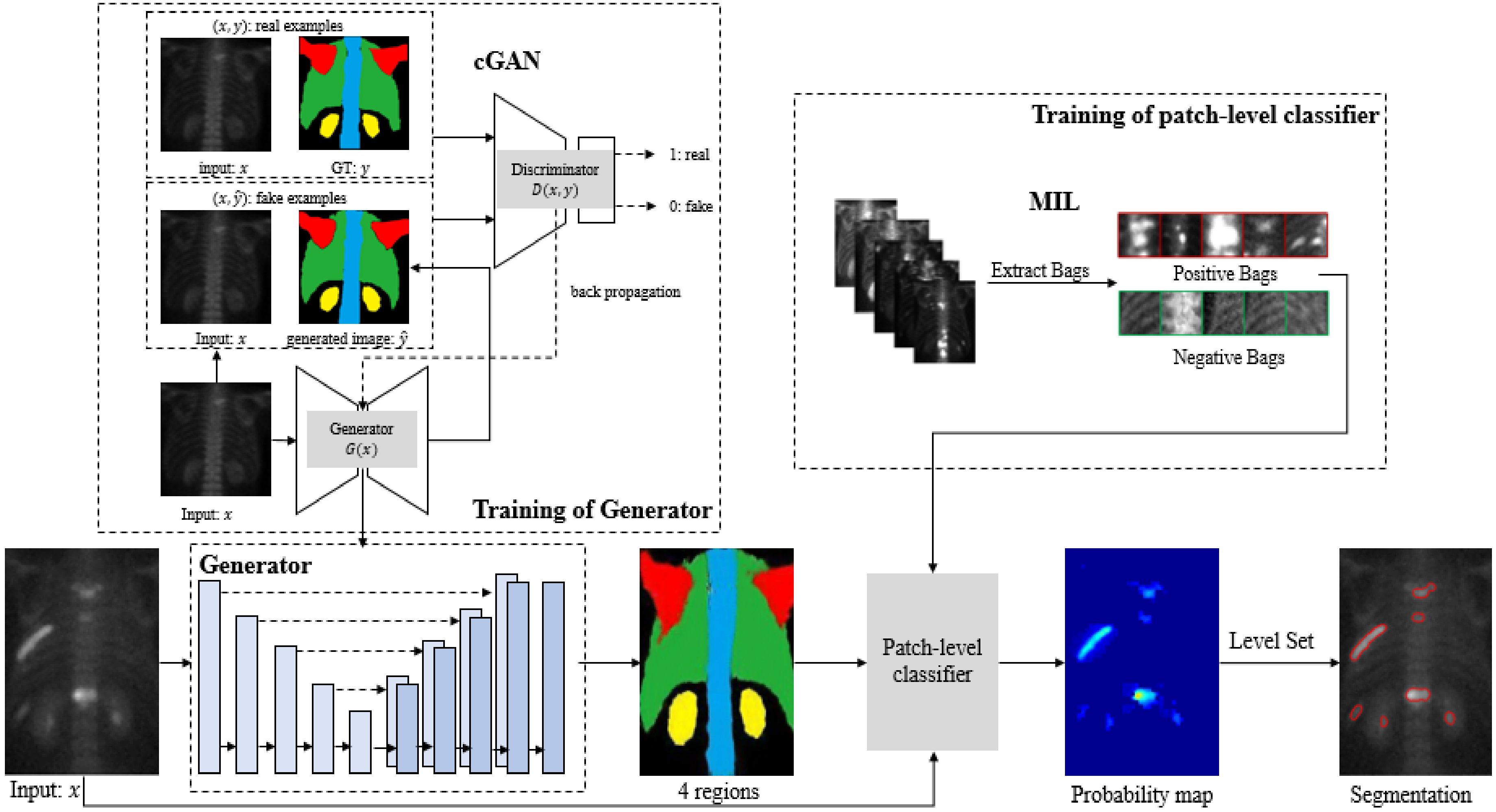
Framework


(x, y): real examples
input: x
GT: y
cGAN
Discriminator
D(x, y)
1: real
0: fake
(x, ŷ): fake examples
Input: x
generated image: ŷ
back propagation
Generator
G(x)
Input: x
Training of Generator
Training of patch-level classifier
MIL
Extract Bags
Positive Bags
Negative Bags
Generator
Input: x
4 regions
Patch-level classifier
Probability map
Level Set
Segmentation

Framework Modules

- Consist of 3 modules
  - Image generator
    - trained with pix2pix model of cGAN
  - Patch-level classifier
    - utilize a 38-dimension feature
    - trained with MIL
  - Final segmentation
    - get initialization from probability map by giving a threshold
    - use Level Set

Image Generator Training

- Train pix2pix model

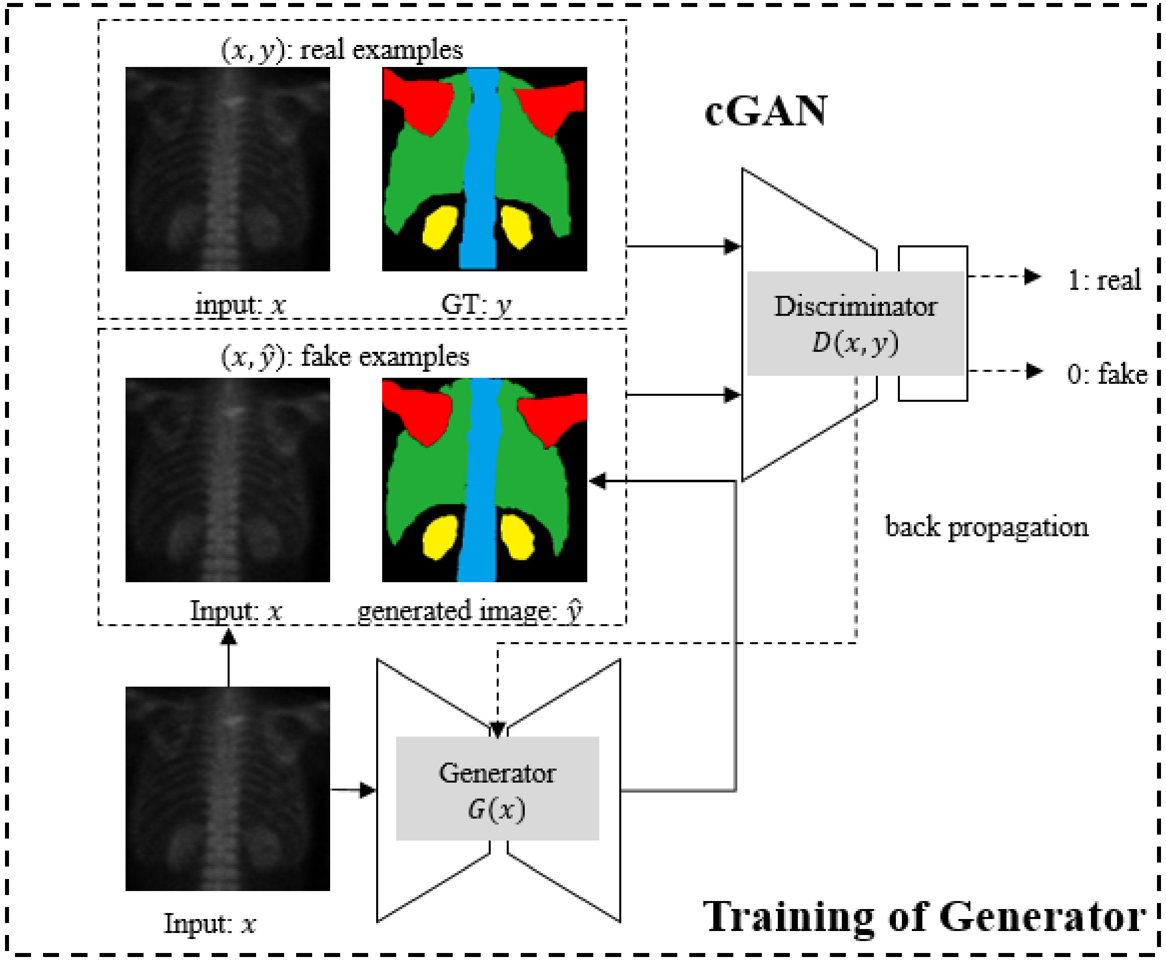


Image Generator

- **Generator structure: U-Net**
- **Minimize loss function**

$$L_{final}(G,D) = \arg\min_G \max_D L_{CGAN}(G,D) + \lambda L_{L1}(G)$$

$$L_{CGAN}(G,D) = \mathbb{E}_{x,y}[\log D(x,y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x,z)))]$$

$$L_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x,z)\|_1]$$

- **Generate images with separated regions**

Patch-level Classifier - Feature

- **Feature extraction: 38-dimension feature vector for a patch**
  - **4-dimension location feature**

$$Loc(k) = \sum_{i=1}^{n} \varphi_k(i)$$

$$\varphi_k(i) = \begin{cases} 1, & pixel(i) \in region(k) \\ 0, & otherwise \end{cases}$$

  - **33-dimension texture feature**
    - **based on Leung-Malik filter bank**
    - **24 directional filters, 6 Gaussian Laplacian filters and 3 Gaussian filters**
  - **1-dimension contrast feature**

Patch-level Classifier - Training

- **Training of the classifier**
  - **bag-level classifier is decided by patch-level classifier**

$$H(x_i) = \max_j(h(x_{ij}))$$

  - **strong classifier consists of a few weak classifiers**

$$h(x_{ij}) = \sum_{i=1}^{n} \alpha_t h_t(x_{ij})$$

  - **train by minimizing the loss function with gradient descent method**

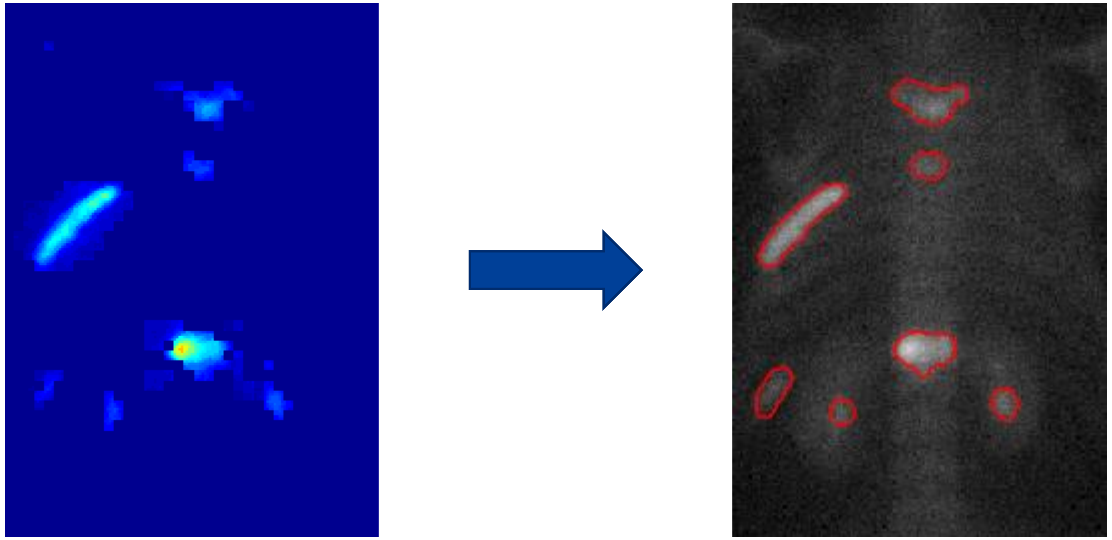
$$L(h) = -\sum_{i=1}^{n} (1(y_i = 1)\log p_i + 1(y_i = -1)\log(1 - p_i))$$

Final Segmentation

- **Set threshold in probability map for initialization of Level Set**

$$\phi_0 = \begin{cases} -C, & x \in \{x|p > threshold\} \\ 0, & x \in \{x|p = threshold\} \\ C, & x \in \{x|p < threshold\} \end{cases}$$

- **Use traditional Level Set method LSD to get final segmentation**



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Experiments

Datasets

- collected from Department of Nuclear Medicine, Shanghai Renji Hospital
- cGAN: 168 pairs for training, 56 pairs for testing
- MIL: 39 positive bags and 33 negative bags, 18947 instances in total

Parameters

- size of patch: 4×4
- threshold for initialization of level set: 0.6

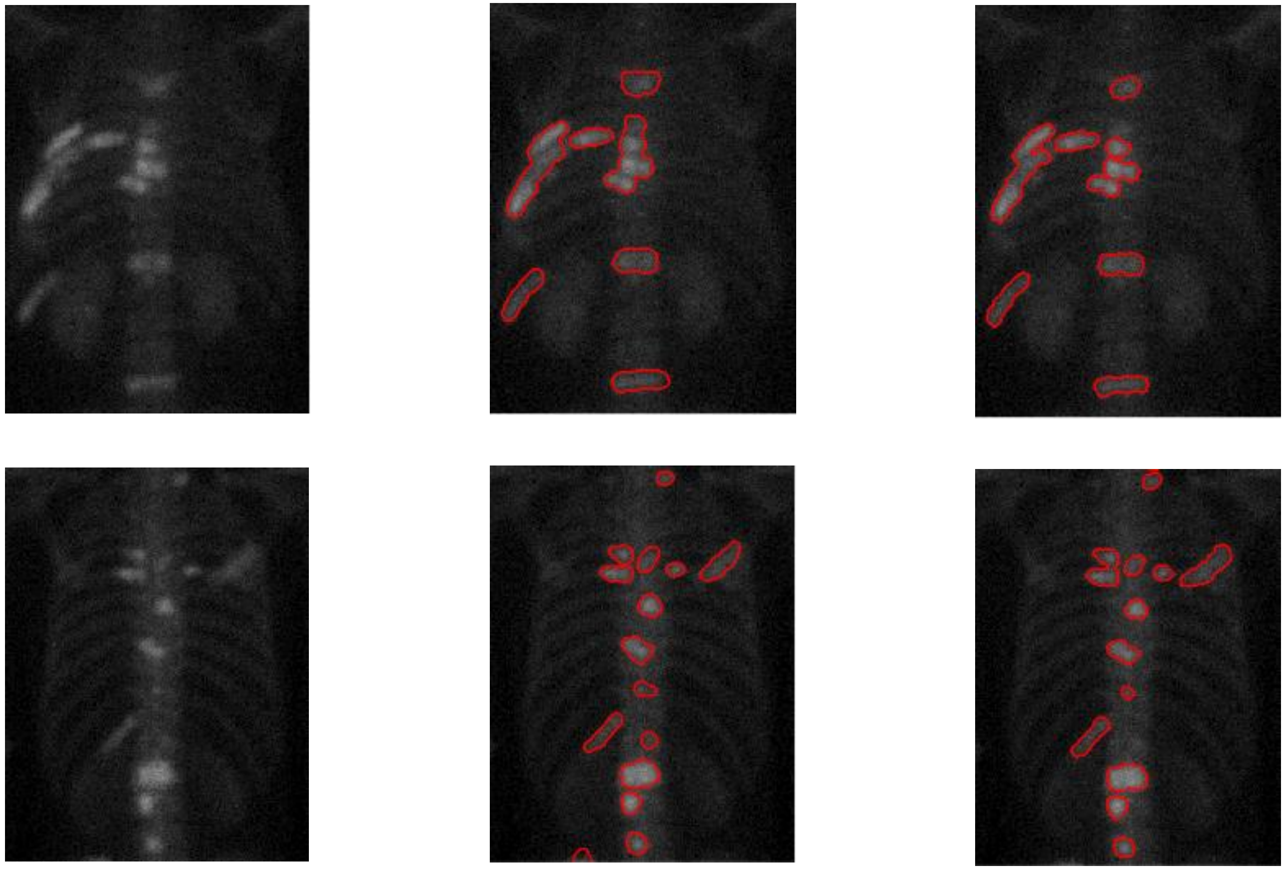
Quantitative Evaluation

Method	Jacc	Dice
RG	0.5853	0.6935
TnR	0.3729	0.5049
LSD	0.5677	0.7029
MIL-29	0.6493	0.7717
Our method	0.7253	0.8319

- **Equipped with proposed framework, performance of Jaccard and Dice index improved by 7.60% and 6.02%**

Experiment

- **Samples**

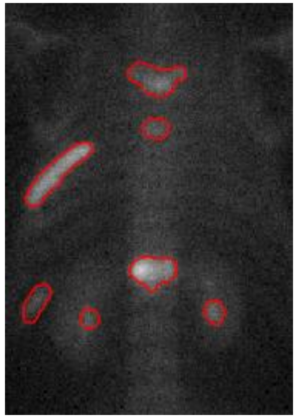


original image   ground truth   segmentation

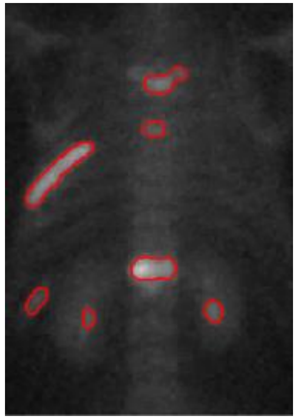
Experiment

- **Comparison**

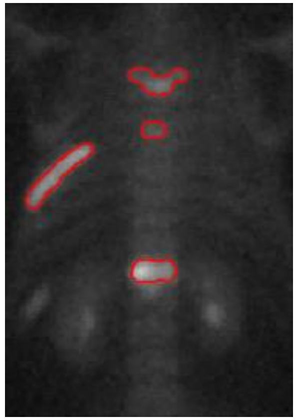
original image



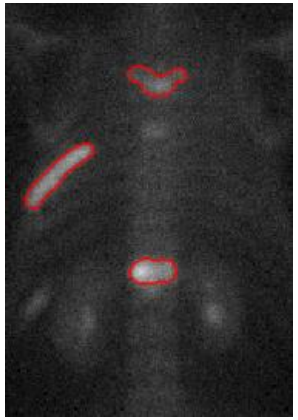
ground truth



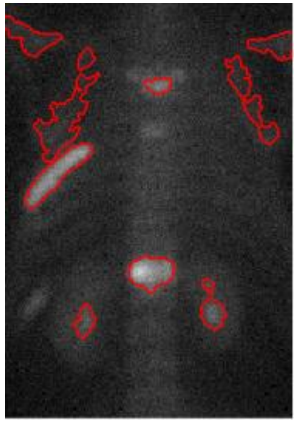
our method



MIL-29



LSD



TnR

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Conclusion

- **Propose an effective framework for hotspot segmentation**
- **Combining cGAN with MIL**
  - **use cGAN to train a generator to obtain separated images**
  - **take into consideraion features of location, texture and contrast**
  - **utilize MIL to train a patch-level classifier, in order to get probability map**
  - **implement final segmentation by Level Set**
- **Outperform other state-of-art methods in experiments**

Thanks