On Efficient Extraction of Pelvis Region from CT Data

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Introduction

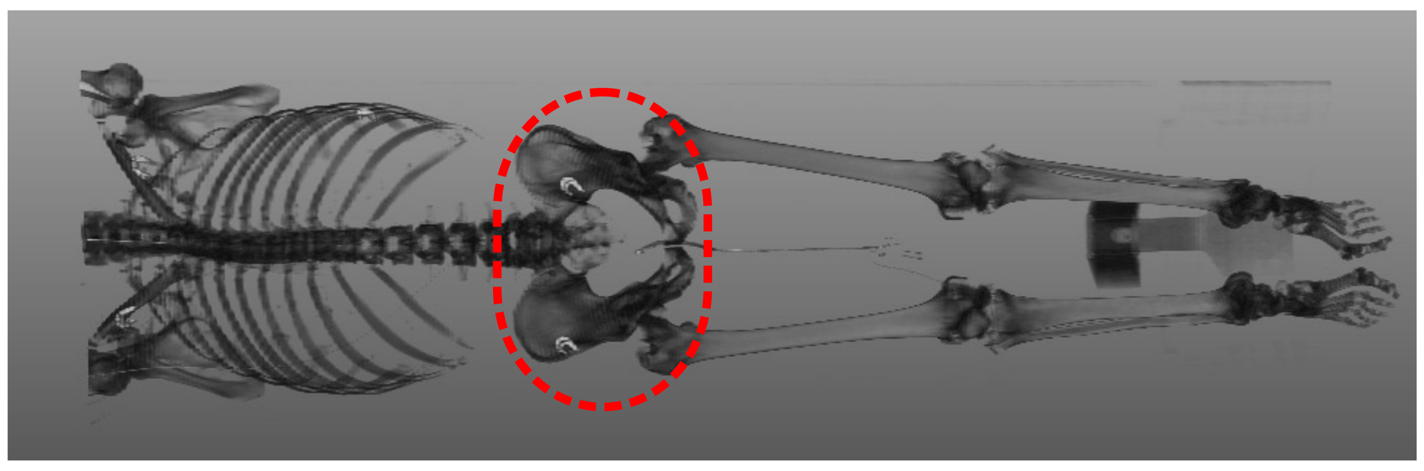
- Body part recognition is the first step in automated analysis of medical volumetric data.
- Goal: detection of slices, where specific body parts are located.
- Main Deep Learning approaches:
  - Supervised Classifier [1]
  - Unsupervised Body Part Regressor (UBR) [2]

Objective

- **Comparison of two body part recognition methods on limited data**
- Extraction of a single region (pelvis) from CT data

Data

- 93 whole-body CT datasets [3] without fractures of pelvis;
- Annotations of pelvis by an experienced observer;
- Spatial resolution: 512×512; with slice thickness of 5 mm;
- Number of slices varied for each patient; average slice number: 236 ± 56;
- Pelvis occupies on average of 43 ± 2.2 slices.



Methods

1. **Minibatch**
   - Classifier: Randomly selected volume, randomly selected 2D slices;
   - UBR: Randomly selected volume, equidistant 2D slices;
2. **Architecture**
   - Classifier: ImageNet pre-trained CNN (VGG Family [4]); the last layer for binary classification;
   - UBR: Classifier: ImageNet pre-trained CNN (VGG Family [4], 5 layers); Global average pooling and a fully connected layer for regression output;
3. **Output**
   - Classifier: Probability that the slice belongs to pelvis;
   - UBR: a score indicating position of the slice in the body.

Training and Testing

- Validation: 9 patients; Test: 10 patients
- Training: 74 patients
- Classifier:
  - Slices resized to 224×224;
  - Intensities clipped $[0, 3000]$ to remove high intensity artifacts
  - Intensities scaled to $[0, 1]$;
  - ImageNet normalization;
  - Standard augmentation: scaling, rotation, horizontal and vertical flips;
- UBR
  - Slices resized to 64×64;
  - Image intensities in Hounsfield units clipped to $[-300, 300]$;
  - Intensities scaled to a range of $[0, 1]$;
  - Augmentation: translation in four directions;
  - A histogram-based method for converting scores to region boundaries.

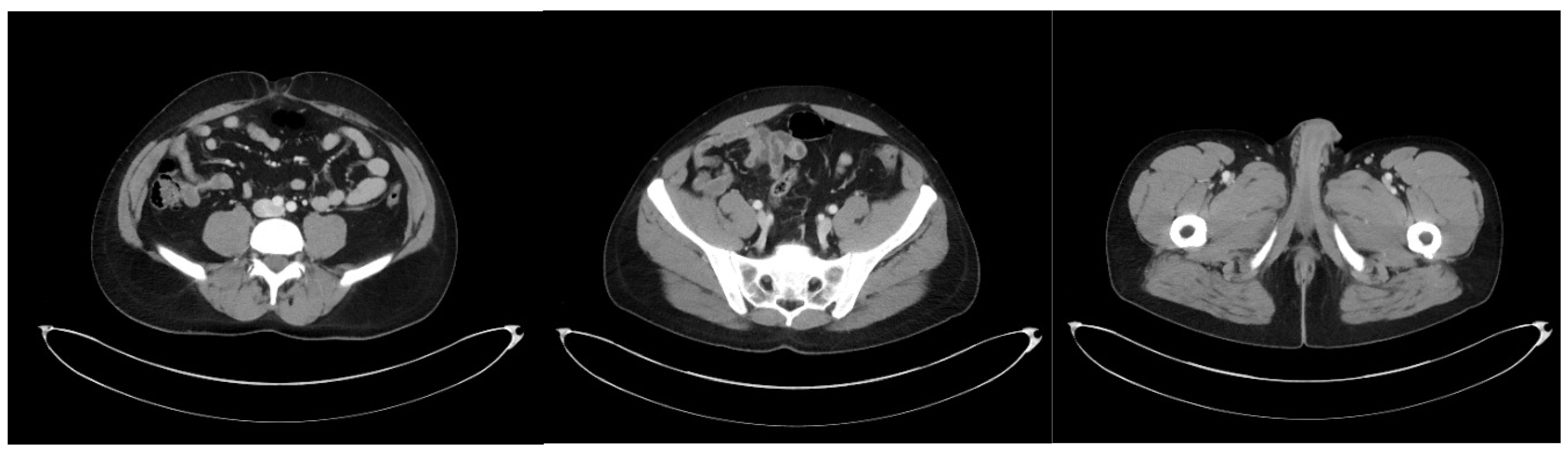
Results

- Classifier: highly accurate results
  - On Test and Val sets: not more than two errors per patient
  - Usually misclassifications lie in the starts and ends of pelvis regions
  - 2D classifier can produce *disjoint regions*, return *FP in other body parts*!
- UBR: on the current amount of data only roughly identifies Pelvis region
  - But always returns *one region* by definition!

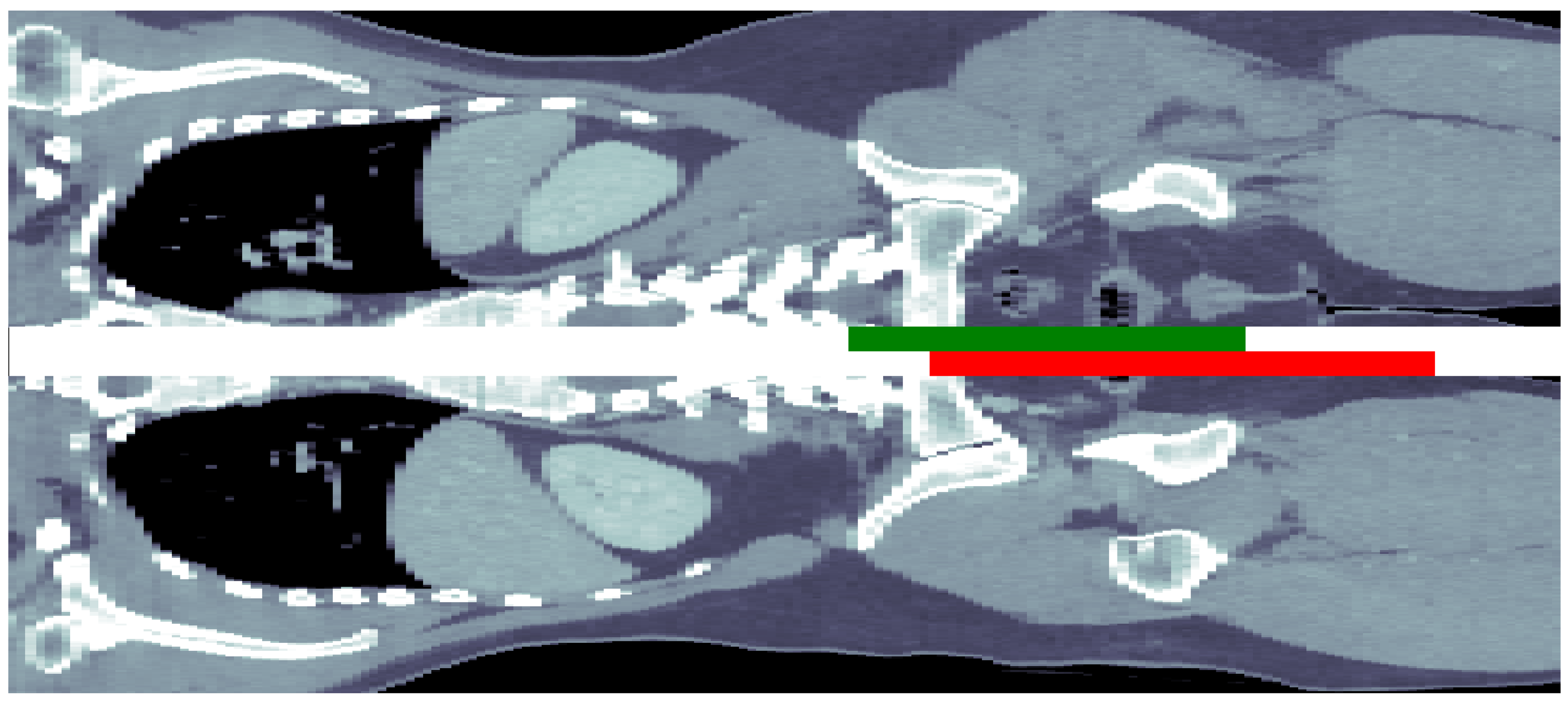
	UBR validation set	UBR test set	VGG validation set	VGG test set
TP	36 ± 6.4	34 ± 4.9	42.6 ± 3.1	43.4 ± 1.8
FP	7.2 ± 5.8	4.8 ± 7.1	0.7 ± 0.9	0.3 ± 0.5
TN	174 ± 57	174 ± 44.5	187 ± 57.4	179 ± 41
FN	7.6 ± 6	9.8 ± 4.8	0.2 ± 0.4	0.3 ± 0.5
A	0.93 ± 0.05	0.93 ± 0.05	0.99 ± 0.02	0.99 ± 0.01
P	0.84 ± 0.1	0.9 ± 0.1	0.98 ± 0.02	0.99 ± 0.01
R	0.83 ± 0.1	0.78 ± 0.1	0.99 ± 0.01	0.99 ± 0.01
F1	0.83 ± 0.1	0.82 ± 0.08	0.99 ± 0.01	0.99 ± 0.08

Examples

- Classifier results
  - Left: FP in the beginning of pelvis,
  - Middle: TP in the middle of pelvis,
  - Right: FN in the end of pelvis



- UBR results
  - Green: user annotations
  - Red: automatic detection
  - Pelvis regions is roughly detected.



Summary and Future Work

- Compared two deep learning approaches for body part detection;
- Results for labeling of pelvic bones;
- High accuracy even on relatively small dataset;
- Hence: Larger dataset and combination of the two approaches will presumably lead to efficient and reliable reduction of CT data for analysis of pelvis.

Future Work:

- Combination of the two approaches (verification of classification results with UBR).

References

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[3] Bryant Furlow. Whole-body computed tomography trauma imaging. *Radiol Technol*, 89(2): 159CT–180CT, 2017.

[4] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

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