Coarse Annotation Refinement for Segmentation of Dot-Matrix Batchcodes

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Agenda

- Objectives
- Related Works
- Proposed Method
- Experiments
- Conclusion

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- Batchcode segmentation - retrieve black dot matrix from images
- Challenges:
    - High variation of size, shape and orientation
    - Object features are tiny discrete dots - easily removed by morphological opening-closing
    - Noise around the batchcode shares similar low level features
    - Other text-like (noisy) features on the background
    - Accurate annotation is very expensive

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Related Works

- Applications:
  - Scene Text Detection
  - Barcode Detection
- Methods:
  - Maximally Stable Extremal Regions (MSER): returns all the subregions with consistent pixel intensity
  - Deep Object Detection Models: anchor-based region proposal networks for multi-class object localisation
  - Semantic Segmentation Networks

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Proposed Method

- Colour Space Transform: remove background noise by colour (contrast).
- Maximise Global Stability: Gradually reduce threshold until the region area is stabilised.

Algorithm 1 MSGR

procedure COLOUR SPACE TRANSFORM

$I_{HED}(x, y, c) \leftarrow f_{HED}(I(x, y, c))$

$t \leftarrow f_{Otsu}(I_{HED}(x, y, 1))$

procedure MAXIMISE GLOBAL STABILITY

$a_0 \leftarrow \infty$

for $\lambda \in \{1, 1-\delta, 1-2\delta, ..., 0.5\}$ **do**

$I_B(x, y) \leftarrow I_{HED}(x, y, 1) > \lambda t$

$a \leftarrow f_{dim}(I_B(x, y))$

if $a - a_0 < 2$ **then**

break

else

$a_0 \leftarrow a$

return $I_B(x, y)$

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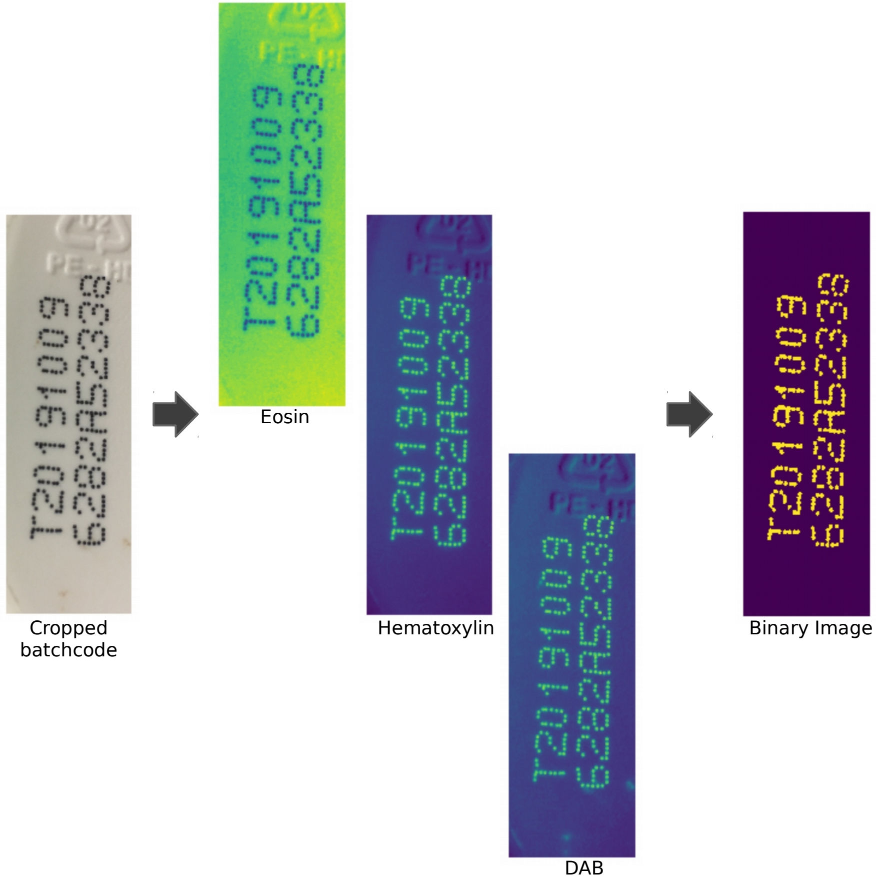

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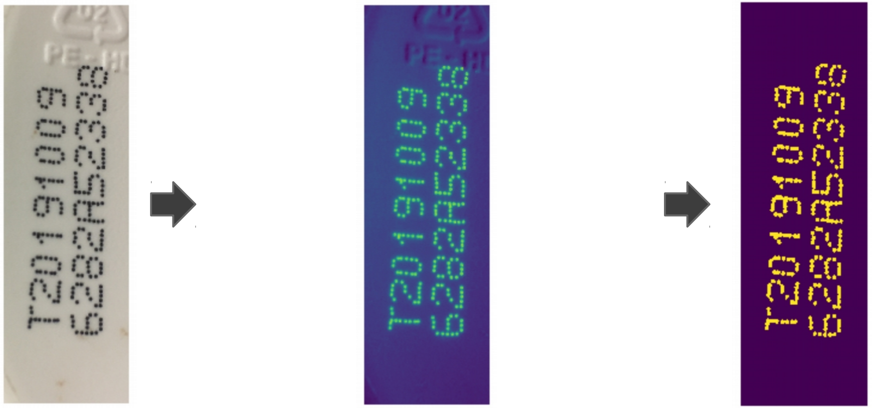

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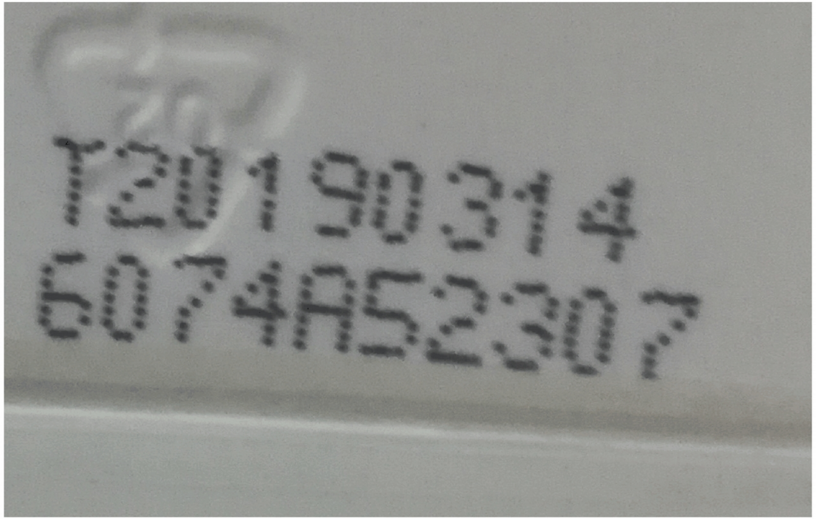
cropped image



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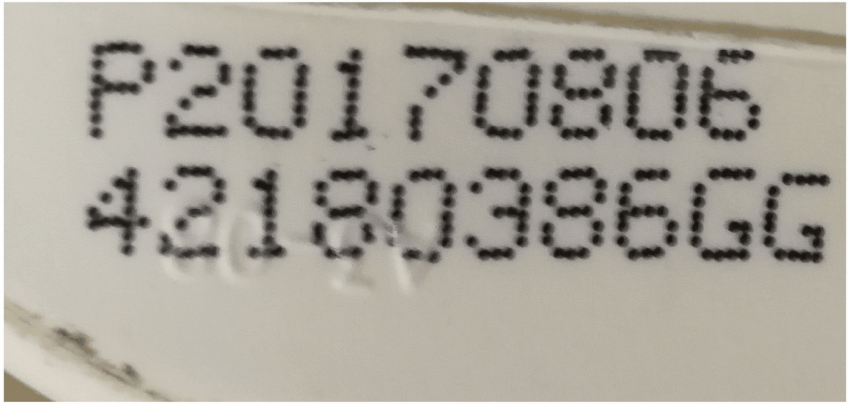
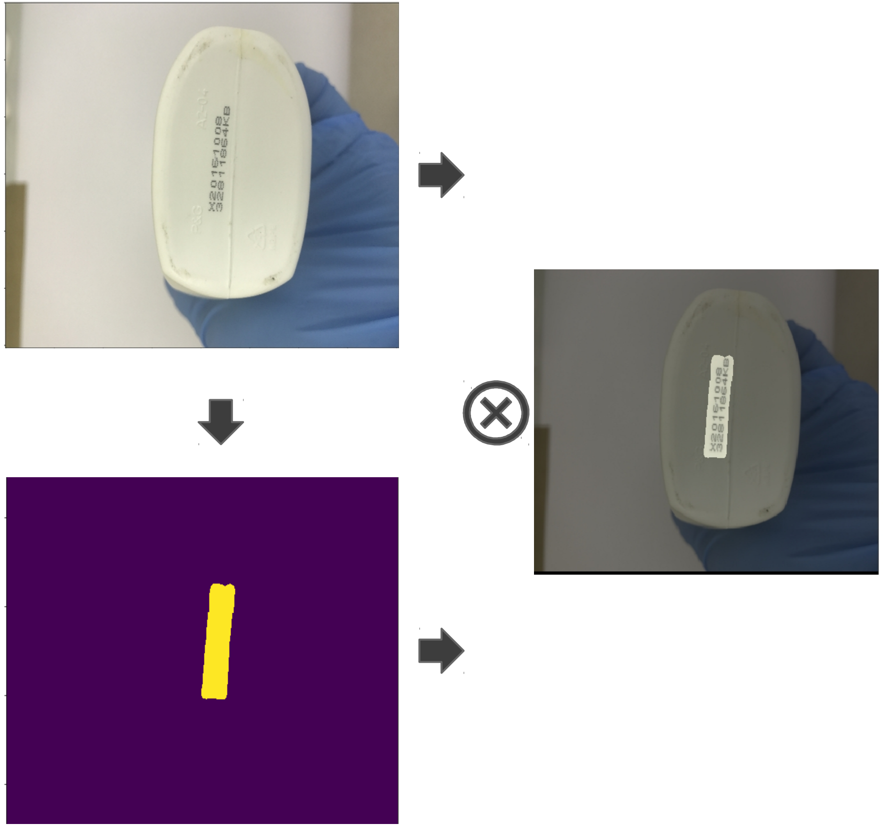


Deep Segmentation Model

- Trained with MSGR refined labels
- Output binary mask that highlight the batchcode region, tightly fit to the batchcode regions
- The results can be further optimised by MSGR



Experiments

- Deep models trained with refined labels outperforms those trained with coarse labels
- MSGR can further improve the prediction accuracy

Model	*p*(%)	*r*(%)	*j*(%)	fps
Result1 (Trained with Coarse Labels)				
FCN	41.26	98.50	40.71	≈12
DeepLabV3	38.96	99.87	38.88	≈9
U-Net	38.77	99.44	38.23	≈23
PSPNet	66.69	61.33	42.51	≈10
Result2 (Coarse Labels + MSGR)				
FCN	86.90	93.91	84.16	≈3.5
DeepLabV3	83.87	97.43	82.11	≈3
U-Net	75.48	95.93	73.56	≈4.5
PSPNet	81.36	58.56	56.24	≈3
Result3 (Trained with Refined Labels)				
FCN	93.29	97.08	90.53	≈12
DeepLabV3	92.22	98.49	**91.04**	≈9
U-Net	92.54	94.86	88.25	≈**23**
PSPNet	91.06	77.84	72.94	≈10
Result4 (Refined Labels + MSGR)				
FCN	95.41	95.63	**91.75**	≈3.5
DeepLabV3	93.83	95.56	91.63	≈3
U-Net	93.73	94.43	90.51	≈4.5
PSPNet	92.79	82.39	78.50	≈3

Questions and Suggestions:

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