Coarse Annotation Refinement for Segmentation of Dot-Matrix Batchcodes

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Presented by Phillip Adey
Agenda

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

- 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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● Batchcode segmentation - retrieve black dot matrix from images (accurately)

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  ○ Object features are tiny discrete dots - easily removed by morphological opening-closing
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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

1: procedure COLOUR SPACE TRANSFORM
2: \[ I_{HED}(x, y, c) \leftarrow f_{HED}(I(x, y, c)) \]
3: \[ t \leftarrow f_{Otsu}(I_{HED}(x, y, 1)) \]
4: procedure MAXIMISE GLOBAL STABILITY
5: \[ a_0 \leftarrow \infty \]
6: for \( \lambda \in \{1, 1 - \delta, 1 - 2\delta, \ldots, 0.5\} \) do
7: \[ I_B(x, y) \leftarrow I_{HED}(x, y, 1) > \lambda t \]
8: \[ a \leftarrow f_{dim}(I_B(x, y)) \]
9: if \( a - a_0 < 2 \) then
10: break
11: else
12: \[ a_0 \leftarrow a \]
13: return \( I_B(x, y) \)
Proposed Method

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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.

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<tr>
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Questions and Suggestions:

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