Evaluating Crowd Density Estimators via Their Uncertainty Bounds
Jennifer Vandoni, Emanuel Aldea, Sylvie Le Hégarat-Mascle
SATIE - CNRS UMR 8029, Paris-Sud University, Paris-Saclay University
{jennifer.vandoni, emanuel.aldea, sylvie.le-hegarat}@u-psud.fr

Context and Objectives
Context:
• Crowd density estimation is a challenging problem due to phenomena such as strong occlusion and visual homogeneity
• Recent deep methods are mostly based on the estimation of a density map whose integral over the region provides the number of people within it
• The estimator evaluation is performed at image scale: compensation between overestimating and underestimating the density in different areas
• Absence of an uncertainty range provided along with the scalar density
Objective:
• We use the Belief Function Theory in order to provide uncertainty bounds to different categories of crowd density estimators.
• Our method allows us to:
  – Compare the multi-scale performance of the estimators
  – Characterize their reliability for crowd monitoring applications requiring varying degrees of prudence

EVIDENTIAL CNN-ENSEMBLE
FE+LFE network:
• Fully convolutional encoder-decoder structure
• Front End (FE) module with increasing dilation factors to consider larger context around small objects
• Local Feature Extractor (LFE) module with decreasing dilation factors to enforce the spatial consistency of the output [Ham+18]
• BatchNorm + ReLU activation functions
• ReLU after the last layer: zero-threshold effect with beneficial effects on backpropagation

Modeling imprecision with BFT:
Belief Function Theory (BFT):
• Basic Belief Assignment (BBA): function \( m \)
• Larger hypotheses set: \( T \)
• We associate a BBA map to every realization \( S \)
• Pixel-wise tailored discounting of each BBA on the basis of its reliability: \( M \)

∀ \( T \)
• We derive the discounted BBA maps for every source \( T \)
• We use the Belief Function Theory in order to provide uncertainty bounds to different categories of crowd density estimators.

Multiscale evaluation strategy:
For each considered scale \( S \) we compute indicators based on all squared subdomains \( S \in \mathcal{S}_S \) by using the derived upper and lower density bounds \( \underline{s}(S), \overline{s}(S) \):

\[
\underline{s}(S) = \min_{x \in S} \overline{BBA}(x) \quad \text{and} \quad \overline{s}(S) = \max_{x \in S} \overline{BBA}(x)
\]

• Prediction Error Probability (PEP):

\[
\text{PEP} = \left| \{ S \in \mathcal{S} \mid \underline{s}(S) \notin [\underline{s}(S), \overline{s}(S)] \} \right| / \left| \mathcal{S} \right|
\]

• Relative Imprecision (RI) interval:

\[
\text{RI} = \left( \overline{s}(S) - \underline{s}(S) \right) / \overline{s}(S)
\]

where \( \overline{s}(S) \) is the ground-truth count over \( S \)

EXPERIMENTS AND RESULTS
Proposed evaluation method for density estimators:

Comparison of different density estimators:
• CNN-ensemble derived using MC-dropout with \( T = 10 \)
• Comparison of the proposed FE+LFE network with respect to:
  – A different network (U-Net)
  – The same network trained on less data
  – A completely different classifier (SVM-ensemble built iteratively by training SVMs with different descriptors through active learning [VAL19])

DENSITY UNCERTAINTY FOR BOUNCING PEDESTRIAN COUNT
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CONCLUSION
We proposed a strategy for associating an uncertainty interval to crowd density estimation using BFT
We proposed a new evaluation method taking into account the output uncertainty at multiple scales
Our work opens a promising avenue for crowd safety applications which account for estimation uncertainty during planning and monitoring

REFERENCES