High Entropy Ensembles for Holistic Figure-ground Segmentation

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1. Problem

- To build an ensemble of algorithms to solve figure-ground segmentation problems
- To combine any kind of algorithms which comply with a simple interface
- To find a strategy to build ensembles that rely on interactions between components rather than on rejection rules

Different algorithms commit different errors, so we expect that enhancing algorithms interactions may help compensate each one errors.

2. Solution

- The algorithms interact in a tree structure
- The creation of this structure is driven by the maximization of a goodness measure
- Instead of looking for optimal combinations, we randomly select most of the parameters, this speeds up the building phase and avoid getting stuck in local minima
- The building phase is an iterative procedure
- Just by using simple algorithms we obtain state-of-the-art results.

3. Method

Components of the ensemble:

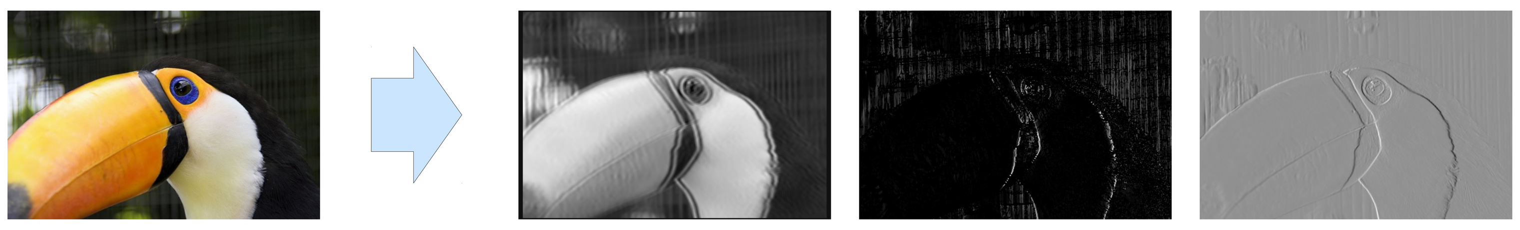
Figure-ground Segmentation Algorithms
- perform a segmentation of the input image
- constitute the nodes of the tree structure

Interface
- **IN**: a set of feature patterns or segmentation maps
- **OUT**: a segmetnation map, that is an image that assigns to each pixel a foreground probability

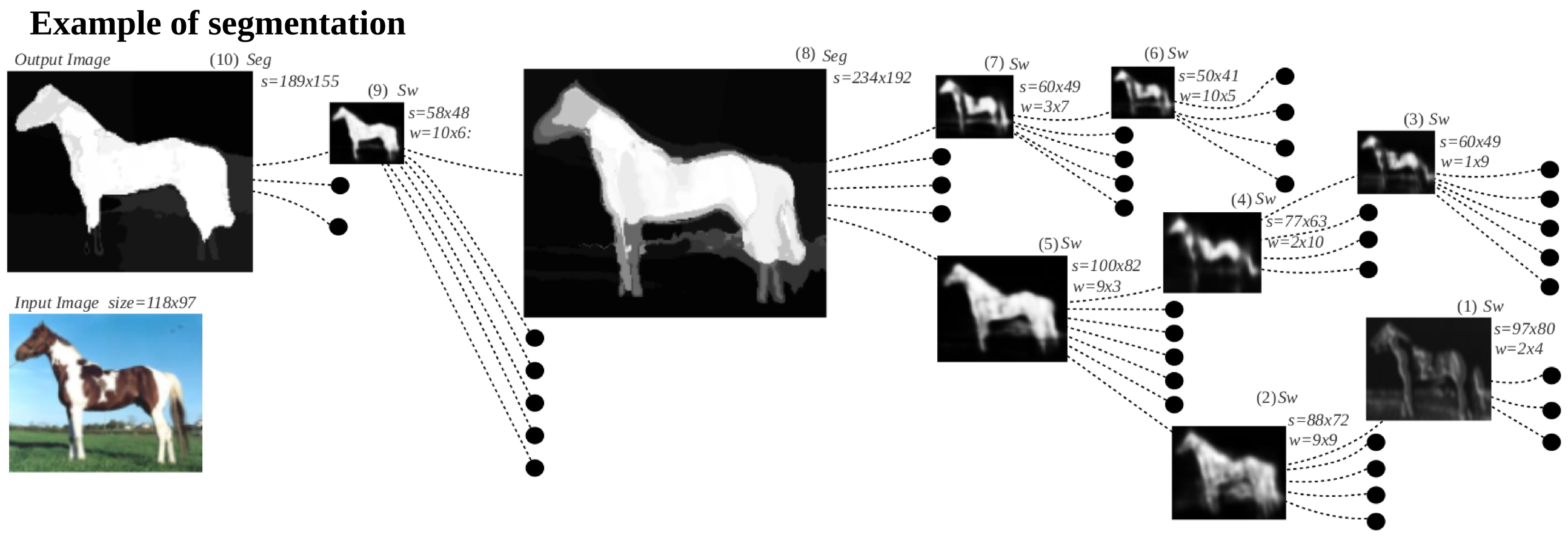
Feature Extractors
- extract specific feature patterns from the input image

Interface
- **IN**: the original image
- **OUT**: a feature pattern

Visualization of extracted features



Example of segmentation



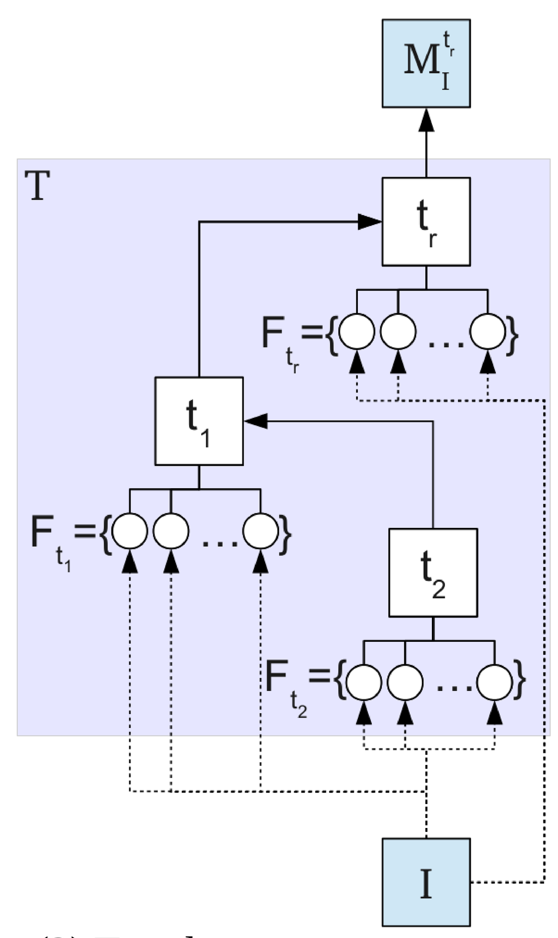
Building phase:

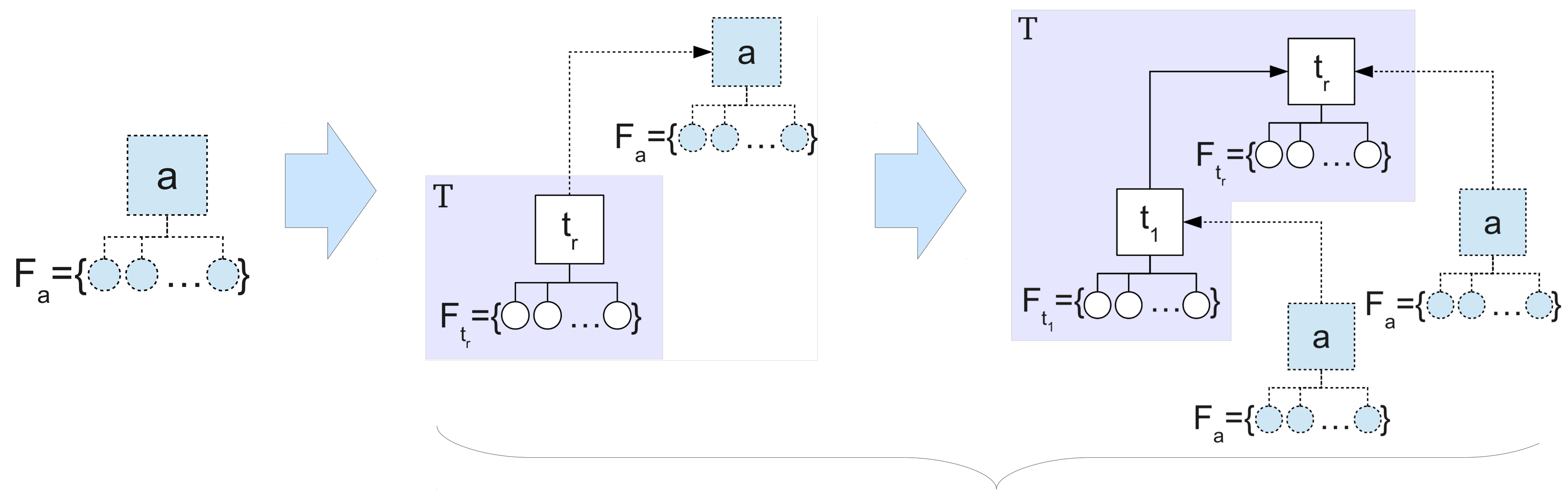
It combines the algorithms and the feature extractors in an ensemble

INPUT: Set of algorithms and feature learners, a figure-ground segmentation dataset

OUPUT: Ensemble of algorithms T

perform base step;
Do
  perform bottom-up step;
  perform top-down step;
  compute G on the dataset;
While (at least one *node is added to T*)

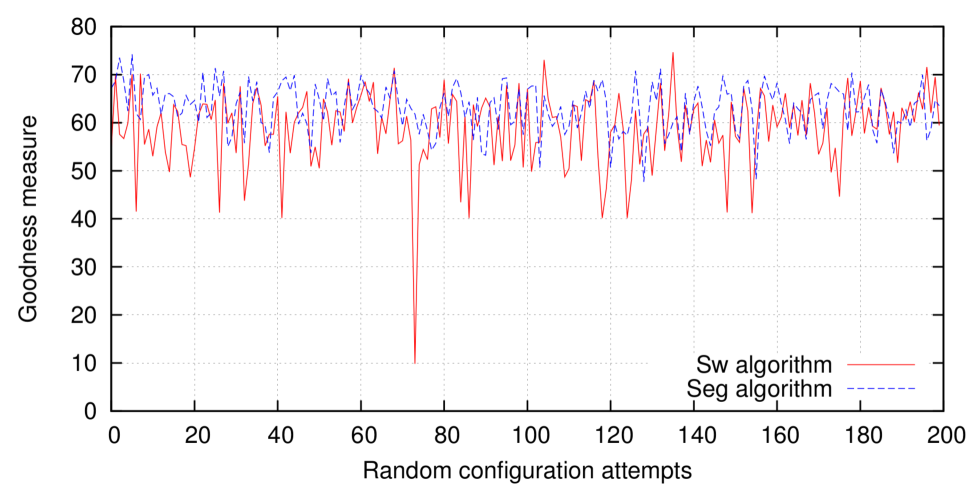




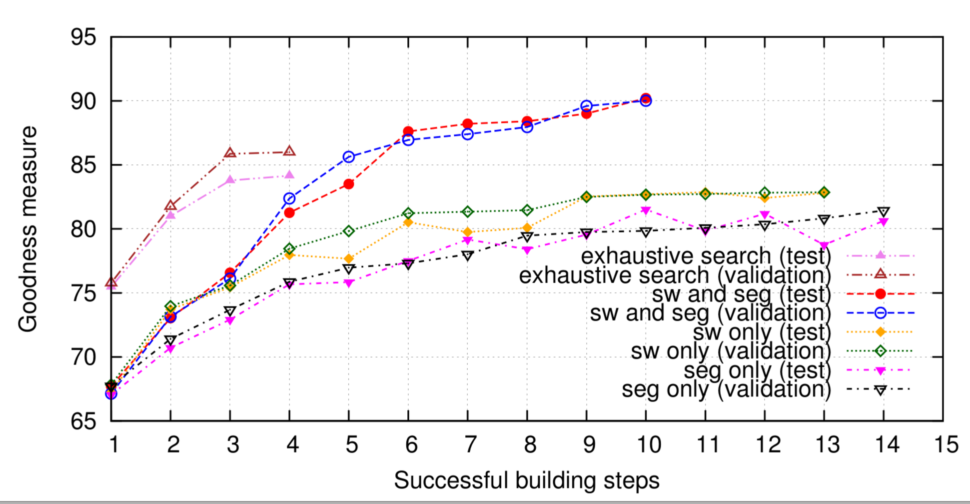
4. Results

In the experiments we use two simple figure-ground segmentation algorithms:
- *Sw* uses sliding windows
- *Seg* classifies partitions of the image

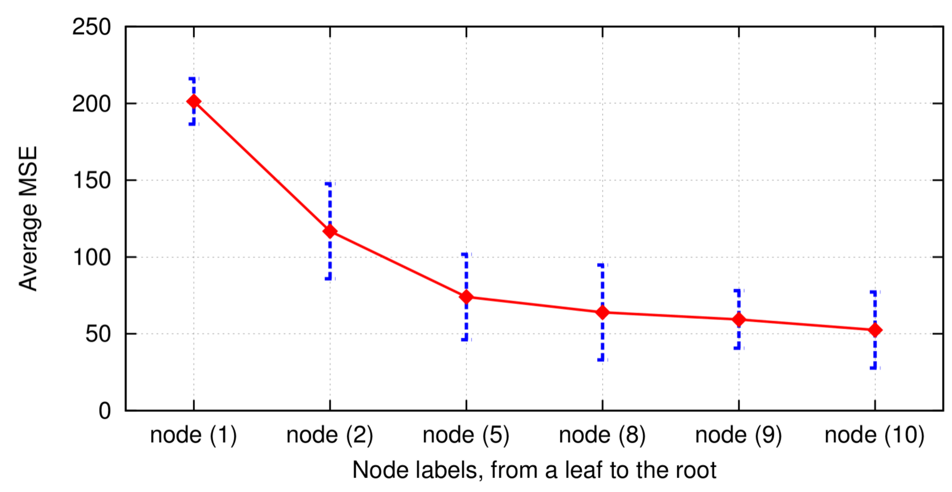
When used alone they achieve poor results



When combined using our algorithm, the performance increases:
- by increasing the size of the ensemble
- by increasing the number of algorithms that are combined



We prove that the information produced by a node is effectively exploited by its parent in order to increase the quality of the segmentation: average *mse* and its standard deviation tend to decrease as we get close to the root node



In order to prove that the tree structure works better than a linear cascade, we modified the building phase to produce a degenerate tree LHEE (without rejection rules)

We tested our strategy to build ensembles of algorithms against other frameworks using the same set of algorithms:
- AdaBoost
- Cascade of Boosted ensembles
- Cascaded Classification Models (2-CCM, 5-CCM)
- Bayesian Averaging

Weizmann Horses

Method	S_a (%)	S_o (%)
Küttel et al.	94.7	/
Bertelli et al.	94.6	80.1
Seyedhosseini et al.	95.4	/
AdaBoost	90.0	72.9
CCM	89.3	79.6
Bayesian Averaging	77.1	58.9
CoBE	90.8	76.0
LHEE	87.1	72.5
HEE	**98.2**	**90.2**

Oxford Flower 17

Method	S_a (%)	S_o (%)
Nilsback et al.	/	94.0
Bertelli et al.	97.7	92.3
Chai et al.	/	90.4
AdaBoost	93.1	85.5
CCM	86.3	84.5
Bayesian Averaging	87.3	81.0
CoBE	95,8	90,6
LHEE	89,6	87,6
HEE	**98.1**	**96.1**

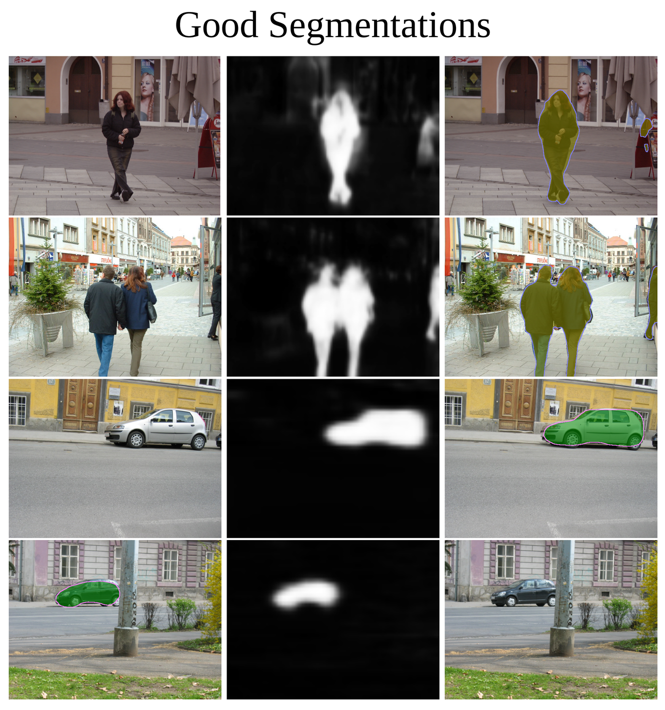
INRIA Graz-02

Method	cars	people	bikes	avg.
Marszałek et al.	53.8	44.1	61.8	53.2
Küttel et al.	74.8	66.4	63.2	68.1
Fulkerson et al.	72.2	66.3	72.2	70.2
AdaBoost	60.1	48.6	63.0	57.2
CCM	62.6	55.9	72.8	64.4
Bayesian Averaging	55.4	53.4	65.3	56.0
CoBE	75.4	67.0	73.8	72.1
LHEE	66,7	54,9	72,1	64.6
HEE	**82.4**	**67.9**	**78.2**	**76.2**

VOC 2010

Method	IoU %
Küttel et al.	48
Carreira et al.	34
Rosenfeld et al.	46
HEE	**56**

Good Segmentations



Bad Segmentations

BMVC 2014: British Machine Vision Conference - Nottingham, UK. September 1-5