Prior knowledge in an end-user trainable machine vision framework

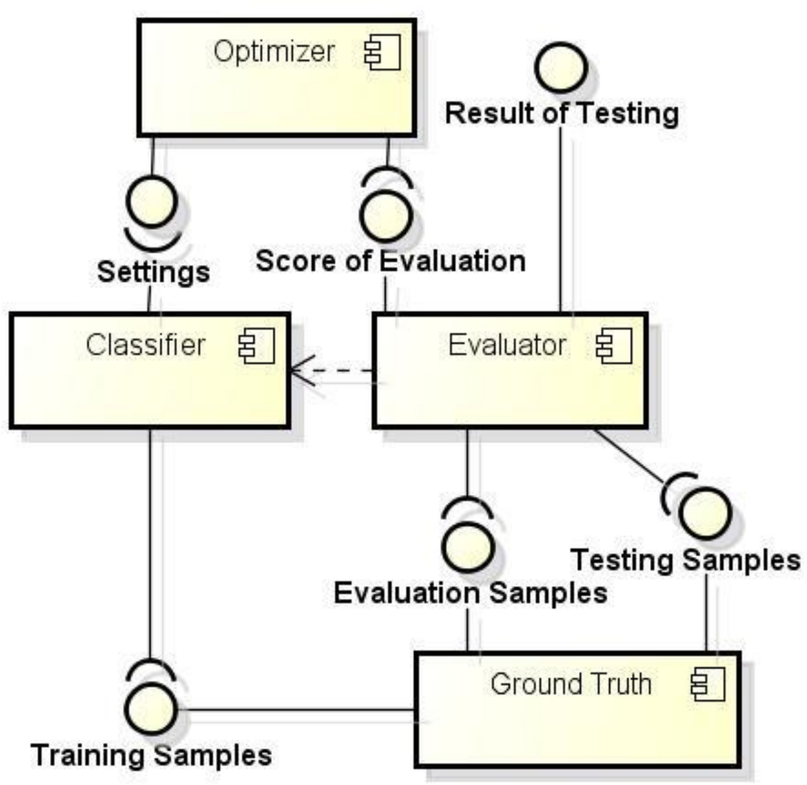
K. Dijkstra[1], J. van de Loosdrecht[1] and W. J. Jansen[1]

1) NHL University of Applied Sciences, Center of Expertise Computer Vision, Leeuwarden

Objectives

The increasing popularity of machine vision based solutions in common applications calls for a structured approach for incorporating the end user's domain knowledge and limiting the solution's dependency on expert knowledge. We propose a framework facilitating optimized classification results and will show several approaches in which prior knowledge on the solution is captured in a neural network or in a geometric pattern matcher. The methodology is applied to disc print reading for antibiotic susceptibility testing by disc diffusion. End-user trainability is maximized when the domain expert can configure the disc print classifier with minimal technological knowledge, and the technology expert can specify the system with minimal domain knowledge.

Methods



2) Limit prior technical knowledge

1) Limit prior domain knowledge by choosing a more general classifier.

2) Limit prior technical knowledge by optimizing using a reinforcement algorithm and evaluate with a ground-truth.

3) Compensate for lack of prior knowledge by searching the solution space more thoroughly.

1) Limit prior domain knowledge

3) Increase thoroughness

Blob Matcher [1]	Multilayer Perceptron [2]
Manual	*Manual*
Genetic Algorithm [3]	*Genetic Algorithm*
Single Parameter Exhaustive Search + Genetic Algorithm	*Genetic Algorithm + higher population size, more generations and three fold cross validation*

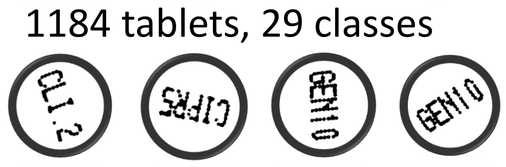
Results

Application: Antibiotic Susceptibility Testing by Disc diffusion. Used to determine Susceptibility of a bacteria to certain antibiotics. [4]

Task: End-user trainable automated disc print reading.

Oxoid
6520 disc, 37 classes

Rosco
1184 tablets, 29 classes



Mixed
390 discs/tablets, 36 classes

Blob Matcher (BM)

Optimization	Manual		
Dataset	*Rosco*	*Oxoid*	*Mixed*
True Positives (0 FP)	**93.8 %**	**96.0 %**	**87.2 %**
Speed	**84.5 ms**	**56.2 ms**	**74.7 ms**
Optimization	**Genetic Algorithm**		
True Positives (0 FP)	**97.9 %**	**99.0 %**	**91.2 %**
Speed	**16.8 ms**	**13.7 ms**	**42.6 ms**
Optimization	**Single Parameter Exhaustive Search + Genetic Algorithm (SPESGA)**		
True Positives (0 FP)	**98.7 %**	**98.8 %**	**90.7 %**
Speed	**10.9 ms**	**5.3 ms**	**22.5 ms**

Multilayer Perceptron (MLP)

Optimization	Manual
Dataset	*Oxoid*
True Positives	**13.3 %**
False Positives	**0.01 %**
Optimization	**Genetic Algorithm**
True Positives	**25.8 %**
False Positives	**0.3 %**
Optimization	**Genetic Algorithm + (GA+)**
True Positives	***74.9 %***
False Positives	**1.6 %**

Conclusions

Classifiers with different levels of prior knowledge produced by this framework are configured automatically and directly from the ground-truth provided by an end-user.

The resulting classifiers are in general more accurate and faster than their manually configured counterparts. These facts show that end-user trainability is achieved using the proposed framework.

With MLP based classifiers a more thorough search through the solution space using GA+ shows increased accuracy. With BM based systems a more thorough search using SPESGA produces faster classifiers.

References

[1] J. van de Loosdrecht. Computer Vision course material. Available online at http://webserv.nhl.nl/ loosdrec/vision course/, 2013.
[2] S. Haykin. Neural Networks and Learning Machines. Pearson Education Inc., 2009.
[3] A. E. Eiben and J. E. Smith. Introduction to Evolutionary Computing. Springer, 2nd edition, 2007.
[4] European Committee on Antimicrobial Susceptibility Testing. http://www.eucast.org, 2013.

ESANN 2013

NHL RESEARCH AND BUSINESS