Face Recognition with Decision Tree-based Local Binary Patterns

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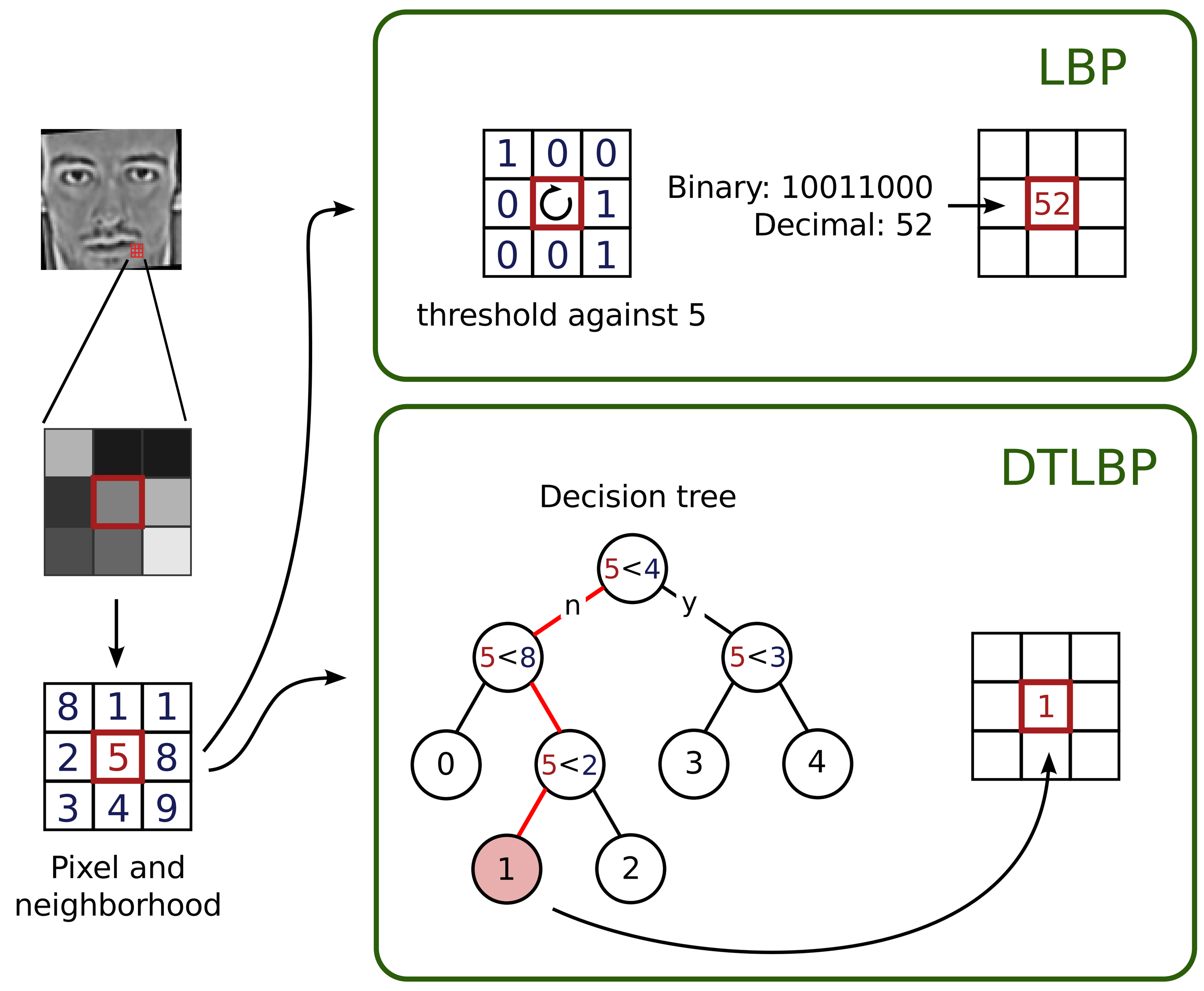
Introduction

Many state-of-the-art face recognition algorithms use image descriptors based on features known as Local Binary Patterns (LBPs) [1]. While many variations of LBP exist, so far none of them can automatically adapt to the training data. We introduce and analyze a novel generalization of LBP that learns the most discriminative LBP-like features for each facial region in a supervised manner. Since the proposed method is based on Decision Trees, we call it Decision Tree Local Binary Patterns or DTLBPs. Tests on standard face recognition datasets show the effectiveness of our approach.

Local Binary Patterns (LBP) and Decision Tree-based Local Binary Patterns (DTLBP)

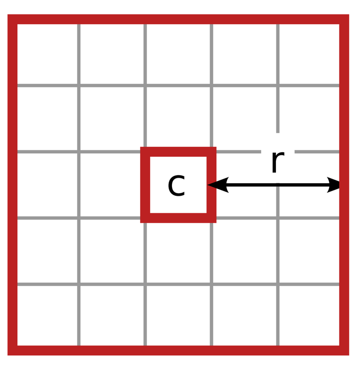
Both LBP and DTLBP act as nonlinear operators that assign a number to each pixel of an image based on the relationship of the pixel to its neighbors.



DTLBP includes LBP as a special case because LBP corresponds to a full tree with $\mathbf{2^n}$ leaf nodes, where $\boldsymbol{n}$ is the number of neighbors (8 in this example).

However, the tree used for DTLBP may be learnt from the data via standard tree induction algorithms such as Quinlan's ID3 [2], which we use in this work. ID3 uses *entropy gain* to decide which pixel comparisons are more informative, resulting in discriminative features. In a sense we are learning discriminative and adaptive quantizers of small neighborhoods.

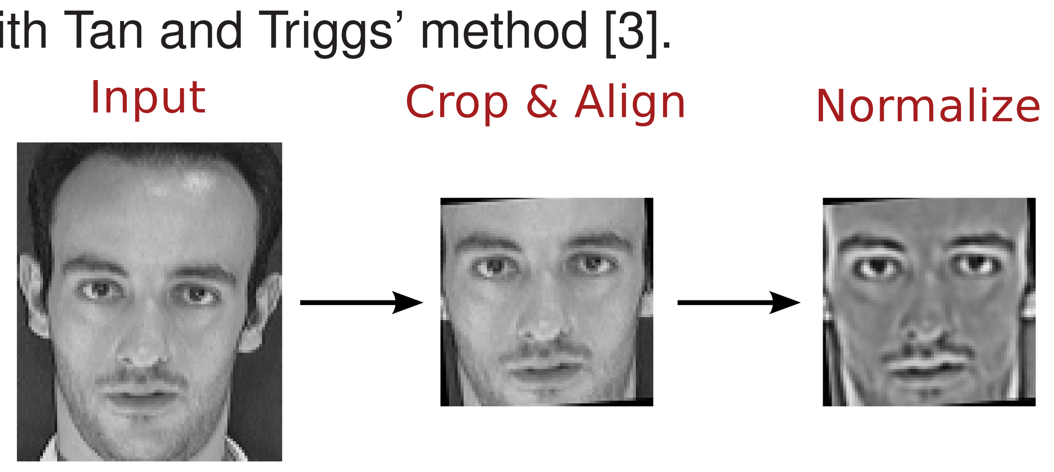
A key advantage of our method is the capability to explore larger neighborhoods than LBP. We define the neighborhood as a square region around the center pixel:



All pixels within this square are considered as potential split candidates. The idea is to let the tree construction algorithm find the most discriminative pixel comparisons.

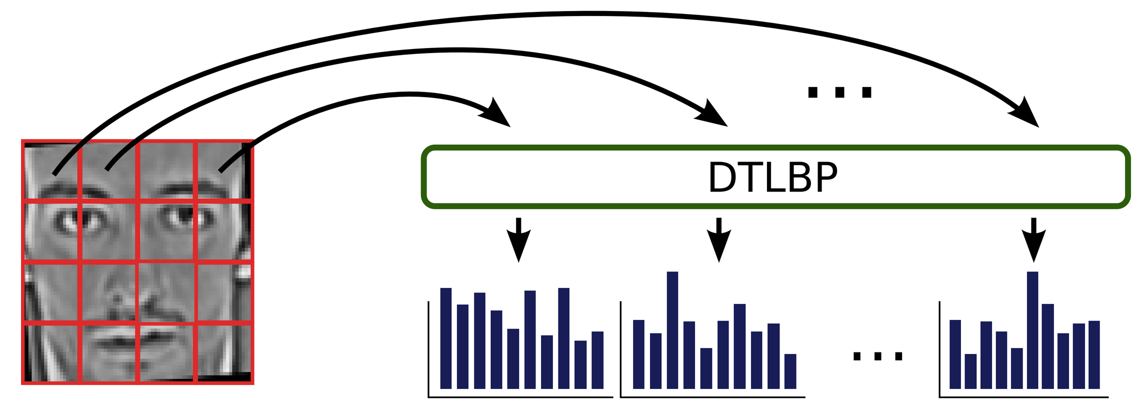
Face Recognition: Preprocessing

The faces are cropped and aligned by eye position. Then illumination is normalized with Tan and Triggs' method [3].



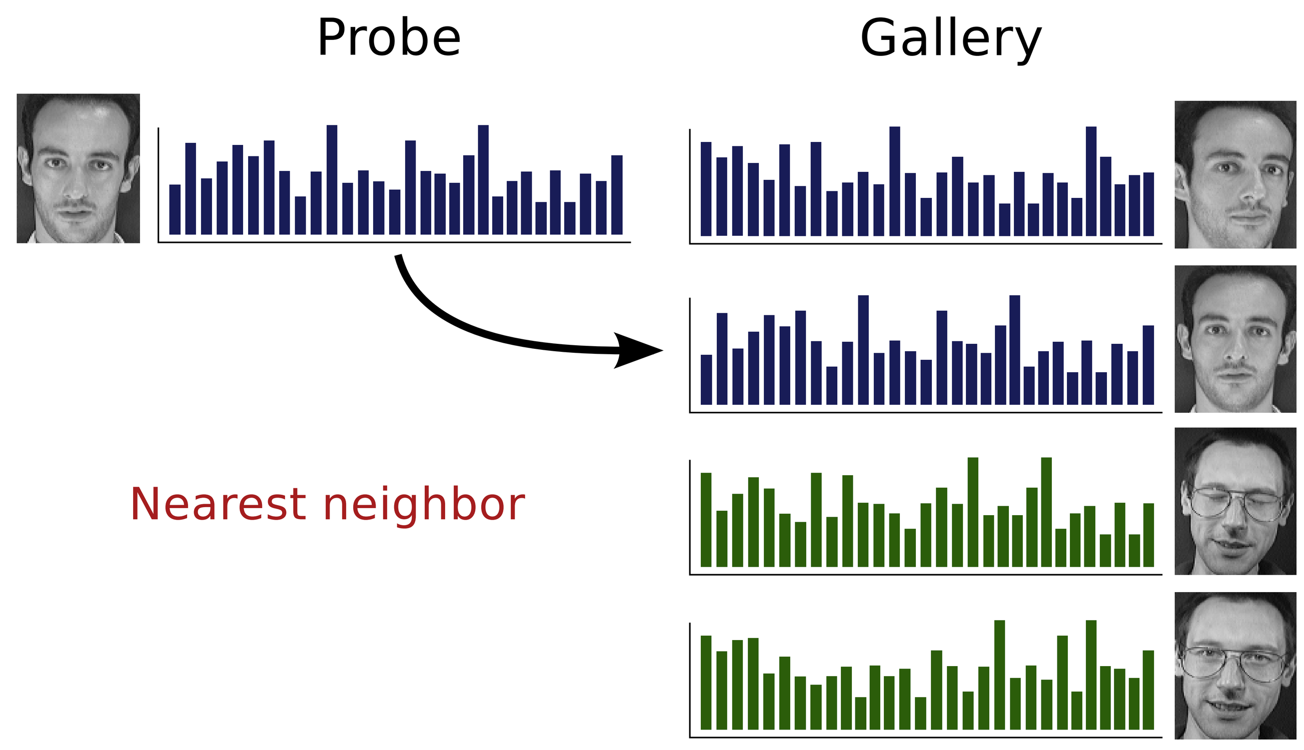
Face Recognition: Feature Extraction

We use Ahonen's methodology to recognize faces, but using DTLBP instead of LBP. We partition each face image into a grid and train a DTLBP for each cell. Then we summarize the DTLBP values in each grid cell with histograms, which are in turn concatenated into one large vector.



Face Recognition: Classification

Our task is *closed set face identification*: given a *gallery* of identified face images, assign an identity (from the gallery) to any give *probe* face image. To assign identity we use the Nearest Neighbor algorithm with the $\boldsymbol{L_1}$ distance metric.



Results

We perform experiments on the well known FERET and CAS-PEAL-R1 benchmark datasets. For each we use standard training, probe and gallery sets. For each experiment we show our results along with results from similar works in the recent face recognition literature (see paper for references).

Method	FERET				CAS-PEAL		
	fb	fc	dup1	dup2	Expr.	Acc.	Light.
LBP	0.93	0.51	0.61	0.50	-	-	-
LGBP	0.94	0.97	0.68	0.53	0.95	0.87	0.51
LVP	0.97	0.70	0.66	0.50	0.96	0.86	0.29
LGT	0.97	0.90	0.71	0.67	-	-	-
HGPP	0.98	0.99	0.78	0.76	0.96	**0.92**	**0.62**
LLGP	0.97	0.97	0.75	0.71	0.96	0.90	0.52
$DTLBP^7_8$, no TT	0.98	0.44	0.63	0.42	0.96	0.80	0.20
$DTLBP^7_{10}$, no TT	0.98	0.55	0.65	0.47	**0.99**	0.87	0.23
$DTLBP^7_{12}$, no TT	**0.99**	0.63	0.67	0.48	**0.99**	0.88	0.25
$DTLBP^7_8$	0.98	0.99	0.79	0.78	0.95	0.89	0.36
$DTLBP^7_{10}$	**0.99**	0.99	0.83	0.78	0.98	0.91	0.39
$DTLBP^7_{12}$	**0.99**	**1.00**	**0.84**	0.79	0.98	**0.92**	0.40
$DTLBP^7_{13}$	**0.99**	**1.00**	**0.84**	**0.80**	0.98	**0.92**	0.41

Accuracy on FERET and CAS-PEAL probe sets. $DTLBP^r_d$ corresponds to a tree of maximum depth $\boldsymbol{d}$ and radius $\boldsymbol{r}$. TT indicates Tan-Triggs normalization. Accuracies for algorithms other than DTLBP come from the respective papers.

Our algorithm obtains the best results on all datasets except for the CAS-PEAL lighting dataset, showing the advantages of an adaptive and discriminative approach. However, it seems DTLBP tends to overfit on datasets with intense illumination variation, specially when no normalization is used.

We are currently working on reducing the size of the resulting histograms without reducing their accuracy. We are also investigating how to improve the robustness of DTLBPs against intense illumination variation.

References

- Ahonen, T., Hadid, A., Pietikäinen, M.: Face description with local binary patterns: Application to face recognition. IEEE TPAMI (2006)
- Quinlan, J.R.: Induction of decision trees. Machine Learning (1986)
- Tan, X., Triggs, B.: Enhanced local texture feature sets for face recognition under difficult lighting conditions. IEEE TIP (2010)