

# Face Recognition using Local Quantized Patterns

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We propose a novel face representation based on Local Quantized Patterns (LQP) [3]. Our this new flexible representation not only outperforms any other representation on challenging face datasets but performs equally well in the intensity space and orientation space (obtained by applying gradient or Gabor Filters) and hence is intrinsically robust to illumination variations. Extensive experiments on two challenging face recognition datasets (FERET [4] and LFW [2]) show that this representation gives state-of-the-art performance (improving the earlier state-of-the-art by around 3%) without requiring neither a metric learning stage nor a costly labelled training dataset, having the comparison of two faces being made by simply computing the Cosine similarity between their LQP representations in a projected space.

**Contributions:** We introduce a complete framework (*c.f.* Figure 1) for face recognition that combines (i) a well designed local pattern descriptor with (ii) a simple PCA-based similarity metric to achieve state-of-the-art accuracy rates. Our presented method is not only very simple and efficient, but also has very good generalization capability: it outperforms any existing unsupervised method and many supervised methods on all the tested datasets.

**Local Quantized Patterns:** LQP [3] is a generalized form of local patterns (Local Binary Patterns (LBP) [1], Local Ternary Patterns (LTP) [5], *etc.*) that uses large local neighbourhoods and/or deeper quantization with domain-adaptive vector quantization to obtain highly discriminant representation. We tailor and use these LQP features for face representation. Precisely we use Disk LQP layout (*c.f.* Figure 2) to sample pixels from the local neighbourhood and use a tolerance value ( $\tau$ ) to generate a pair of binary codes (as in LTP) and quantize each one using a separately learned codebook. We propose two different types of Disk LQP features for face representations: (i) *I-LQP*: LQP features are computed on simple raw intensity images; (ii) *G-LQP*: LQP features are computed from Gabor filtered images obtained by convolving the image with multi-scale multi-orientation Gabor kernels – we use 40 different Gabor kernels that span 5 different scales and 8 different orientations over the range  $0$  to  $2\pi$ . Moreover in *G-LQP*, we concatenate the LQP computed codes from the neighbouring scales and orientations at the local pattern level. This helps to capture the patterns co-occurrence statistics over neighbouring scales and orientations and leads to a highly discriminant face descriptor.

**Matching Faces via Cosine Similarity Metric:** For comparing face images we use Cosine similarity in a reduced feature space. Precisely, we first use Principal Component Analysis (PCA) to project high dimensional LQP features to a low-dimensional uncorrelated space. Next, to reduce the influence of leading principal components and to have the projected features with same variance, we perform data sphering and divide all the principal components by square-roots of their corresponding eigenvalues. Finally, unlike conventional approaches (*e.g.* [1]) that use a distance-based similarity metric such as Euclidean, we use angle-based Cosine Similarity (CS) (*i.e.*  $CS(d_1, d_2) = (d_1^T \cdot d_2) / (||d_1|| ||d_2||)$ ) metric to compare faces in the normalized projected space. Although we also tested other metrics such as Pearson Correlation Coefficient which gave similar results, but Cosine similarity metric was preferred due to its fast computation time.

**Experiments:** We have experimentally validated our approach on two different face recognition tasks: i) *Face verification*, for this task we used the popular Labeled Faces in the Wild (LFW) dataset [2]; ii) *Face identification*, for this task we use the Face Recognition Technology (FERET) dataset [4]. Table 1 compares the performance of our methods with several competing supervised and unsupervised methods on FERET dataset. Table 2 reports comparative results<sup>1</sup> on LFW test set (View 2).

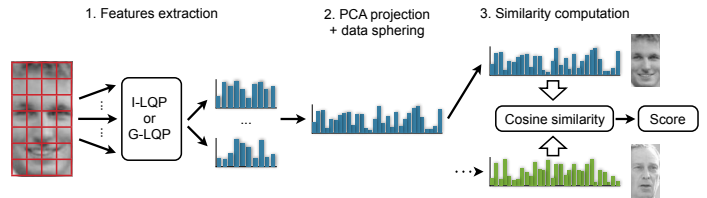


Figure 1: Overview of our face recognition framework.

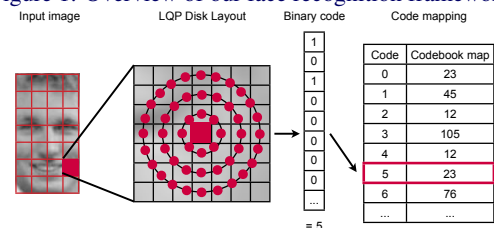


Figure 2: Overview of LQP feature computation. LQP samples pixels from a Disk layout around a central pixel and generates a binary/ternary vector and then map the resulting code to nearest codebook word via a pre-built lookup/hash table.

Methods	Fb	Fc	Dup-I	Dup-II	Mean	Comments
1 HOG	90.0	74.0	54.0	46.6	66.2	
2 LBP	93.0	51.0	61.0	50.0	63.8	
3 LGBPHS	94.0	97.0	68.0	53.0	78.0	Gabor+LBP
4 LGBPWP*	98.1	98.9	83.8	81.6	90.6	Gabor+LBP+WPCA
5 POEM*	99.6	99.5	88.8	85.0	93.2	Gradient+LBP+WPCA+R.Filtering
6 Tan&Triggs	98.0	98.0	90.0	85.0	92.8	Gabor+LBP+DoG Filtering+supervised
7 <b>I-LQP</b>	99.2	69.6	65.8	48.3	70.7	Computed on intensity images
8 <b>I-LQP*</b>	99.8	94.3	85.5	78.6	89.6	
9 <b>G-LQP</b>	99.5	99.5	81.2	79.9	90.0	Computed on Gabor-filtered images
10 <b>G-LQP*</b>	<b>99.9</b>	<b>100.0</b>	<b>93.2</b>	<b>91.0</b>	<b>96.0</b>	

Table 1: Comparative results on FERET dataset. Superscript ‘\*’ is used to differentiate methods using PCA-projected features with Cosine similarity metric from the ones using raw features with Chi-squared distance metric.

Methods	Accuracy (%)±SE	Methods	Accuracy (%)±SE	Comments
SD-MATCHES	64.1±0.62	SLE+holistic	81.2± 0.53	
GJD-BC-100	68.5±0.65	DML-eig SIFT	81.3± 0.23	
H-XS-40	69.5±0.48	Hybrid	84.0± 0.35	
LARK	72.2±0.49	POEM*	84.9± 0.45	
POEM	75.2±0.73	LARK	85.1± 0.59	
POEM*	82.7±0.59	LBP + CSML	85.3± 0.52	
<b>G-LQP</b>	<b>75.3±0.26</b>	DML-eig comb	85.7± 0.56	
<b>G-LQP*</b>	<b>82.1±0.26</b>	Combined b/g	86.8± 0.34	10 features+Metric learning+SVM
<b>I-LQP</b>	<b>75.3±0.80</b>	CSML + SVM	88.0± 0.37	6 features+WPCA+CSML+SVM
<b>I-LQP*</b>	<b>86.2±0.46</b>	HTBIF	88.4± 0.58	1000+ Gabor filters+4 distances+SVM

Table 2: Comparative results of our methods with (left) unsupervised and (right) supervised methods on aligned LFW View 2 dataset.

## References

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<sup>1</sup>Majority of the results are reproduced from the LFW dataset webpage.