Assignment #1: Basic Recognition

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I. Introduction

In this work we implement and evaluate performance of the Multiscale Local Binary Patterns (MLBP) and Uniform LBP (ULBP) feature extractor and report our findings.

II. Related Work

[1] proposed a rotation invariant version of the classic LBP, they show that so called uniform patterns and their occurrence histogram are a powerful feature for texture classification. Great robustness against monotonic transformation of the gray scale and angle rotation is achieved by combining occurrence statistics of uniform patterns and their variance. [2] proposed the so called robust LBP, which is robust to the noise present in the images. The robustness of the classic LBP is improved by changing the coding bit of LBP (i.e a unlikely LBP code is replaced by a code that is more probable).

III. Methodology

We have implemented a MLBP and ULBP feature extractors. For baseline we used a feature extractor that simply returns the flattened image. As proposed in [1] the LBP code is computed for each pixel I_{ij} by sampling P neighboring points at radius R and comparing their values to the central pixel (if the neighbouring pixel has a value greater than the central pixel we store a 1, otherwise we store a 0). Neighbouring pixels are sampled in circular fashion. Bi-linear interpolation of pixel values is performed when a sampling point does not fall directly in the center of a pixel. In the case of ULBP we count the number of circular bitwise $0/1$ transitions in the LBP code (as proposed in [1]), if the number of transitions is ≤ 2, the pattern is said to be uniform and we take its corresponding value, otherwise we store the value $P+1$. LBP image is than split into K tiles and a local histogram of pixel values (histogram has 2^P bins in case of MLBP and $P+1$ bins in case of ULBP) is computed for each tile. Finally a feature vector is constructed by concatenating local histograms.

IV. Experiments

Algorithms were evaluated on the Annotated Web Ears dataset (AWE). Dataset has a 1000 samples of 10 classes. For each implementation we report the rank 1 score and vary the following parameters: radius R, number of sampling points P, size of the tile S_t and a distance metric d. Table I shows rank 1 score of the baseline feature extractor. Table II shows performance of the MLBP without histograms (i.e feature vector is just the flattened LBP image). Table III shows performance for MLBP with histograms. Table IV and Table V show performance of ULBP without histograms and ULBP with histograms respectively. Table VI shows performance of the Scikit's MLBP implementation.

V. Results and Discussion

A. Results

TABLE I
Rank 1 score for baseline feature extractor

d	$rank_1$
cosine	0.167
euclidean	0.132
manhattan	0.132

TABLE II
Rank 1 score for MLBP without histograms

R	P	d	$rank_1$
2	16	manhattan	0.33
2	12	manhattan	0.329
3	24	manhattan	0.304
2	16	euclidean	0.301
1	8	manhattan	0.3
3	24	euclidean	0.282
2	12	euclidean	0.272
1	8	euclidean	0.222
2	16	cosine	0.211
3	24	cosine	0.207
2	12	cosine	0.201
1	4	manhattan	0.188
1	8	cosine	0.184
1	4	euclidean	0.123
1	4	cosine	0.122

B. Discussion

We see that the best rank 1 score of 0.446 is achieved by the MLBP with histograms which is greater than the baseline by the factor of 2.90. The next best score is obtained by MLBP without histograms with rank 1 of 0.33. Than ULBP with histograms with the rank 1 of 0.183 and finally ULBP without histograms with rank 1 of 0.068. In both cases adding histograms boost the performance, this is likely because the estimated distribution of detected LBP structures is less sensitive to intra-class variation than just storing detected structures. We also see that MLBP outperforms ULBP by a factor of 2.44. ULBP is known to greatly reduce the size of the feature vector, and is based on the idea that uniform patterns occur more frequently than non uniform patterns. ULBP likely underperforms because uniform patterns are not frequent enough in our dataset, or are not good enough representations of

TABLE III
RANK 1 SCORE FOR MLBP WITH HISTOGRAMS

R	P	d	S_t	$rank_1$
2	16	manhattan	16	0.446
2	12	manhattan	16	0.438
1	8	manhattan	16	0.374
2	16	manhattan	32	0.35
2	12	manhattan	32	0.345
2	12	cosine	16	0.337
1	8	cosine	16	0.334
2	16	cosine	16	0.321
1	4	manhattan	16	0.304
1	4	cosine	16	0.287
2	16	euclidean	16	0.278
1	8	manhattan	32	0.276
1	8	euclidean	16	0.268
2	12	euclidean	16	0.266
2	12	cosine	32	0.249
2	16	cosine	32	0.241
1	4	euclidean	16	0.241
1	8	cosine	32	0.235
2	16	euclidean	32	0.227
2	12	euclidean	32	0.223
1	4	manhattan	32	0.217
1	8	euclidean	32	0.207
1	4	cosine	32	0.185
1	4	euclidean	32	0.179

TABLE IV
RANK 1 SCORE FOR ULBP WITHOUT HISTOGRAMS

R	P	d	$rank_1$
3	24	manhattan	0.068
3	24	cosine	0.035
2	16	manhattan	0.026
1	8	manhattan	0.025
1	4	manhattan	0.024
3	24	euclidean	0.022
2	12	manhattan	0.021
2	16	cosine	0.016
1	4	euclidean	0.015
2	12	cosine	0.015
1	8	cosine	0.013
2	16	euclidean	0.013
1	4	cosine	0.012
2	12	euclidean	0.012
1	8	euclidean	0.01

the classes. We see that larger values of R and P generally improve performance, this is likely because higher values of R and P tend to detect high level details, these are more consistent among the samples from the same class. We can also see that best results are obtained using the manhattan distance metric, which is known to perform well on high-dimensional data. For both MLBP and ULBP with histograms tile size of 16×16 yields slightly better results. Finally we can see that very similar results are obtained using the Scikit's implementation (results for other configurations are similar but are omitted here due to lack of space).

VI. CONCLUSION

We have shown that on the AWE dataset the MLBP with histograms achieved the highest performance. We have shown that ULBP with histograms performs just slightly above the baseline, while ULBP under-performs the baseline. Finally we have shown that the manhatten distance metric yields the best results for all implementations.

TABLE V
RANK 1 SCORE FOR ULBP WITH HISTOGRAMS

R	P	d	S_t	$rank_1$
2	16	manhattan	16	0.183
2	12	manhattan	16	0.177
2	16	cosine	16	0.17
2	16	euclidean	16	0.151
2	12	cosine	16	0.148
1	8	cosine	16	0.139
1	8	manhattan	16	0.134
2	12	euclidean	16	0.133
1	4	manhattan	16	0.127
1	8	euclidean	16	0.127
2	16	manhattan	32	0.124
1	4	cosine	16	0.112
1	4	euclidean	16	0.109
2	16	cosine	32	0.107
2	12	manhattan	32	0.103
2	16	euclidean	32	0.103
2	12	cosine	32	0.09
1	8	manhattan	32	0.085
2	12	euclidean	32	0.083
1	8	cosine	32	0.077
1	8	euclidean	32	0.075
1	4	manhattan	32	0.065
1	4	euclidean	32	0.058
1	4	cosine	32	0.056

TABLE VI
SCIKIT'S MLBP WITH HISTOGRAMS

R	P	d	S_t	$rank_1$
2	16	manhattan	16	0.42
2	12	manhattan	16	0.416
1	8	manhattan	16	0.35
2	12	manhattan	32	0.327
2	12	cosine	16	0.323
2	16	manhattan	32	0.322
1	8	cosine	16	0.318
1	4	manhattan	16	0.308
2	16	cosine	16	0.304
1	4	cosine	16	0.288
1	8	manhattan	32	0.262
2	12	euclidean	16	0.253
1	8	euclidean	16	0.249
2	12	cosine	32	0.245
1	4	euclidean	16	0.242
2	16	euclidean	16	0.239
2	16	cosine	32	0.233
1	8	cosine	32	0.219
1	4	manhattan	32	0.216
2	12	euclidean	32	0.211
2	16	euclidean	32	0.209
1	8	euclidean	32	0.206
1	4	cosine	32	0.197
1	4	euclidean	32	0.179

REFERENCES

[1] T. Ojala, M. Pietikainen, and T. Maenpaa, “Multiresolution gray-scale and rotation invariant texture classification with local binary patterns,” *IEEE Transactions on pattern analysis and machine intelligence*, vol. 24, no. 7, pp. 971–987, 2002.

[2] J. Chen, V. Kellokumpu, G. Zhao, and M. Pietikäinen, “Rlbp: Robust local binary pattern.” in *BMVC*, 2013.