Assignment #1: Basic Recognition

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I. Introduction

The Local Binary Pattern (LBP) is a very flexible algorithm. It became a popular approach in numerous applications due to its computational simplicity and discriminative power. It works by taking a window of pixels of an image and labeling them by whether or not they are above a certain threshold. After that, it considers the result as a binary number.

In this paper, I compared and reviewed some of the variations of this algorithm. AWE was the dataset used to make that analysis.

II. Related Work

The basic LBP was developed by David Harwood in 1992. Back then the value of such a method was still unclear but soon LBPs showed great potential and were further researched. [1] Many different kinds of LBPs were then developed to improve the limitations of the basic one. Some examples are Uniform LBPs and locally rotation invariant LBPs. Uniform patterns were proposed as a way to reduce the high dimension of the original LBP feature vector. [2] Locally rotation invariant LBPs, on the other hand, have allowed for an increase in performance for image rotation, as well as fewer patterns.

However, despite its success in early experiments, LBPs' results in different fields were found unsatisfactory. Thus, researchers have taken this algorithm and improved it keeping in mind a specific application for a certain field. This approach resulted in great success, namely in the fields of texture analysis and face recognition. [3]

III. Methodology

Firstly, I wanted to have a base for the comparison of the performance of the LBPs. For that, I chose to use the pixel-by-pixel representation of the image. So, in this case, the feature vectors extracted from the image were each pixel value.

Secondly, I had to choose an LBP to be the baseline for all others. Consequently, I chose the simplest possible one, the LBP with Radius 1 (a 3x3 matrix) and no overlapping.

Then, I implemented variations of the LBP. They are stated below:

1) LBP with Radius 2, non-overlapping
2) LBP with Radius 3, non-overlapping
3) LBP with Radius 4, non-overlapping
4) LBP with Radius 5, non-overlapping
5) LBP with Radius 1, overlapping
6) LBP with Radius 2, overlapping
7) LBP with Radius 3, overlapping
8) LBP with Radius 4, overlapping
9) LBP with Radius 5, overlapping
10) Uniform LBP with Radius 1, non-overlapping
11) Uniform LBP with Radius 2, non-overlapping
12) Uniform LBP with Radius 3, non-overlapping
13) Uniform LBP with Radius 4, non-overlapping
14) Uniform LBP with Radius 5, non-overlapping
15) scikit's LBP with a Radius of 4, Number of points 8 and default method

For the algorithms considered, the world length was always 8. The points were also always the same, on the outer square of the matrix.

When overlapping is used, the overlapped region is calculated using the radius. As an example, let's take the "Uniform LBP with Radius 3, overlapping". Since the radius is 3, the dimension of the matrix is 7x7 and the overlapped region will be 3.

IV. Experiments

As mentioned previously, the data used was from the AWE dataset. This dataset consisted of 100 classes, each with 10 pictures.

Firstly, the dataset was loaded and each image was converted into a 128 by 128 pixels matrix, as a grayscale version. Then, by flattening that matrix, we obtain the first feature vector, the pixel-by-pixel. After that, I ran each LBP algorithm with the criteria and parameters described in the Methodology section.

Upon having all the feature vectors of all the implemented LBP variations, I measured their accuracy. To do that, I chose to use the Rank-1 metric, as I was only interested in knowing whether the algorithm could detect the correct class as its first choice. I started by calculating the average of the feature vectors for each class. Then, for each picture, I recalculated the average of its class but without the chosen image, to avoid bias. Afterwards, I applied the cosine similarity metric to measure distances. The class considered the closest by that metric was picked by Rank-1. Knowing the number of correct matches between an image and its correct class allowed me to calculate the score.

V. Results and Discussion

We can now draw some conclusions from the results obtained.

A. Results

Below we can see the results obtained from all the LBPs analyzed. If we look at Table I we can see the percentage of the Rank-1 score for each algorithm and by looking at Fig.1 we can observe the visualization of the result in the table:

- In yellow, the simplest comparison, pixel-by-pixel.
- In red, the baseline for LBP comparison, the LBP with Radius 1 and no overlap.
- Finally, in pink, the best result, scikit's implementation of LBP with the parameters deemed best, judging by the other LBP results.

TABLE I
Rank-1 scores for the different LBPs tested

Name	Rank-1 score [%]
Pixel-by-pixel	7,3(9)
Baseline LBP	10,5
LBP with Radius 2, non-overlapping	10,80
LBP with Radius 3, non-overlapping	9,30
LBP with Radius 4, non-overlapping	10,00
LBP with Radius 5, non-overlapping	8,30
LBP with Radius 1, overlapping	10.2(9)
LBP with Radius 2, overlapping	13,40
LBP with Radius 3, overlapping	13,90
LBP with Radius 4, overlapping	15,80
LBP with Radius 5, overlapping	16,20
Uniform LBP with Radius 1, non-overlapping	1,00
Uniform LBP with Radius 2, non-overlapping	1,30
Uniform LBP with Radius 3, non-overlapping	2,50
Uniform LBP with Radius 4, non-overlapping	3,40
Uniform LBP with Radius 5, non-overlapping	4,30
scikit's LBP	19,80

B. Discussion

The worst-performing LBPs were the Uniform LBPs. This could be because they, despite being rotation invariant, will also lose the sense of place for every window they analyze. A light region with some dark spots could be read the same as a window perfectly divided in two, one side dark and one light. The increase in window size also proved to be an improvement factor.

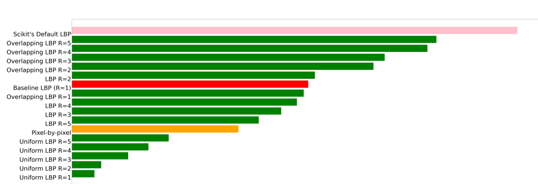

Fig. 1. Ranking the performance of all the implemented LBP algorithms from best to worst.

Following the Uniform LBPs come the non-overlapping LBPs. Not only do they have fewer features to correlate when compared to the overlapping ones, but they also don't show an explicit improvement as the radiuses keep increasing. The best-performing non-uniform LBP is the one with a radius of 2. However, the difference between that one, the LBP with radius 1 and with radius 4 is small.

Lastly, the best-performing LBPs were the overlapping ones. They also show an increase in performance as the radius increases. This means the overlapping region is bigger too (stated in the Methodology section). The increase in performance can be explained. A small window that focuses on the immediate section surrounding the center pixel so the information it gets from the surrounding area may not be relevant. A bigger window, on the other hand, will still only focus on the region around the pixel, but will also provide some more relevant information, not being so focused on the immediate area around that pixel.

As expected, the implementation from scikit performed the best. Besides being an optimal implementation, the parameters were chosen based on the best results from the LBPs implemented by scratch.

VI. Conclusion

In conclusion, this paper found that overlapping increases the performance of an LBP algorithm. Besides that, in the majority of the cases analyzed, an increase in window size is also beneficial. However, since only three implementations were compared, this cannot be extended to the generality of the cases.

In the future, other implementations can also be tested to further understand the extent to which these conclusions hold true. Some examples of future work are varying the word length, changing the shape of the points of the LBP, for example, an ellipse instead of a square, and experimenting comparing the values as a histogram.

References

[1] M. Pietikäinen, A. Hadid, G. Zhao, and T. Ahonen, *Computer vision using local binary patterns*. Springer Science & Business Media, 2011, vol. 40.

[2] O. Lahdenoja, J. Poikonen, and M. Laiho, "Towards understanding the formation of uniform local binary patterns," *International Scholarly Research Notices*, vol. 2013, 2013.

[3] K.-C. SONG, Y.-H. YAN, W.-H. CHEN, and X. ZHANG, "Research and perspective on local binary pattern," *Acta Automatica Sinica*, vol. 39, no. 6, pp. 730–744, 2013. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1874102913600518