Super Resolution and 3D Alignment Effects on Unsupervised Face Recognition in The Wild

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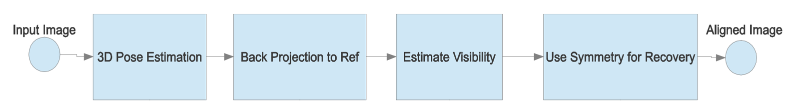
Abstract

Majority of face recognition algorithms use query faces captured from uncontrolled, in the wild, environment. It is common for these captured facial images to be blurred or low resolution. Super resolution algorithms are therefore crucial in improving the resolution of such images especially when the image size is small requiring enlargement. This paper aims to demonstrate the effect of one of the state-of-the-art algorithms in the field of image super resolution. To demonstrate the functionality of the algorithm, various before and after 3D face alignment cases are provided using the images from the Labeled Faces in the Wild (lfw). Resulting images are subjected for testing on a closed set face recognition protocol using unsupervised algorithms with high dimension extracted features.

Face Alignment

First to transform the captured image to its canonical pose a 3D aligning system is required. The aligning system used in this work is based on face frontalization algorithm used in [1]. Block diagram and example of the system is provided in Figure 1.



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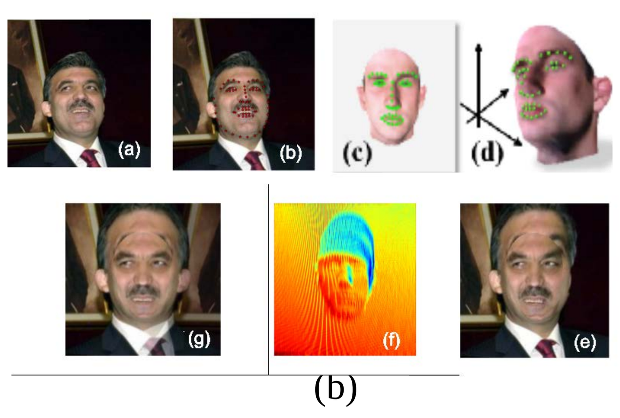


(b)

Figure 1, Block diagram and example of the face alignment process.

Super-Resolution

In this work, a super-resolution image algorithm based on Convolutional Neural Network (CNN) as in [2]. The system first generates low resolution higher dimension image from the input image using bicubic interpolation. This image is then applied to a CNN network structure as shown in Figure 2.

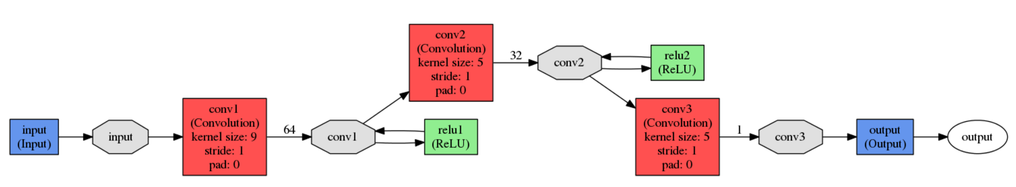


Figure 2, Block diagram for the used SRCNN.

High Dimensional Features

LBP [4] features have provided remarkable unsupervised face recognition outcomes for faces in controlled environment. Therefore, the same Chi square metric given is used in the testing of the extracted features from the lfw dataset [3] as in the next equation.

$$\chi^2(X,Y) = \sum_{i,j} \frac{\left(x_{i,j} - y_{i,j}\right)^2}{x_{i,j} + y_{i,j}}$$

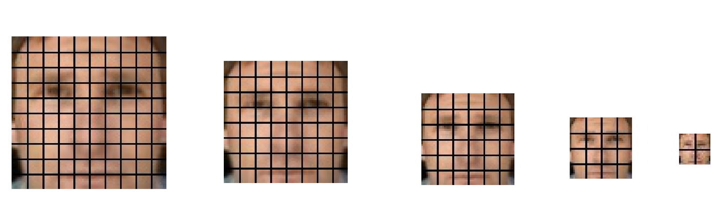
where, X and Y are the histograms extracted from faces under test, i and j are the indices of the *i-th* bin in histogram corresponding to the *j-th* local region.

Three types of LBP has been tested:

1) Single scale by dividing the 90x90 face into 10x10 blocks, each being 9x9 pixels. Following this$\left(LBP_{8,2}^{u2}\right)$ neighborhoods are calculated for each block.

2) Multi-Scale by applying the same last step on 5 different scales.

3) HighDimLBP as described in [5]



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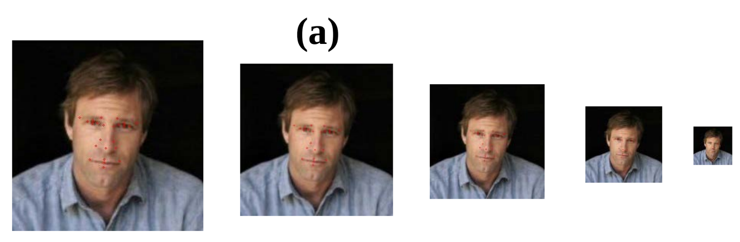
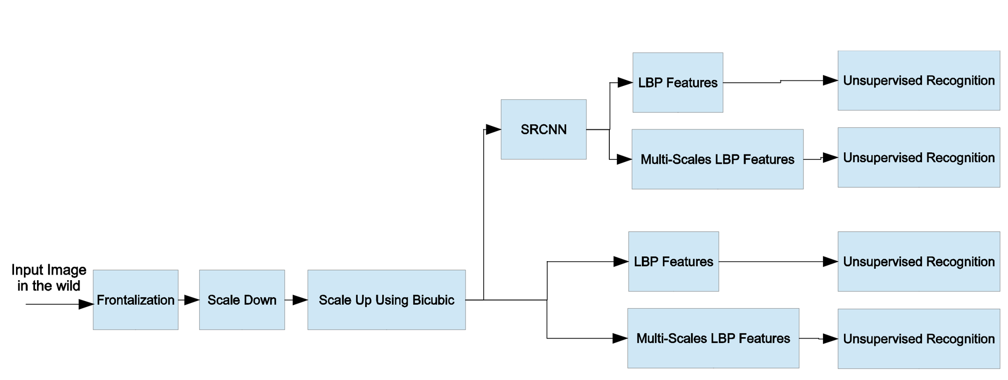


(b)

Figure 3, Two high dimensional LBP features a)Multi-Scale LBP b)HighDimLBP

Experiments Description

This paper proposes two experiments to examine the effect of image super-resolution and the order of applying it with alignment to unsupervised face recognition process based on the features described before.



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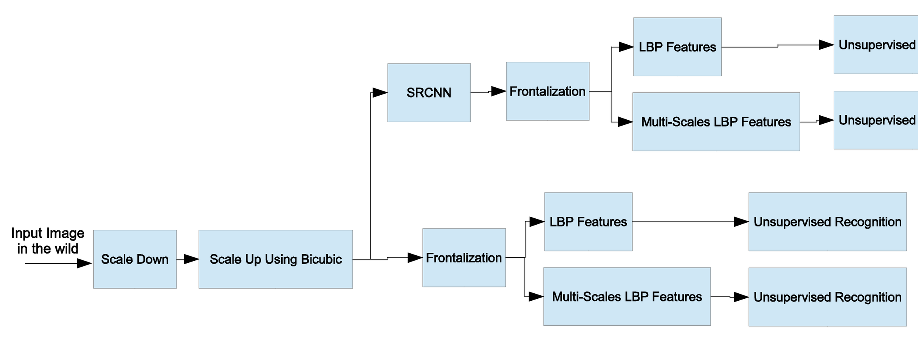


(b)

Figure 4, Proposed experiments a)Alignment first b)Scaling and SR first

Results

First, a comparison between the three types of LBP features has been applied to lfw dataset and Chi square metric has been used as an unsupervised face recognition metric with protocol proposed in [6]. As shown in Figure 5 Multi-Scale LBP features outperform other LBP types. However, as shown in table 1 both Multi-Scale LBP and HighDimLBP with Chi square distance have close recognition rates. It should also be noted that the computation time of Chi square distance for HighDimLBP is significantly high compared to other LBP types due to the length of the vector representation.

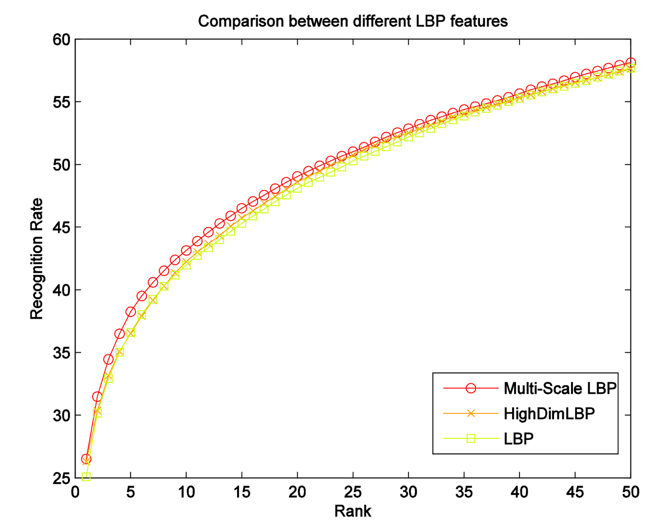
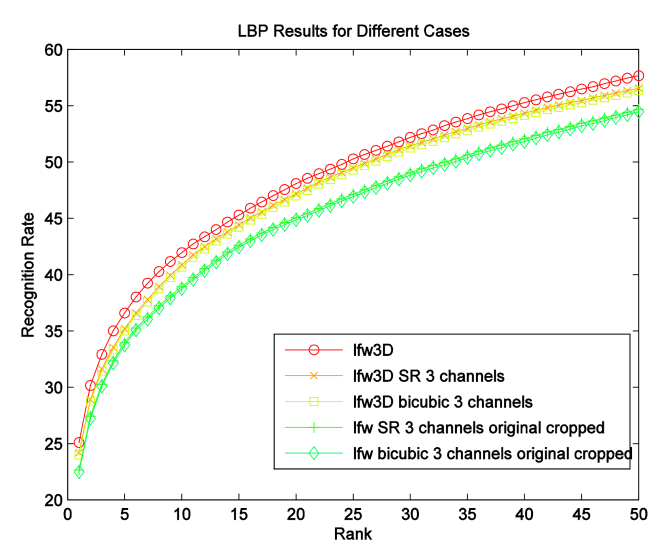


Figure 5, Average percentage recognition rate for 3 different LBP features. .

Features	Rank 1 Recognition Rate (%)
LBP	25.09
Multi-Scale LBP	26.51
HighDimLBP	26.30
HighDimLBP+PCA [6]	16.50

Table 1, Average percentage recognition rate for 3 different LBP features.

For the two experiments, the SRCNN algorithm is implemented, but, instead of applying SR algorithm on the *y* component only of the *ycbcr* domain, in this test the SR algorithm has been applied on the three channels of the RGB domain to enhance both the edges and colors of the estimated pixels by the *bicubic* scaling. Results are shown in Figure 6 and Table 2.



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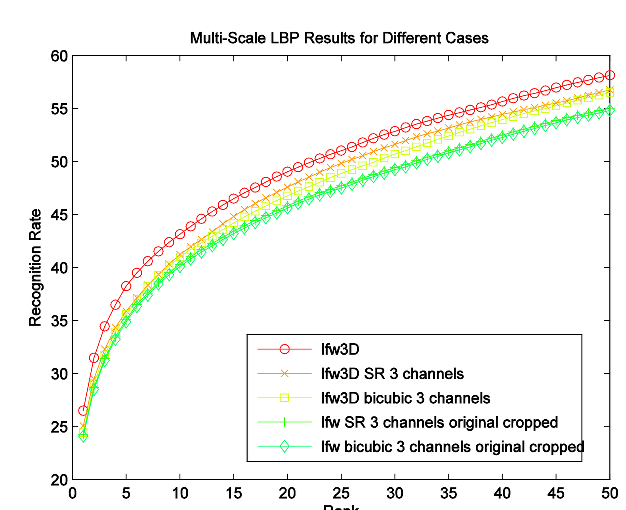

(b)

Figure 6, Average percentage recognition rate results for both a)LBP b)Multi-scale LBP.

	LBP	Multi-Scale LBP
lfw3D	25.09	26.51
lfw3D SR 3 channels	24.09	24.93
lfw3D bicubic 3 channels	23.99	24.38
lfw SR 3 channels orig.	22.65	24.22
lfw bicubic 3 channels orig.	22.46	24.04

Table 2, Average rank 1 recognition rate of all cases in the experiments.

Conclusions

This work utilized an unsupervised face recognition with images from the Labeled Faces in the Wild (lfw) dataset with LBP and Multi-Scale LBP based extracted features. The results indicate that Multi-Scale LBP outperforms both LBP and HighDimLBP features with reasonable extraction and distance calculation time. Two experiments have also been introduced to measure the performance of applying single image super-resolution algorithm on faces captured in the wild and the effect of order of applying it with face frontalization algorithm. It can be concluded that applying super resolution on frontalized faces provides better results as opposed to applying super resolution first. This is because face frontalization uses interpolation to calculate some pixel values, similar to bicubic scaling, which will be enhanced with super-resolution techniques. The results also indicate that applying super-resolution on bicubic scaled faces shows slight enhancement in unsupervised face recognition process for both experiments with the two types of features.

References

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