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The Application of Modified Least Trimmed Squares with Genetic Algorithms Method in Face Recognition

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Abstract

Severely occluded face images are the main problem in low performance of face recognition algorithms. In this paper, we apply a new algorithm, a modified version of the least trimmed squares (LTS) with a genetic algorithms introduce by [1]. We focused on the application of modified LTS with genetic algorithm method for face image recognition. This algorithm uses genetic algorithms to construct a basic subset rather than selecting the basic subset randomly. The modification in this method lessens the number of trials to obtain the minimum of the LTS objective function. This method was then applied to two benchmark datasets with clean and occluded query images. The performance of this method was measured by recognition rates. The AT&T dataset and Yale Dataset with different image pixel sizes were used to assess the method in performing face recognition. The query images were contaminated with salt and pepper noise. The modified LTS with GAs method is applied in face recognition framework by using the contaminated images as query image in the context of linear regression. By the end of this study, we can determine this either this method can perform well in dealing with occluded images or vice versa.

Keyword: *face recognition, genetic algorithm, least trimmed squares, LTS with GAs, noise images*

1. Introduction

Face recognition may be a standout amongst those the greater part momentous abilities that human might do. This is likewise a principle field about examination for biometric indicator transforming. In years, it additions an ever-increasing amount consideration from claiming marketers. A few investigations were led for face recognition [2-5]. There exist different frameworks and algorithms for a face recognition framework. Despite the impressive achievements that have been made, it is still open under unconstrained environments, with variations of illumination, expression, head pose, as well as partial occlusions. Face recognition process will be a whole lot influenced by outliers. Outliers in face recognition is also known as noise or occlusion. Noise is a random variation of image intensity. An image should show the true pixels value. But, when an image does not, this indicates that the image have noise [6]. This study was done to explore the application of modified least trimmed squares with genetic algorithms (LTS with GAs) method in face recognition. This paper is arranged as follows. The face recognition using LTS with GAs method is presented in Section 2. Also, examination results alongside area 3. The paper at long last finishes up in segment 4.

2. Modified LTS with Genetic Algorithm (LTS-GAs)

This method was introduce by [1]. The LTS-GA method was refined to enhance its performance when the dataset contains outliers by using the best 50% of observations to obtain initial parameter estimates for getting initial residuals.

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$$initial\ observations = {}^{n}/_{2} \tag{1}$$

where *n* is the number of total observations in data. The contaminated observations are detected in C-steps. Afterward those recognized 50% contaminated observations are trimmed. Each observation will be allocated with a weight based on a cut-off value which will give a zero weight for any observation with residual error greater than the cut-off value and a weight “1” otherwise. These weights will ensure the regression coefficient estimates are not affected by the presence of outliers as the observations with a higher level of noise will receive weights close to zero. A robust standard deviation was used and computed as follows.

$$\hat{\sigma}_{robust} = \text{median}\left(e_{lts}^{i} - median\left(e_{lts}^{i}\right)\right)/0.6475 \tag{2}$$

The weight for each residual is formulated as follows:

$$w_i = \begin{cases} 1, & \text{if abs}(e) \leq 2 \times \hat{\sigma}_{robust} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

The refinement in the existing LTS-GA is described as follows:

Input: Matrixes of training sample set $A_i = \left[x_i^{(1)}, x_i^{(2)}, \dots, x_i^{(p)}\right]$ for p classes and $A_i \in \mathbb{R}^{q \times p}$Matrixes for test sample set $B_{ti} = \left[x_{ti}^{(1)}, x_{ti}^{(2)}, \dots, x_{ti}^{(p-j)}\right] y \in \mathbb{R}^{q \times (p-j)}$
for each subject i do
    fitness function ()
    function fitness (candidates) {
    newbetas: = cstep (candidates)
    residuals: = calculate residuals using newbetas
    apply equation (2) and (3) to compute robust standard error and residuals
    fitness: = calculate LTS criterion using residuals.
return (fitness);}
end
Output: identify (y) = arg min d(y,i).

The pseudocode for the c steps are as below:

c-step ()

function cstep (candidates) {
res: = calculate residuals using candidates
set indices: = Indices of p observations from equation (1)
    for i = 1 to number of c-steps
    {
        ols: = Calculate OLS using the subset (indices);
        residuals: = Get residuals from (ols);
        ordering of residuals: = Order (abs(residuals));
        indices: = First *h* elements of ordering of residuals;
    } **end**
set betas: = Coefficients of OLS;
return (betas);}
evaluate fitness values and perform selection, crossing over, and mutation operations on the chromosomes until maximum number of iterations reached. Get the best chromosome and perform C-steps using best chromosome.

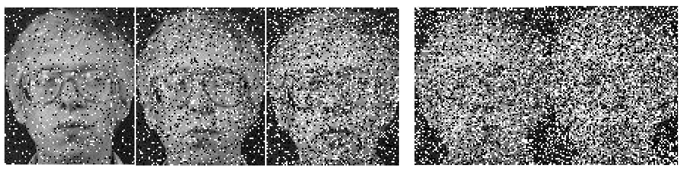
3. Results and Analysis

For this study, the AT&T dataset and Yale dataset were used to apply the modified LTS with GAs method in face recognition analysis. Images from both data sets have different pixel size. Two different levels of image pixels; size 78x64 pixels and size 112x92 pixels were created for the AT&T database. As for the images from the Yale database were down sampled to the size of 32x32 pixels. Images from all datasets were divided into two parts each. Half images from each subject of each datasets were used as query images while the latter half were for testing images [7]. Salt and Pepper noise were added artificially to the query images with five different levels; 10%, 20%, 30%, 40% and 50%. Images in query image set cannot be the same images in the training images set. An image from query image set is ruled to be match with the training images set when the differences between the query image from query images set has the minimum distance when compared with all images in the training images set. The recognition rate used in face recognition study here represents the percentage of the total number of correctly matched images between the two sets.

3.1. AT&T Database

Table 1 and Table 2 gives face recognition rates of AT&T dataset with size 78x64 pixels and size 112x92 pixels. Figure 1 is the examples of images from AT&T Dataset while Figure 2 is the example of images from AT&T dataset with various levels of Salt and Pepper Noise. From both Table 1 and Table 2, when the percentage of noise getting higher, it can be seen clearly that the percentage of recognition rate drops. When we compare the percentage of recognition rate between Table 1 and Table 2, the images with size 78x64 pixels from Table 1 gave higher recognition rate for occluded images.

Figure 1. Examples of images from AT&T Dataset



(a) 10% (b) 20% (c) 30% (d) 40% (e) 50%

Figure 2. Examples of images from AT&T Dataset contaminated with different levels of Salt and Pepper Noise

Table 1. Face Recognition Rates for AT&T Database Images with size 78x64 pixels

Noise (%)	Recognition Rate Using Method MODIFIED LTS With Gas (%)
0	86.50
10	84.50
20	77.50
30	71.00
40	54.50
50	45.00

Table 2. Face Recognition Rates for AT&T Database Images with size 112x92 pixels

Noise (%)	Recognition Rate Using Method MODIFIED LTS With Gas (%)
0	88.00
10	81.50
20	77.50
30	69.00
40	50.50
50	34.50

3.2. Yale Database

Table 3 displays recognition rates for Yale data set images. We can see that the recognition rate is high when the the data is clean. Eventually, the recognition rate dropped when the level of noise increases till the image was contaminated at 30% level of noise. Starting from the level of 40% of noise in test images, we can see that the recognition rate of this method was improved. The recognition rate when the noise is at 50% is higher than other noise percentage level.

Figure 3. Example of images from Yale dataset

Figure 4. Example of images from Yale dataset with different level of Salt & Pepper Noise

Table 3. Face Recognition Rates for Yale Database Images

Noise (%)	Recognition Rate Using Method Modified Lts With Gas (%)
0	66.67
10	20.00
20	24.44
30	15.56
40	31.11
50	55.56

4. Conclusion

This study is about the application of modified LTS with GAs in face recognition. The AT&T and Yale datasets with three different image pixels sizes were used to measure the recognition rate when modified LTS with GAs method was use in face recognition analysis. All images were added with artificial noise with different level of Salt and Pepper noise. It can be concluded that when the image data set is clean, the dataset from AT&T images with size 112x92 pixels gives better recognition rate. However, when there is noise in the images, the dataset from Yale images with size 32x32 pixels are better. In the near future, a study about the strength of this modified LTS with GAs method in comparison with the existing algorithms in the application of images recognition should be done.

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