Facial Expression Recognition Using Signed Local Directional Pattern

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Declaration

I, hereby, declare that the work presented in this thesis is the outcome of the investigation performed by me under the supervision of name of your super visor , Professor, Department of Computer Science and engineering, East West University. I also declare that no part of this thesis has been or is being submitted elsewhere for the award of any degree.

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(Kazi Md. Jamil Hasan, 2014-1-60-092)

Abstract

"Facial expression recognition has many implications nowadays. But due to lack of performance, human computer interaction is not a pleasurable experience yet. In this paper we have proposed a better version of the LDP (Local Directional Pattern). In the previous LDP calculation the Kirsch masks directional information were lost because of taking the absolute value. So we have proposed the sLDP approach. In this approach we are not going to lose the directional information of the Kirsch mask. Thats why we have taken the signed value for the LDP calculation. By applying sLDP we were able to get a significant improvement over the previous one for the 6-class expression of the cohn dataset. We also got a little bit of improvement of the 7-class expression as well. "

Acknowledgments

As it is true for everyone, We have also arrived at this point of achieving a goal in our life through various interactions with and help from other people. However, written words are often elusive and harbor diverse interpretations even in one's mother language. Therefore, We would not like to make efforts to find best words to express my thankfulness other than simply listing those people who have contributed to this thesis itself in an essential way. This work was carried out in the Department of Computer Science and Engineering at East West University, Bangladesh.

First of all, We would like to express my deepest gratitude to the almighty for His blessings on us. Next, our special thanks go to our supervisor, "Dr. Taskeed Jabid", who gave us this opportunity, initiated us into the field of "Facial Expression Detection", and without whom this work would not have been possible. His encouragements, visionaries and thoughtful comments and suggestions, unforgettable support at every stage of our BS.c study were simply appreciating and essential. His ability to muddle us enough to finally answer our own question correctly is something valuable what We have learned and We would try to emulate, if ever We get the opportunity.

There are numerous other people too who have shown me their constant support and friendship in various ways, directly or indirectly related to our academic life. We will remember them in our heart and hope to find a more appropriate place to acknowledge them in the future.

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Chapter 1

Introduction

Facial expression recognition is a critical problem in image processing. With image processing we can detect human face expressions. To do this we need to extract image features. We have to use an efficient algorithm to detect the mood perfectly. Facial expression recognition is an important field right now in the world. It is important for HCI (Human Computer Interaction). We will detect the mood using Local Binary Pattern (LBP) and Local Directional Pattern (LDP). Then we will try to improve the LDP technique. Both are popular techniques to detect human moods of human by extracting features. LDP is more accurate than LBP for extracting the image features.

1.1 Related Works

We have studied different types of algorithms to reach our goals. LBP is one of the most popular and simplest approach to detect facial expression. LBP is the particular case of the Texture Spectrum model proposed in 1990. It has since been found to be a powerful feature for texture classification. LDP is also a facial expression detection technique. it is more accurate but a complex one. it works with edge response values of face and gives a better result.

1.2 Our Approach

Our objective is to do an improvement over LDP technique to get a better face recognition accuracy.

Chapter 2

Local Binary Pattern

2.1 Introduction

We have studied LBP to clear our understandings to extract features from an image first. In this chapter We will discuss the technique very shortly.

LBP is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.

2.2 Method

The LBP operator was originally designed for texture description. The operator assigns a label to every pixel of an image by thresholding the 3x3-neighborhood of each pixel with the center pixel value and considering the result as a binary number. Then, the histogram of the labels can be used as a texture descriptor.

The information of surrounding neighbors are stored into the center which is denoted

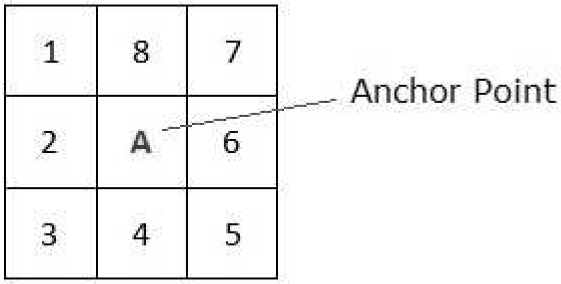


Figure 2.1: Anchor Point.

by the Anchor Point. The Anchor Point represents the information of that 3x3 area using LBP technique. This is called Thresholding.

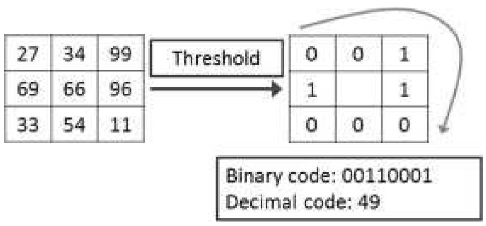


Figure 2.2: Thresholding

In the LBP approach for texture classification, the occurrences of the LBP codes in an image are collected into a histogram. The classification is then performed by computing simple histogram similarities. However, considering a similar approach for facial image representation results in a loss of spatial information and therefore one should codify the texture information while retaining also their locations. One way to achieve this goal is to use the LBP texture descriptors to build several local descriptions of the face and combine them into a global description. Such local descriptions have been gaining interest lately which is understandable given the limitations of the holistic representations. These local feature based methods are more robust against variations in pose or illumination than holistic methods.

Chapter 3

Local Directional Pattern

3.1 Introduction

Our main focus is improving the accuracy of LDP technique. So we need to know clearly how LDP works. In this section, we are going to discuss briefly about LDP technique.

3.2 Method

LDP computes the edge response values in different directions and uses these to encode the image texture.

Since the edge responses are less sensitive to illumination and noise, LDP is more efficient in collecting features of an image than some other algorithms.[4].

3.2.1 Edge Detector

Edge detector is important for LDP technique as it works with the edge response values of an image. The edges of face hold more information about expression or emotion. To detect the edges perfectly, we need to use edge detectors. Kirsch mask is one of the famous edge detectors.

We will use kirsch mask to detect the edges of face because it is better than any other edge detectors. It is more efficient because it is not symmetric and the directional values are more accurate. The proposed LDP method assigns an 8 bit binary code to each pixel of an input image. This pattern is then calculated by comparing the relative edge response values of a pixel in different directions.

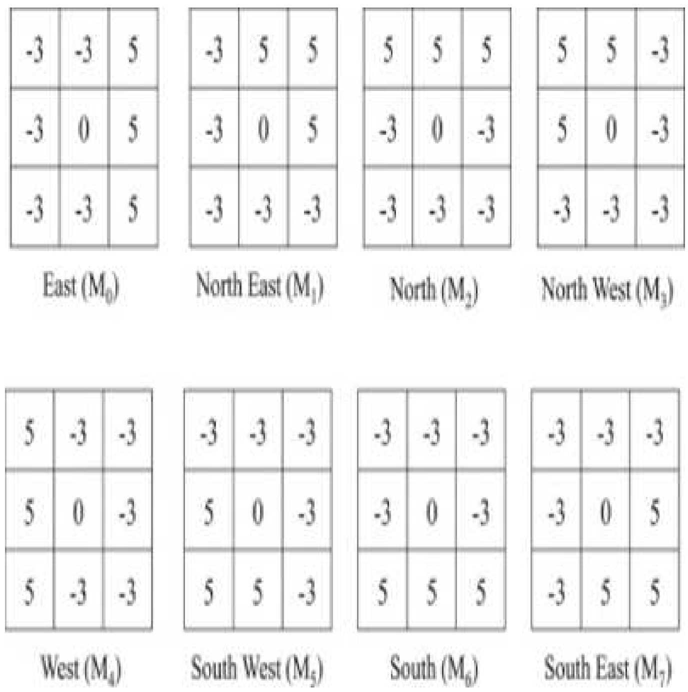


Figure 3.1: Kirsch Masks

The Kirsch edge detector detects different directional edge responses more accurately than the others because it considers all 8 neighbours.

3.3 Computation

At first we will multiply our image with all the 8 kirsch masks. We will get 8 different mask images. By doing this, we will get 8 different mask images representing different edge responses at different directions. The multiplication is normal element to element multiplication. It is not matrix multiplication.

99	106	125
112	116	111
101	102	96

X

-3	-3	5
-3	0	5
-3	-3	5

Resultant matrix:

-297	-318	625
-336	0	555
-303	-306	480

Figure 3.2: Mask Multiplication

LDP method takes the absolute values of the multiplication result. We will now compare all the values of same index of 8 different mask images. We need to generate an 8 bit binary number from it. The positions where mask images values are the highest, we will set 1 for those positions. We will take 3 maximum positions (k = 3) because it gives the best accuracy. The other 5 places will be represented by 0. We will get an 8 bit binary number and will convert that to a decimal number. The decimal number will represent that particular pixel value of the LDP image.

value	-297	-380	575	671	101	456	-210	-510
position	1	2	3	4	5	6	7	8

Absolute value:

value	297	380	575	671	101	456	210	510
position	1	2	3	4	5	6	7	8

Sorted:

value	671	575	510	456	380	297	210	101
position	4	3	8	6	2	1	7	5

Position	8	7	6	5	4	3	2	1
Binary	1	0	0	0	1	1	0	0

Binary to decimal: 10001100 -> 140

Figure 3.3: LDP Computation

We will get a number for each pixel like this for an image. The computed matrix is our LDP image. Now we can count the features from it and check the accuracy.

Chapter 4

Signed Local Directional Pattern

4.1 Introduction

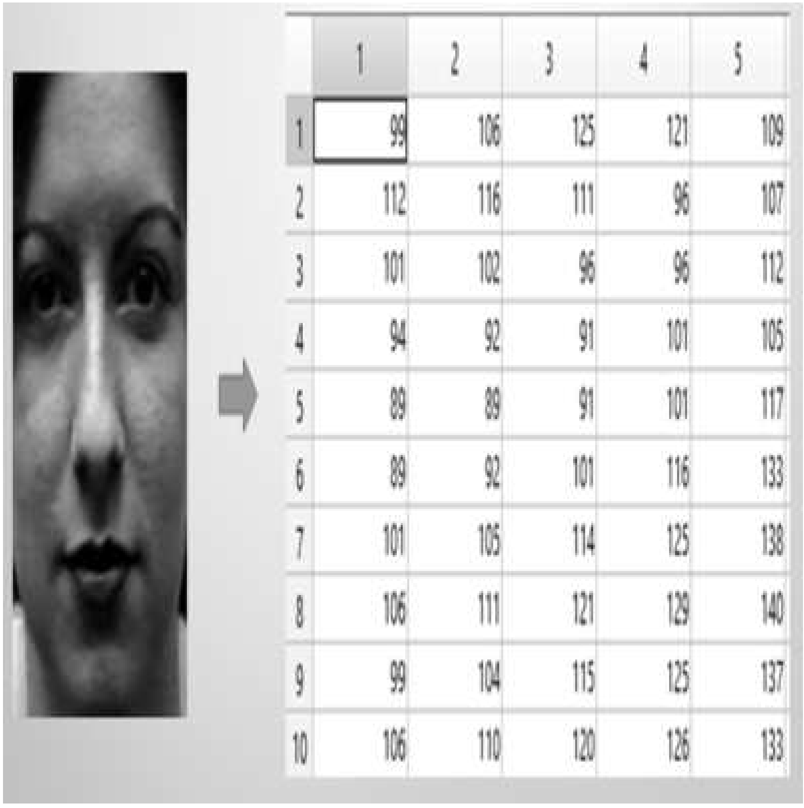
We have proposed a new technique to calculate LDP with an even better cross validation accuracy. As we know the LDP algorithm uses edge detectors to calculate its LDP values. But the previous LDP algorithm used the absolute values after applying the famous edge detector Kirsch Mask as we are now well aware that the kirsch mask has directional information as well represented by the negative values. So LDP values were calculated by taking the modulus values eliminating the directional information. So we have proposed the sLDP approach to keep that direction information of sLDP intact.

4.2 Method

In sLDP, the calculation is almost same except we r not going to the absolute values after multiplying with the kirsch mask. We took the negative values as well. Then we have sorted the array. The positive values got more priority then.

4.3 Computation

We took the grey scale image for this LDP calculation. A gray scale image only carries the intensity information of a picture. So, basically a gray scale is nothing but a 2D matrix.



	1	2	3	4	5
1	99	106	125	121	109
2	112	116	111	96	107
3	101	102	96	96	112
4	94	92	91	101	105
5	89	89	91	101	117
6	89	92	101	116	133
7	101	105	114	125	138
8	106	111	121	129	140
9	99	104	115	125	137
10	106	110	120	126	133

Figure 4.1: sample Facial Image

Now we are going to compute the sLDP value for each and every pixel for all the images in the data set. For calculating the sLDP value we are going to consider the first 3 rows and columns. Then multiply with all of the kirsch masks and get 8 more resultant matrices.

For the first kirch mask the calculation is given below. This multiplication is not our typical matrix multiplication. This is the scalar multiplication.

99	106	125
112	116	111
101	102	96

X

-3	-3	5
-3	0	5
-3	-3	5

Resultant matrix:

-297	-318	625
-336	0	555
-303	-306	480

Figure 4.2: Mask Multiplication

Then we will use the first element of the 8 resultant matrix and calculate a 2D array with the mask number as position value and the actual value. And then we will simply sort the matrix without taking the absolute value. And then compute the sLDP value.

value	-297	-380	575	671	101	456	-210	-510
position	1	2	3	4	5	6	7	8

Sorted:

value	671	575	456	101	-210	-297	-380	-510
position	4	3	6	5	7	1	2	8

Position	8	7	6	5	4	3	2	1
Binary	0	0	1	0	1	1	0	0

Binary to decimal: 00101100 -> 44

Figure 4.3: Signed LDP Computation

Then we will compute the sLDP value for all the pixels for the image and then for the whole dataset. Then with the bSVM we got the cross validation result.

4.4 Dataset Preparation

We selected a very famous dataset, the Cohn dataset for 6-class expression and 7-class expression and calculated the accuracy and compared it with the previous LDP and got an improvement without using any type of filters as well.

Figure 4.4: Facial Expressions

Chapter 5

Comparison and Analysis

5.1 Comparison

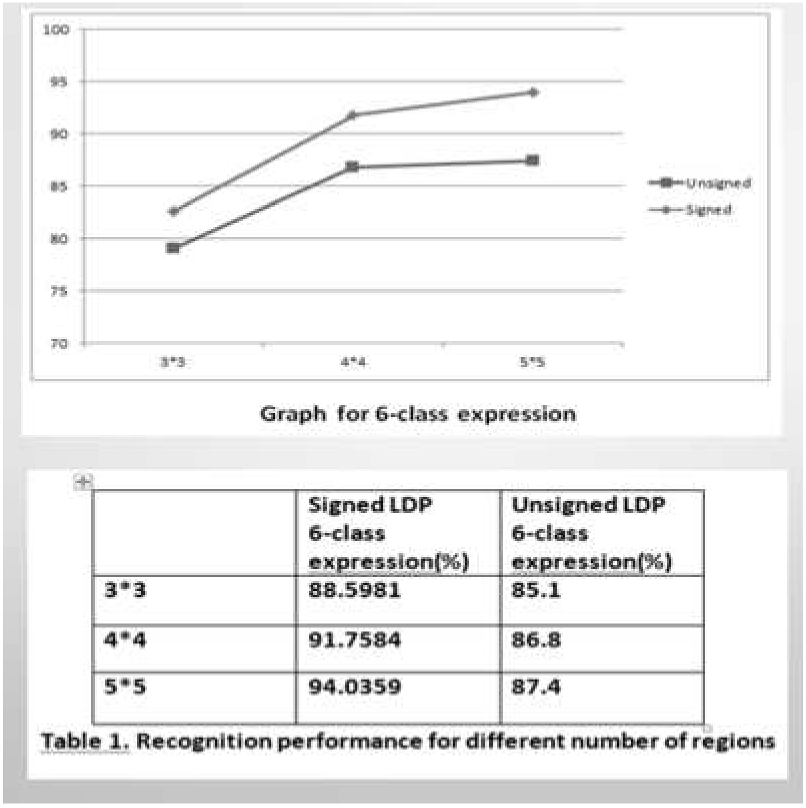
This is comparison for the 6-class expression is given below:

And the following graph and the table are for the 7-class expression:

The sLDP approach gave us an improvement over the last LDP calculation. For the 6-class expression the accuracy got very high and it was a 6.6 percentage of improvement over the last algorithm.

5.2 Analysis

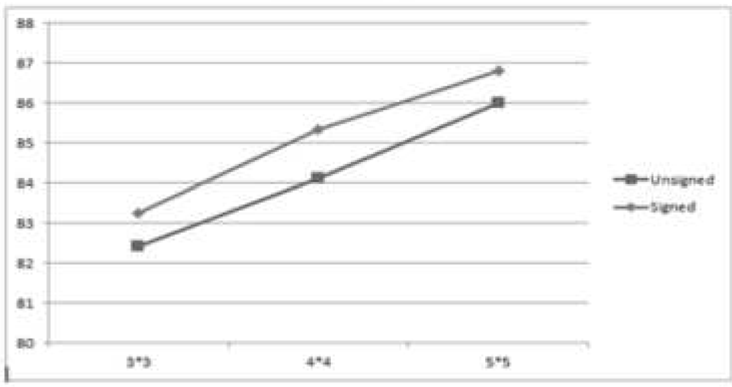
The reason for this improvement is because of the directional property of the kirsch mask that we used. As the kirsch masks are asymmetric matrices and contain the directional value as well we didnt get rid of the directional value of the resultant matrices thus the information came handy. For this reason the accuracy improved over the previous LDP algorithm.



	Signed LDP 6-class expression(%)	Unsigned LDP 6-class expression(%)
3*3	88.5981	85.1
4*4	91.7584	86.8
5*5	94.0359	87.4

Table 1. Recognition performance for different number of regions

Figure 5.1: Comparison for 6-class expression



Graph for 7-class expression

	Signed LDP 7-class expression(%)	Unsigned LDP 7-class expression(%)
3*3	83.2481	82.5
4*4	85.3492	84.3
5*5	86.8260	86.0

Table 2. Recognition performance for different number of regions

Figure 5.2: Comparison for 7-class expression

Chapter 6

Conclusion

In future we will try to implement sLDP in depth images. In depth images, the edges are more significant and they hold more information. So the result can be better. Recently some work is going on with depth image. if we apply signed LDP in on depth image, the result can be much better because the technique works with edge response values of the facial image.

In this research we tried to improve the human expression detection technique LDP. We have studied LBP and LDP. We will keep researching to improve the accuracy even more.

Bibliography