Soft Local Ternary Pattern For Decision Making System Based On Human Emotions

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Abstract— *In fast growing life we need to organize the events efficiently by making consistent decisions. Most of the human experts and administrators strongly believe that emotions of a person play crucial role in decision making. The effective and quality decisions are made when person is in normal state of emotion but not in abnormal state of emotions. During the past two decades research is going on to detect the emotions but no technique has given fruitful results because of illumination changes and noise. The Soft computing techniques imitate the notable human Abilities for making decision in ambiguous environment. In this paper new method is developed by integrating soft computing with LTP operator and named as Soft Local Ternary Patterns (SLTP).The soft LTP operator exploits the computational power of selecting the threshold for decision making with the greater efficiency. This method has produced better emotional recognition rate in uncertainty.*

Keywords— Fisher-faces, LDA, DRLTP, FLTP, Emotions and Decision making

1. Introduction

Face recognition is a very active research in the field of decision making pattern recognition and biometrics [1].The key issue in emotional recognition is to find operative features in emotion appearance. For the past two decades, emotion recognition for decision making has received substantial attention from researchers on numerous approaches like holistic and local descriptor techniques. The different holistic techniques such as principal component analysis (PCA) [2], fisher faces [3], neural networks [4], and Facial emotion recognition by adaptable bunch graph matching techniques [5], linear discriminate analysis (LDA) [6]. The most of these techniques were initially developed with facial emotional images collected under relatively well trained and well-controlled images and in practice they have difficulty in dealing with the range of appearance changes that commonly occur in unconstrained facial emotional images due to illumination, pose, and facial emotions. The emotion recognizing partially occluded, emotions variant faces from single training image per person with soft kNN and SOM ensemble in [7], and some manifold learning methods [8], sparse representation methods [9], LBP [10],ALBP [11],the Gabor volume built on LTP for face representations and recognition [12].Nearest feature line-based subspace analysis [13], and DLBP [14].The LBP against boosting were analyzed for emotion recognition and comparative analysis is performed for Local binary patterns technique and its derivatives for emotion recognition [15]. An extension of Local binary patterns to try-value codes has been proposed, which is called local ternary patterns (LTP) and Further in [16] not only considered the neighboring in spatial relationship domain but it also exploits those between different orientations and scales for emotion faces. The models like PCA against local ternary pattern [17], LTP against LDP [18] models are some representative approaches to learn different local subspaces. Try-level emotional face features for emotion recognition built on center-symmetric local ternary pattern CS-LTP [19] and in [20]the relaxed Local Ternary Pattern are proposed and achieved better recognition performance rates for emotional face recognition applications than Local ternary patterns techniques. In [21] presented innovative technique for facial emotion recognition under uneven controlled lighting conditions created on robust pre-processing, an extension of LTP and matching metrics for emotions recognition. In [22] LTP operator is studied for different region selections of emotions recognition still gray level images. This technique includes two main steps one is to extract the face features based on LTP and another is for classification of emotions based on entropy. This technique opened new directions to work on different gray spaces with optimized LTP regions for next level of recognition. However these techniques could not predict the remarkable human Competence for making decision in ambiguous environment. In this paper Soft Local Ternary Patterns (SLTP) operator is developed as the face analysis technique to find a kind of emotions used in decision making system.

2. LBPoperator

Local binary pattern operator shows its superiority in recognizing emotional expressions. This LBP operator thresholds pixels in a sub space of the template size of 3x3based on the gray value of the central pixel of that subspace.

$$LBP(x) = \sum_{i=0}^{7}(xc - xp)\, 2\hat{}i \qquad (1)$$

Where **xp** is the neighborhood pixels and **xc** is central pixel value. This technique is simple and efficient for emotion recognition. Yet it has some fit falls like1) the Local binary patterns operator is high sensitive to noise especially in near uniform regions of face image 2) the LBP operator cannot differentiate two pixels one is nearer and little bit above the central pixel and other is nearer and little bit below the central pixel so that micro patterns are not recognized such as beauty spots like moles and sticker on the fore head. 3) the LBP operator could not distinguish far below and far above pixel values so that intra class variance cannot be reduced4) the face image contains nearly same gray level pixel values, if slightly added noise to these pixels the LBP gives 0 value for some bits and value 1 for others the values so the LBP operator will not be suitable for analyzing low contrasted and multi resolution face images.

3. DRLTP operator

To overcome limitations which arises in LBP operator and the differential robust local ternary pattern technique is proposed in [22].This method is described mathematically as in eq2.

$$DRLTP = \sum_{i=0}^{m-1} 1 \sum_{j=0}^{n-1} E(i) RLTP(i) \qquad (2)$$

Where E(i) is computed based on second order canny edge filter with suitable threshold value to improve the edge strength and the RLTP(i) is used for removing intra class variances and is define as in eq3.

$$RLTP(i) = min\{(\mathrm{LTP(i)}, 2^\wedge(\mathrm{B}-1) - \mathrm{LTP(i)})\} \qquad (3)$$

Where LTP used for removing noise in face images and is defined mathematically as in eq(4) and $2^{\wedge(B-1)}$-LTP(i) is the complement code of LTP

$$\mathrm{LTP(i)} = \begin{cases} 1 & if pc - pi \geq 0 \\ 0 & if pc - pi = 0 \\ -1 & if pc - pi < 0 \end{cases} \qquad (4)$$

Where pc is the central pixel value and pi is neighborhood value. However this technique is very less effective for uncertainty in the face images because selection of optimal threshold is difficult task. To overcome these limitations soft Local Ternary Patterns operator is presented

4.FLTP operator

Fuzzy logic is one of the enhanced soft computing techniques to remove uncertainty in the face images with optimal threshold. The soft computing is integrated with Local Ternary Pattern Operator and named it as Soft Local Ternary Patterns (SLTP) operator. Local ternary pattern is a three valued code. With LTP technique if the pixel value is within the range of threshold say T and –T then0 is assigned and for the value is greater than T is assigned 1 and for the value less than –T is assigned -1.This technique gives better results that traditional LTP operator. This LTP operator is defined mathematically as in eq.5 to remove uncertainty in face emotions.

$$LTP(i) = \begin{cases} 1 & if pc - pi \geq T \\ 0 & if -T \leq pc - pi < T \\ -1 & if pc - pi < -T \end{cases} \qquad (5)$$

Where **T** is user defined threshold value, **pc** is central pixel value and **pi** is the neighborhood pixel value. This technique can reduce the noise levels better than traditional LTP technique. However it is difficult to select the threshold value **T**. if threshold is larger the micro patterns are removed as noisy pixels and if threshold value is smaller noise could not be removed properly. To overcome this uncertainty fuzzy logic rules are applied in between T and –T.

Rule0: it is defined as more negative **Δpi** is greater the certainty that makes background of face image and assigned -1.

Rule1: it is defined as more positive **Δpi** is greater the certainty that makes foreground of the face images and assigned 1.

The pixel value in between more negative and more positive is considered as uncertainty pixel value. This uncertainty can be removed efficiently with fuzzy rules. We computed mean as **m0** and standard deviation as $\boldsymbol{\sigma 0}$ with rule0 within the range of **0** and **–T**. Mathematically the rule0 is defined as in eq.6

$$\mu 0 = \begin{cases} 0 & if \Delta pi \geq (m0 + \sigma 0) \\ \frac{(x-m0)^\wedge 2}{2\sigma 0^\wedge 2} if\ (m0 - \sigma 0) \leq \Delta pi < (m0 + \sigma 0) & \\ -1 & if \Delta pi < (m0 - \sigma 0) \end{cases} \qquad (6)$$

We computed mean as **m1** and standard deviation as $\boldsymbol{\sigma 1}$ with rule1 within the range of **0** and **T**. Mathematically the rule1 is defined as in eq.7

$$\mu 1 = \begin{cases} 1 & if \Delta pi \geq (m1 + \sigma 1) \\ \frac{(x-m1)^\wedge 2}{2\sigma 1^\wedge 2} if\ (m1 - \sigma 1) \leq \Delta pi < (m1 + \sigma 1) & \\ 0 & if \Delta pi < (m1 + \sigma 1) \end{cases} \qquad (7)$$

Finally LTP operator is computed as in eq.8

$$LTP(i) = \sum_{i=0}^{7} di.2^\wedge i)(8)$$

Where di value may be in set {-1,0,1} of values. The SLTP exploits the computational power of predicting the threshold for decision making with the greater efficiency.

5. MatchingTechnique

Thecorrelation technique is more powerful to compare two face features and it discusses to any of a comprehensive class of statistical relationships connecting dependence. The correlation techniques are useful since they can indicate a predictive relationship whichis exploited in practice. For example, both the images are similar it return zero, if both the images are dissimilar it return none zero value. Eq.8 shows the correlation formula where P(i,j) , X(i,j) are pixel values $\mu u, \mu v$ and$\sigma u, \sigma v$ are means and standard deviations of both database and query faces respectively.

$$\sum_{i=0}^{G-1} 1 \sum_{j=0}^{G-1} (P(i,j)X(i,j) - (\mu u X \mu v))/\sigma u X \sigma v \qquad (9)$$

6. Experimental results

In this paper DRLTP and FLTP methods have been tested on face databases like ORL, PIE, Sterling and our own databases with image features like lips, left eye, nose, right eye, eye pair and mouth for emotion recognition for decision making. The correlation technique is applied to generate the relationships between emotions of database images and emotions of Query images on both DRLTP and

FLTP methods and produced outcomes in the form of tables and graphs. If both the images are similar it returns nearer value to zero otherwise it returns nearer value to 1.The values of three databases which are shown in fig1, fig2 and fig3 are kept as the results. In this paper six emotions from three databases are considered to draw the tables and graphs for both DRLTP and FLTP. Tables 1 to table 6 are shown that emotion recognition rate by DRLTP and FLTP for happy, sad, disgust, fear, surprise and anger, respectively. In the tables the least value shows the recognized emotion and in the graphs the deep valleys shows the corresponding emotion.The graph1 to graph6 demonstrating that the FLTP operator produced 100% recognition rate for all emotions for images of same data bases and images from different databases.

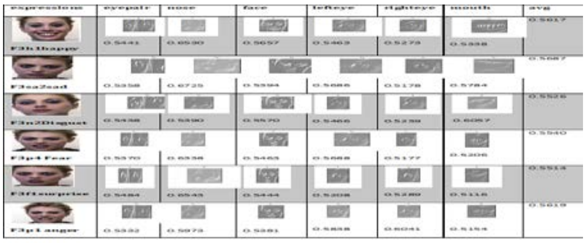


Fig1

Fig2

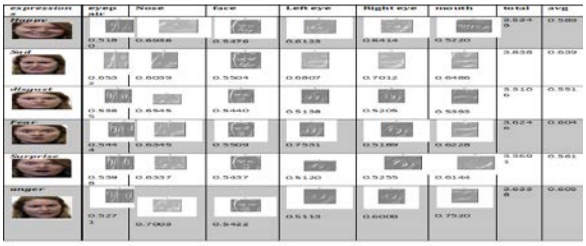


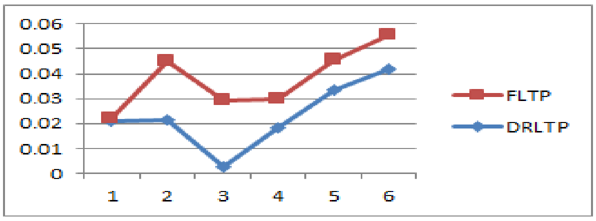
Fig3

					happy	0.5592	
					query		
EXP	DATA1	DATA2	DATA3	data1	data2	data3	avg
happy	0.5891	0.5602	0.5617	0.0299	0.01	0.0025	*0.01113*
sad	0.6396	0.5612	0.5687	0.0804	0.02	0.0095	0.0306
disgust	0.5517	0.5398	0.5526	0.0075	0.0194	0.0066	0.0116
fear	0.6041	0.5531	0.554	0.0449	0.0061	0.0052	0.0112
surprise	0.5615	0.549	0.5514	0.0023	0.0102	0.056	0.021
angry	0.6056	0.5764	0.5619	0.0464	0.0172	0.0027	0.0221
		she	is	happy			

Table1 a) FLTP

				query	happy	avg	0.7201
exp	data1	data2	data3	data1	data2	data3	avg
happy	0.7083	0.68035	0.7089	0.0118	0.0397	0.0112	*0.0209*
sad	0.7425	0.7593	0.71191	0.0224	0.0386	0.0082	*0.023*
disgust	0.7261	0.67311	0.7209	0.006	0.0469	0.008	*0.0179*
fear	0.7126	0.6731	0.70811	0.0075	0.047	0.0119	*0.0221*
surprise	0.7164	0.6982	0.7182	0.0037	0.0219	0.0019	*0.0091*
anger	0.7221	0.674	0.7461	0.002	0.0461	0.026	*0.0247*
	she	is	happy				

b) DRLTP



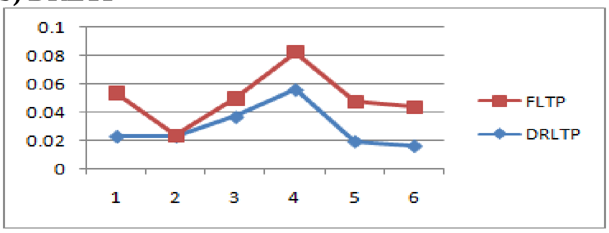
Graph1

					sad	0.5495	
					query		
EXP	DATA1	DATA2	DATA3	data1	data2	data3	avg
happy	0.5891	0.5602	0.5617	0.0299	0.001	0.0025	0.0235
sad	0.6396	0.5612	0.5687	0.0901	0.0117	0.0192	**0.011**
disgust	0.5517	0.5398	0.5526	0.0248	0.0367	0.0031	0.0215
fear	0.6041	0.5531	0.554	0.0546	0.0086	0.0045	0.0209
surprise	0.5615	0.549	0.5514	0.012	0.0005	0.0019	0.048
angry	0.6056	0.5764	0.5619	0.0561	0.0269	0.0124	0.0318
		she	is	sad			

Table2 a) FLTP

			sad	0.7207
exp	data1	data2	data3	avg
happy	0.7083	0.68035	0.7089	**0.023**
sad	0.7425	0.7593	0.71191	**0.023**
disgust	0.7261	0.67311	0.7209	**0.0368**
fear	0.7126	0.6731	0.70811	**0.0562**
surprise	0.7164	0.6982	0.7182	**0.0194**
anger	0.7221	0.674	0.7461	**0.0162**
	She	is	Anger	

b) DRLTP



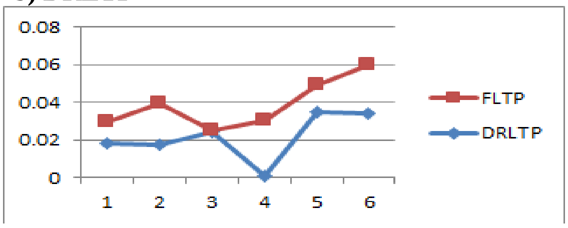
Graph2

					disgust	0.5765	
					query		
EXP	DATA1	DATA2	DATA3	data1	data2	data3	avg
happy	0.5891	0.5602	0.5617	0.0126	0.0163	0.0148	0.0145
sad	0.6396	0.5612	0.5687	0.0631	0.0153	0.0078	0.0133
disgust	0.5517	0.5398	0.5526	-0.0248	-0.0367	0.0239	**0.0125**
fear	0.6041	0.5531	0.554	0.0276	0.0234	0.0225	0.0245
surprise	0.5615	0.549	0.5514	0.015	0.0275	0.0225	0.0216
angry	0.6056	0.5764	0.5619	0.0291	0.0001	0.0146	0.0146
		she	is	disgust			

Table3 a) FLTP

				query	disgust	avg	0.7011
exp	data1	data2	data3	data1	data2	data3	avg
happy	0.7083	0.68035	0.7089	0.0196	0.0483	0.078	0.02523
sad	0.7425	0.7593	0.71191	0.0414	0.0582	0.01081	0.0368
disgust	0.7261	0.67311	0.7209	0.0254	0.02799	0.0198	0.0243
fear	0.7126	0.6731	0.70811	0.01154	0.028	0.00701	0.0155
surprise	0.7164	0.6982	0.7182	0.0153	0.0029	0.0171	0.01176
anger	0.7221	0.674	0.7461	0.021	0.0271	0.045	0.03103
	she	is	fear				

b) DRLTP



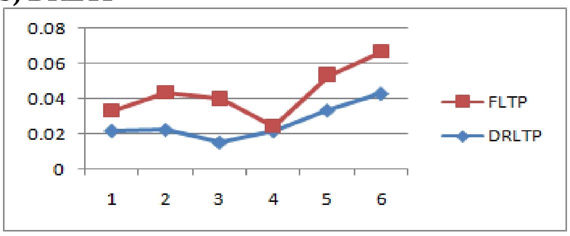
Graph3

					fear	0.568	
					query		
EXP	DATA1	DATA2	DATA3	data1	data2	data3	avg
happy	0.5891	0.5602	0.5617	0.0211	0.0078	0.0063	0.0117
sad	0.6396	0.5612	0.5687	0.0716	0.0068	0.0007	0.0263
disgust	0.5517	0.5398	0.5526	0.0163	-0.0282	-0.0154	0.0199
fear	0.6041	0.5531	0.554	0.0361	-0.0149	-0.014	0.0024
surprise	0.5615	0.549	0.5514	0.0065	0.019	0.0166	0.014
angry	0.6056	0.5764	0.5619	0.0376	0.0084	-0.0061	0.0136
		she	is	Fear			

Table4 a) FLTP

				query	fear	avg	0.6817
exp	data1	data2	data3	data1	data2	data3	avg
happy	0.7083	0.68035	0.7089	0.0266	0.00135	0.0272	0.01838
sad	0.7425	0.7593	0.71191	0.0608	0.0776	0.03021	0.0562
disgust	0.7261	0.67311	0.7209	0.0444	0.0086	0.0392	0.00113
fear	0.7126	0.6731	0.70811	0.0309	0.0086	0.02641	0.02197
surprise	0.7164	0.6982	0.7182	0.0347	0.0165	0.0365	0.0292
anger	0.7221	0.674	0.7461	0.0404	0.007	0.0644	0.01603
	she	is	happy				

b) DRLTP



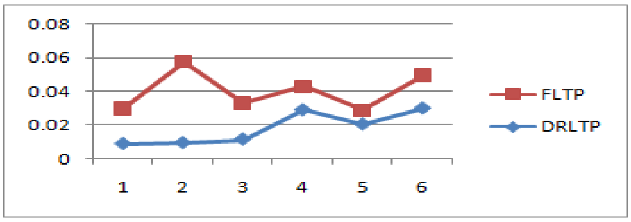
Graph4

					surprise	0.5625	
					query		
EXP	DATA1	DATA2	DATA3	data1	data2	data3	avg
happy	0.5891	0.5602	0.5617	0.0266	0.0023	0.0008	0.0099
sad	0.6396	0.5612	0.5687	0.0771	0.0013	0.0062	0.282
disgust	0.5517	0.5398	0.5526	0.0108	0.0227	0.0099	0.01446
fear	0.6041	0.5531	0.554	0.0416	0.0094	0.0085	0.0198
surprise	0.5615	0.549	0.5514	0.001	0.0135	0.0111	0.0085
angry	0.6056	0.5764	0.5619	0.0431	0.0139	0.0006	0.0192
		she	is	surprise			

Table5 a) FLTP

				query	surprise	avg	0.73161
exp	data1	data2	data3	data1	data2	data3	avg
happy	0.7083	0.68035	0.7089	0.0233	0.05125	0.0227	0.033241
sad	0.7425	0.7593	0.71191	0.0109	0.0277	0.0196	0.0194
disgust	0.7261	0.67311	0.7209	0.0055	0.0885	0.0171	0.0349
fear	0.7126	0.6731	0.70811	0.01901	0.0585	0.0235	0.03367
surprise	0.7164	0.6982	0.7182	0.0152	0.0334	0.01341	0.02067
anger	0.7221	0.674	0.7461	0.00951	0.05761	0.01449	0.0272
	she	is	sad				

b) DRLTP



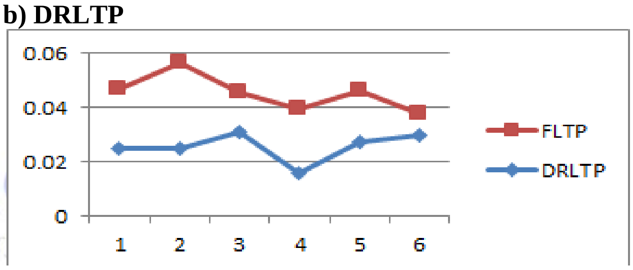
Graph5

					angry	0.5625	
					query		
EXP	DATA1	DATA2	DATA3	data1	data2	data3	avg
happy	0.5891	0.5602	0.5617	0.0156	0.0133	-0.0118	0.0135
sad	0.6396	0.5612	0.5687	0.0661	-0.0123	-0.0048	0.0277
disgust	0.5517	0.5398	0.5526	0.0218	0.0337	0.0209	0.0254
fear	0.6041	0.5531	0.554	0.0306	0.0204	0.0195	0.0235
surprise	0.5615	0.549	0.5514	-0.012	-0.0245	0.0221	0.0195
angry	0.6056	0.5764	0.5619	0.0321	0.0029	-0.0116	0.0078
		she	is	angry			

Table6 FLTP

					anger	avg	0.7411
exp	data1	data2	Data3	data1	data2	data3	avg
happy	0.7083	0.68035	0.7089	0.0327	0.0608	0.0322	0.0419
sad	0.7425	0.7593	0.71191	0.0014	0.0182	0.02919	0.0162
disgust	0.7261	0.67311	0.7209	0.015	0.06799	0.0202	0.0343
fear	0.7126	0.6731	0.70811	0.0285	0.06799	0.03299	0.04316
surprise	0.7164	0.6982	0.7182	0.0247	0.0429	0.0229	0.03016
anger	0.7221	0.674	0.7461	0.019	0.0671	0.005	0.003
		she	is	anger			

b) DRLTP



Graph6

7. Conclusions

In this paper Soft Local Ternary Patterns (SLTP) operator is developed as the face analysis technique to find a kind of emotions used in decision making system. The FLTP contains three steps first is to detect face images from non-face images by localizing the size and shape of the face. Second is feature extraction by cropping face image into smaller features like lips, left eye, right eye, eye pair, nose and mouth and third is to analyze features to find the kind of emotions used in decision making system. This technique is suitable to select improved and efficient feature for identifying polluted pixels and to develop optimal threshold to recognize facial emotions for decision making which produced reliable results. This method is suitable for low contrasted, rotation variant and noise faces for emotion recognition. However it nosedives for intentional emotions.

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