

Signal and Image Based Analysis of Human Fear using FPGA



Swagata Sarkar

Abstract: Human emotion detection is a very important part to enhance the human machine interaction. Emotions can be classified as pure emotions and mixed emotions. Classification of emotions based on single domain feature set is not perfect enough. In this paper six emotions such as fear, anger, surprise, happy, neutral and sad are considered for analysis. Facial emotions and physical parameters are considered for the analysis. Human fear is analyzed predominantly out of all six emotions.

The features for each emotion are implemented using FPGA. It is seen that the number of slices and look up table are varying according to the change of emotion. The slices and lookup table are taken as features for facial emotions and combined with physical parameter features to give better result. The combined features are classified by back propagation algorithm. Out of all emotions fear emotion has the more sensitivity and specificity of 97.36% and 91.67% respectively. The sensitivity and specificity for only physical parameters and facial images are 58.62%, 79.41%, 81.25%, 47.62% respectively. The fear emotion is best classified by taking combined feature set other than single feature set like human emotional faces or physical parameters.

Keywords: EEG signal, Emotion, Facial Images, Physical Parameters

I. INTRODUCTION

Human computer interface is an essential stream in recent scenario. Human nature, behavior, emotional states are attempted to be identified from the combined FPGA features of facial images and human physical parameters. Nowadays due to excessive work pressure lots of mental disorder cases are emerging. Proper analysis of human emotions can minimize the probability of mental disorder and other psychological diseases in near future. In this paper KDFD facial emotional image database is used. Fourteen physical experimental parameters are used for emotion detection along with facial images. The FPGA parameters used for facial images are slices and lookup table. Physical parameters are fuzzified and fused with facial images by wavelet and regression model. [1][2]

In this work 14 experimental parameters and their existing emotional ranges are considered. All the fourteen parameters have significant impact on human emotions. The definition and ranges of parameters are given below:

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1. Electroencephalography (EEG): EEG measurements are given in frequency ranges. It has four linguistic variables, alpha (13-15 Hz), beta (7.5-13 Hz), Theta (2.5-8), delta (<4 Hz). [3]
2. Heart Rate (HR): The ranges for heart rate with three fuzzy linguistic variables are Low heart rate(LHR) from 20 to 70 BPM, Normal Heart Rate (NHR) 45 to 100 BPM, High Heart Rate (HHR) from 84 to 120 BPM.
3. Heart Rate Variability (HRV): HRV has three fuzzy linguistic variables. They are High HRV (HHRV) from 0.15 to 0.4 Hz, Low HRV (LHRV) from 0.04 to 0.15 Hz, Very Low HRV (VLHRV) from 0.003 to 0.4 Hz.
4. Pre-Ejection Period (PEP): The three fuzzy linguistic variables for PEP are Low PEP (LPEP) from 0 to 800 ms, Normal PEP (NPEP) from 0 to 1000 ms and High PEP (HPEP) from 500 to 1100 ms.
5. Stroke volume (SV): Three linguistic variables are Low SV (LSV) from 10 to 144 ml. Normal SV (NSV) from 10 to 250 ml, High SV (HSV) from 240 to 400 ml.
6. Systolic blood pressure (SBP): Three linguistic variables for SBP are Low SBP (LSBP) from 100 to 121 Hg, Normal SBP (NSBP) from 110 to 134 Hg. and High SBP (HSBP) from 120 to 147 Hg.
7. Diastolic blood pressure (DBP): Three linguistic variables for DBP are Low DBP (LDBP) from 77 to 87 Hg, Normal DBP (NDBP) from 81 to 91 Hg. and High DBP (HDBP) from 85 to 91 Hg.
8. Skin Conductance Response (SCR): Three linguistic variables for SCR are LSCR from 0 to 0.2 ms, NSCR from 0.1 to 1 ms and HSCR from 0.85 ms to 1.5 ms.
9. Tidal Volume (TV): Three linguistic variables for TV are Rapid TV (RTV) from 100 ml/breath to 150 ml/breath, Quiet TV (QTV) from 200 ml/breath to 750 ml/breath and 600 ml/breath to 1200 ml/breath.
10. Oscillatory Resistance (OR): Three linguistic variables for RO are Low RO (LRO) from 0 to 0.49, Normal RO (NRO) from 0.4 to 0.88 and High RO (HRO) from 0.5 to 1.
11. Respiration Rate (RR): Three linguistic variables for RR are Low RR (LRR) from 5 to 10 breaths/minute, Normal RR (NRR) from 7 to 23 breaths/minute and High RR (HRR) from 15 to 24 breaths/minute.
12. Non Specific Skin Conductance Response (NSCR): Three linguistic variables for NSCR are Low NSCR (LNSCR) from 0 to 2 per minute, Normal NSCR (NNSCR) from 1 to 3 per minute and High NSCR (HNSCR) from 2 to 5 per minute.
13. Skin Conductance level (SCL): Three linguistic variables for SCL are Low SCL (LSCL) from 0 to 2 ms, Normal SCL (NSCL) from 2 to 25 ms and High SCL (HSCL) from 20 to 25 ms.



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Finger Temperature (FT): Three linguistic variables for FT from 75 to 85 °F and High FT (HFT) from 80 to 90 °F. are low FT (LFT) from 65 °F to 75 °F, Normal FT (NFT)

Table-I: Definitions, measurements of fourteen parameters

Serial No.	Parameters	Functions	Methods of Measurements	Waveforms
1.	Electroencephalogram	Measurements of brain waves	10-20 Electrode System	
2.	Heart Rate	No. of contraction of the heart per minute	Electrocardiogram Machine	
3.	Heart Rate Variability	Time Interval between the heart beats	Electrocardiogram Machine	
4.	Pre Ejection Period	Systolic time interval using R peak of ECG waveform	Electrocardiogram Machine	
5.	Stroke Volume	The amount of blood expelled from a ventricle of the heart specifically from the left ventricle with each heart beat measured by milliliters per bit	Electrocardiogram Machine	
6.	Systolic Pressure	Blood pressure rises with each heart beat	Blood pressure measurement system	
7.	Diastolic Pressure	Blood pressure falls with relaxation.	Blood pressure measurement system	
8.	Skin Conductance Response	It is a phenomenon that the skin momentarily becomes a better conduction of electricity.	Skin Conductance Sensor	
9.	Tidal Volume	It is the lung volume representing the normal volume of air displaced between normal inhalation and exhalation when extra effort is not applied.	Spirometer	
10.	Oscillatory Response	It is a measurement of lung resistance	Spirometer	
11.	Respiration Rate	No. of breaths per minute	Spirometer	
12.	Non specific Skin Conductance Response	Skin conductance response with stimulus	Skin Conductance Sensor	
13.	Skin Conductance Level	Level of skin conductance	Skin Conductance Sensor	
14.	Finger Temperature	Temperature and Humidity measurement of the finger	Finger Pulse Oximeter	

In reference [4], physical parameters are used for Human emotion detection based on Artificial Neuro Fuzzy logic system. In the above paper they have used Gaussian membership function for fuzzy model and width and height of the membership function is adjusted by neural network. They have used artificial neuro fuzzy system for mixed model emotion detection. They have done classification by real range of data. In the above paper based on epochs the results are going to change.

For the first experiment there are 22 emotions before training, after training it is 15.4 happiness, 6.48 fear and 8.3 sadness crying.

In the paper of J. Kotelainen [5] was taken only two physical parameters, Heart Rate Variability and Respiration Frequency and third parameter as Facial Expression. The output for the paper is 54.5% for arousal and 38% for valance after KNN classification.

In the paper of G. Caridakis [6] Facial features, body gestures and speech features are considered. Bayesian classifier output is 70%.

K. Tang [7] worked with 2D, 3D features along with speech. He got the result of 70% after Canonical Correlation Analysis.

M. Soleymani [8] established his result with EEG features, pupilliary response and gaze distance with SVM classifier. He got the result as 68.5% for valence and 76.4% for arousal.

W. Zheng [9] worked with EEG features and pupillary response and classified by SVM classifier. He got the result of 73.59% and 72.98% respectively.

Finally J. Wagner [10] worked with vocal features, facial expressions and gestures. He used Navie Bayesian classifier. All the features used for the above cases are multimodal.

In FPGA logic resources can perform logic functions. Logic resources are grouped in slices to create configurable logic blocks. A slice contains LUTs, flip-flops and multiplexers. A LUT is a collection of logic gates hard-wired on the FPGA. Figure 1 below shows the FPGA internal blocks.

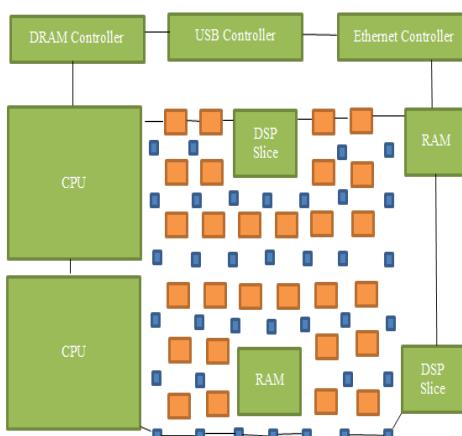


Fig. 1. FPGA Blocks

RTL schematic, Technology schematic, Xilinx power analyzer and plan ahead are analyzed from the FPGA implementation. The flow of the work is explained in figure 2.

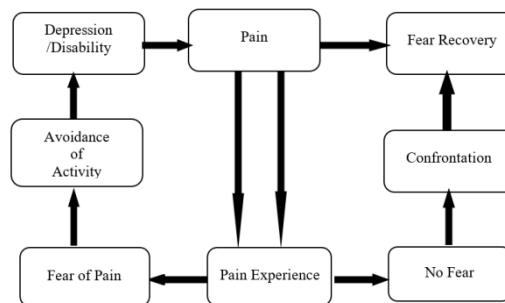


Fig. 2. Flow Diagram

Figure 3 shows the sample images of KDF database.



Fig. 3. KDF Facial Databases

II. METHODS

Fuzzification is the first step in the fuzzy inference process. This involves a domain transformation where crisp inputs are transformed into fuzzy inputs. Crisp inputs are exact inputs measured by sensors and passed into the control system for processing, such as temperature, pressure, rpm's, etc. Each crisp input that is to be processed by the FIU has its own group of membership functions or sets to which they are transformed. This group of membership functions exists within a universe of discourse that holds all relevant values that the crisp input can possess. [11][12]

Out of 14 physical parameters four physical parameters are taken as sample. Those are Heart Rate, Heart Rate Variability, Systolic Blood Pressure, and Diastolic Blood Pressure. The membership functions are defined according to the above-mentioned range. The output variables are six emotions. Six rules are framed.

From the rule viewer output it is seen that for Heart Rate 102, HRV 0.275, SP 134, DP 88, fuzzified output emotion value is 0. 576. It is seen from the output range that, 0576 is the value of the emotion happy. It is satisfied and verified from the rule base also.

One type of network sees the nodes as 'artificial neurons. These are called artificial neural networks (ANNs). An artificial neuron, as shown in figure 4, is a computational model inspired in the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal through the axon. This signal might be sent to another synapse, and might activate other neurons. [13][14]

The Artificial Neural Network is a mimic of biological neural network. Any type of problems whether they are simple or complex can be modeled by artificial neural network. So, some specific types of problems where input output relationship are not well defined can be solved by appropriate algorithms of neural network. Particular test functions can be used for system identification which is not possible for fuzzy based designs.

The complexity of real neurons is highly abstracted when modeling artificial neurons, as shown in figure 10. These basically consist of inputs (like synapses), which are multiplied by weights (strength of the respective signals), and then computed by a mathematical function which determines the activation of the neuron.

Another function (which may be the identity) computes the output of the artificial neuron (sometimes in dependence of a certain threshold). ANNs combine artificial neurons in order to process information.

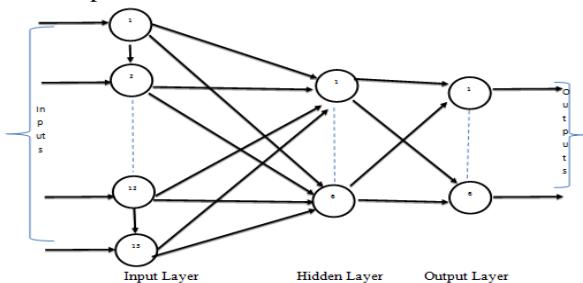


Fig. 4. An Artificial Neuron

The back-propagation algorithm (Rumelhart and McClelland, 1986) is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals “forward”, and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back-propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back-propagation algorithm is to reduce this error, until the ANN learns the training data. The training begins with random weights, and the goal is to adjust them so that the error will be minimal. [15]

The activation function of the artificial neurons in ANNs implementing the back-propagation algorithm is a weighted sum (the sum of the inputs x_i multiplied by their j th respective weights w_{ji}):

$$A_j(\bar{x}, \bar{w}) = \sum_{i=0}^n x_i w_{ji} \quad (1)$$

We can see that the activation depends only on the inputs and the weights. If the output function would be the identity (output=activation), then the neuron would be called linear. But these have severe limitations. The most common output function is the sigmoid function:

$$\sigma_j(\bar{x}, \bar{w}) = \frac{1}{1 + e^{-A_j(\bar{x}, \bar{w})}} \quad (2)$$

Fuzzification is used to get more precise and well defined data. After preprocessing and fuzzification the data is given for classification with the help of Back Propagation Network (BPN) algorithm. Comparison is done based on preprocessed data without Fuzzification and preprocessed data with fuzzification. It is seen that sensitivity and specificity improve for preprocessed data with fuzzified input. [16] Fuzzification is required to convert crisp data into fuzzified data. Crisp data cannot be classified distinctively as it may have associativity with both the ranges. For example, Heart Rate is divided into three categories, Low Heart Rate (20-70), Medium Heart Rate (45-100), and High Heart Rate (84-120). An experimental data we got 87.1. It can be the member of both Medium Heart Rate and High Heart Rate. For distinct precise classification of emotion, it can cause problem. Fuzzification can overcome this. After doing fuzzification three distinct associativity obtained 0, .3686 and .21. So, it is easy to include the data for the Medium Heart Rate as .3686 is the highest value. Defuzzification is not required in this case because fuzzified values itself are taken as feature set to avoid vagueness. How the fourteen physical parameters have direct impact on human emotions, is shown in the sample rule base.

Human emotion detection by facial images is done by different algorithms in different ways. Different features obtained from the analysis are classified by using different classification algorithms. But FPGA based emotional facial features are not used in any paper. The facial emotional image is given directly as the input for FPGA. It is converted to bit file. It is seen that for different emotional facial images the number of slices, look up table values, maximum, minimum asynchronous delays are changing. These four parameters are taken as additional features to enhance the sensitivity and specificity along with the 14 fuzzified physical parameters.

The analysis of 50 subjects is carried out. The analysis of 50 subjects of age group 23 to 26 is carried out. Ethical approval received from Sree Jayam Clinical Laboratory, Tambaram, Chennai. Informed consent was obtained from all individual participants included in the study. The results are encouraging.

The following terms are fundamental to understanding the utility of biomedical parameter-based tests:

1. True positive: the subject has the emotion and the test is positive.
2. False positive: the subject does not have the emotion but the test is positive.
3. True negative: the subject does not have the emotion and the test is negative
4. False negative: the subject has the emotion but the test is negative.

Sensitivity

The sensitivity of a clinical test refers to the ability of the test to correctly identify those patients with the disease.

$$\text{Sensitivity} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}}$$

Specificity

The specificity of a clinical test refers to the ability of the test to correctly identify those patients without the disease.



$$\text{Specificity} = \frac{\text{True negatives}}{\text{True negatives} + \text{False positives}}$$

Positive predictive value

The PPV of a test is a proportion that is useful to clinicians since it answers the question: 'How likely is it that this patient has the disease given that the test result is positive?' [17]

$$\text{Positive predictive value} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}}$$

Negative predictive value

The NPV of a test answers the question: 'How likely is it that this patient does not have the disease given that the test result is negative?'

$$\text{Negative predictive value} = \frac{\text{True negatives}}{\text{True negatives} + \text{False negatives}}$$

Likelihood ratio

A final term sometimes used with reference to the utility of tests is the likelihood ratio. This is defined as how much more likely is it that a patient who tests positive has the disease compared with one who tests negative.

$$\text{Likelihood ratio} = \frac{\text{Sensitivity}}{1 - \text{Specificity}}$$

The lookup table and slices are compared for different emotions which are discussed in following table.

III. RESULTS

Fourteen physical parameters and four FPGA based facial parameters are taken as features. The four FPGA based facial parameters are LUTs, No. of slices, Maximum Asynchronous Delay and Minimum Asynchronous Delay. The total eighteen features are classified by using Back Propagation Algorithm and compared with existing facial image features and physical parameter features. Table 1 depicts the no. of slices and LUTs used for different emotions. Table 2 analyses the FPGA components for different emotions.

Table-II: FPGA analysis of facial images

Emotions	LUTs	No. of Slices
Fear	234	127
Angry	250	137 (max.)
Surprise	229	124(min.)
Happy	246	134
Neutral	244	132

Sad	240	130
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The asynchronous delay for different emotions is also analyzed. Asynchronous delay is defined by the set of worst delays applicable for different emotions. Maximum LUTs and no. of slices are used for angry and minimum is used for surprise. The 20 worst nets by delay for fear are as follows. Table 3, Table 4, Table 5, Table 6, Table 7, Table 8 depicts the asynchronous delay parameters for different emotions.

Table-III: Asynchronous delays for fear

Max Delay	Net name
3.831	address_5_IBUF
3.682	address_6_IBUF
3.528	address_2_IBUF
3.454	Mrom_data_rom00001
3.399	address_1_IBUF
3.060	address_0_IBUF
2.986	address_8_IBUF
2.961	address_7_IBUF
2.932	address_4_IBUF
1.698	N34
1.676	Mrom_data_rom00006
1.634	Mrom_data_rom000018
1.575	N19
1.534	Mrom_data_rom00001391_9_f81
1.448	Mrom_data_rom000021
1.374	Mrom_data_rom00001391_8_f8
1.369	Mrom_data_rom000010
1.357	N15
1.258	Mrom_data_rom000035
1.203	Mrom_data_rom00004

Table-IV: Asynchronous delays for angry

Max Delay	Net name
4.069	address_4_IBUF
3.648	address_5_IBUF

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3.387	address_1_IBUF	1.495	N21
3.102	address_6_IBUF	1.470	N12
3.077	address_8_IBUF	1.430	Mrom_data_rom000011
3.061	Mrom_data_rom00002	1.390	Mrom_data_rom000015
3.022	address_0_IBUF	1.339	address_10_IBUF
2.864	address_2_IBUF	1.291	Mrom_data_rom00001501_12_f8
2.858	address_7_IBUF	1.268	Mrom_data_rom00001501_10_f8
1.906	N111	1.241	N37
1.864	Mrom_data_rom000016		
1.695	Mrom_data_rom0000115		

Table-V: Asynchronous delays for surprise

Max Delay	Net name
5.104	address_3_IBUF
4.970	address_2_IBUF
4.826	address_1_IBUF
4.769	address_0_IBUF
4.379	address_7_IBUF
4.194	address_4_IBUF
3.799	address_5_IBUF
3.757	address_6_IBUF
3.175	address_8_IBUF
2.484	N36
1.804	Mrom_data_rom000015
1.794	Mrom_data_rom000017
1.666	N27
1.619	Mrom_data_rom0000101
1.540	N100
1.531	Mrom_data_rom00008
1.517	N17
1.414	address_10_IBUF
1.398	Mrom_data_rom000068
1.319	N35

Table-VI: Asynchronous delays for happy

Max Delay	Net name
5.443	address_1_IBUF
5.321	Mrom_data_rom000021
5.160	address_2_IBUF
4.672	address_0_IBUF
4.091	address_7_IBUF
3.617	address_6_IBUF
3.590	address_5_IBUF
3.546	address_4_IBUF
2.202	address_8_IBUF
1.831	Mrom_data_rom0000103
1.762	N29
1.611	Mrom_data_rom000019
1.539	Mrom_data_rom000015
1.501	Mrom_data_rom000014
1.495	Mrom_data_rom000030
1.430	Mrom_data_rom00001441_11_f81
1.430	Mrom_data_rom000012
1.426	address_10_IBUF
1.401	Mrom_data_rom000016
1.400	Mrom_data_rom000032

Table-VII: Asynchronous delays for neutral

Max Delay	Net name
5.053	address_6_IBUF
4.864	address_5_IBUF
4.074	address_0_IBUF
4.067	address_1_IBUF
4.017	address_7_IBUF
3.951	address_4_IBUF
3.563	address_3_IBUF
3.452	address_2_IBUF
3.211	address_8_IBUF
2.083	Mrom_data_rom000025
1.766	Mrom_data_rom00001331_11_f81
1.708	Mrom_data_rom0000105
1.611	N27
1.575	Mrom_data_rom00001331_6_f5
1.488	Mrom_data_rom000013
1.390	address_10_IBUF
1.367	N161
1.353	Mrom_data_rom000016
1.293	Mrom_data_rom00001331_17_f6

1.204 Mrom_data_rom00001

Table-VIII: Asynchronous delays for sad

Max Delay	Net name
5.353	address_1_IBUF
4.963	address_2_IBUF
4.850	Mrom_data_rom00002
4.455	address_5_IBUF
4.373	address_0_IBUF
4.321	address_6_IBUF
3.254	address_4_IBUF
3.198	address_7_IBUF
2.960	address_8_IBUF
2.243	Mrom_data_rom000069
2.069	Mrom_data_rom000014
1.896	address_9_IBUF
1.606	Mrom_data_rom000031
1.593	N36
1.586	Mrom_data_rom000092
1.479	Mrom_data_rom000048
1.386	Mrom_data_rom00001401_11_f81
1.315	address_11_IBUF
1.299	Mrom_data_rom000012
1.277	N24

Out of 20 worst delays the maximum and minimum delays are changing for different emotions. It is found that the fear has the minimum asynchronous delay of 1.203 ns where as happy has the maximum asynchronous delay of 5.443 ns. Table 9 shows the minimum and maximum asynchronous delays for different emotions.

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Table-IX: Maximum and minimum asynchronous delays for different emotions

Emotions	Maximum Delay	Minimum Delay
Fear	3.831	1.203
Angry	4.069	1.241
Surprise	5.104	1.319
Happy	5.443	1.400
Neutral	5.053	1.204
Sad	5.353	1.277

In Figure 5 technology schematic of facial image is shown.

Fig. 5. Technology Schematic for facial image

Total .034 W powers are utilized based on no of slices and LUTs used for the particular emotion. Figure 6 shows the power analysis of facial images.

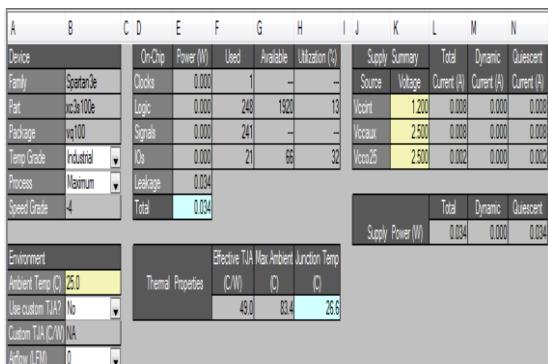


Fig. 6. Power Analyzer for facial image

The following figure explains the placement of the component for the facial image.

In Table 10 & 11 six different emotions are classified based on physical parameters. Fear has the highest sensitivity of 81.25% and angry has the highest specificity of 90.90%.

Table-X: Classification result for emotional physical parameters

S. No.	Types of Emotions	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)
1	Happy	21	8	10	11
2	Sad	18	11	12	9
3	Fear	27	13	3	7

4	Angry	20	15	13	2
5	Neutral	22	12	12	4
6	Surprise	15	17	10	8

Table-XI: Analyses of different emotions for physical parameters

S. N o.	Types of Emotions	Sensitivity	Average Sensitivity	Specificity	Average specificity
1	Happy	63.63	56.67	44.44	75.07
2	Sad	66.66		47.82	
3	Fear	79.41		81.25	
4	Angry	90.90		53.57	
5	Neutral	84.61		50	
6	Surprise	65.21		62.96	

In Table 12 & 13 the classifications are based on facial images. Neutral has the highest sensitivity of 86.36% and happy has the highest specificity of 68.42%. [18]



Table-XII: Classification result of image

S. No.	Types of Emotions	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)
1	Fear	17	10	11	12
2	Angry	20	10	11	9
3	Happy	22	13	6	9
4	Neutral	19	15	13	3
5	Sad	21	12	13	4

6	Surprise	16	17	9	8
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Table-XIII: Specificity & sensitivity of image

S. No.	Types of Emotions	Sensitivity	Average sensitivity	Specificity	Average Specificity
1	Fear	58.62	72.6	47.62	54.80
2	Angry	68.97		47.62	
3	Happy	70.97		68.42	
4	Neutral	86.36		53.57	
5	Sad	84.00		48.00	
6	Surprise	66.67		65.38	

In table 14 and 15 classifications are based on combined parameters. In this analysis fear has the highest sensitivity of 97.36% and highest specificity of 91.67%.

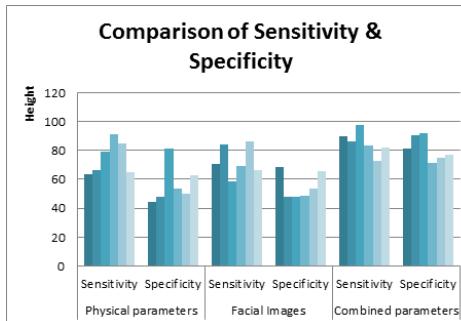
Table-XIV: Classification results of combined parameters

S. No.	Types of Emotions	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)
1	Happy	26	17	4	3
2	Sad	25	19	2	4
3	Fear	37	11	1	1
4	Angry	30	10	4	6
5	Neutral	19	18	6	7
6	Surprise	23	17	5	5

Table-XV: Specificity & sensitivity of combined parameters

S. N o.	Types of Emotions	Sensitivity	Average sensitivit y	Specificity	Average Specificity
1	Happy	89.66	85.295	80.94	81.13
2	Sad	86.2		90.47	
3	Fear	97.36		91.67	
4	Angry	83.33		71.42	
5	Neutral	73.08		75	
6	Surprise	82.14		77.27	

Figure 7 show the comparison between sensitivity and specificity for different emotions.

**Fig. 7: Comparisons of sensitivity & specificity**

If the specificity and sensitivity are compared for all the three types of models, it is seen that for combined parameters fear got the much improvement. The specificity and sensitivity of fear are 91.67% and 97.36% respectively.

IV. DISCUSSIONS

Human emotion analysis is an emerging area of research. Different data types, methods are used to identify the human emotions. The emotions are identified based of facial images, EEG signals, fMRI images, speech signals, fusion of multiple parameters, physical parameters and so on. Other than that so many different classification methods like K-NN classifier, SVM classifier, Fuzzy classifier, neural network classifier etc. are used. Arousal and valence model are used for some works. Some researchers are attempted to identify compound emotions.

But, in our work we have concentrated on two major data fields. Human face and physical parameter are the features which are heavily affected by emotional difference. In our work human facial expressions for different emotions are not directly taken as feature. Here six basic emotions are considered for analysis.

Human facial images are given as input for FPGA and features collected are Slice no. variation, no. of LUTs, and maximum, minimum asynchronous delay. These are the four new parameters considered as facial emotion feature set. These features are not considered for any other previous work.

The physical parameters are also not taken directly from the experimental value. Fuzzified physical parameters are more precise and accurate than experimental data. EEG alpha value also combined along with the physical parameter feature set. These 18 features are new for classification using Back propagation algorithm.

Separately analysis has been done based on facial image features, fuzzified physical parameters. The combined parameters classification has given the best result for most of the output. This combine feature set classification is very much dominant for fear analysis. The sensitivity and specificity for facial image based emotion analysis are 58.62% and 47.62%. The specificity and sensitivity for physical parameter-based emotions are 79.41% and 81.25% respectively. But the sensitivity and specificity for combined features are 97.36% and 91.67% respectively. So, combined feature set classification is very much effective for fear analysis.



In reference [4], physical parameters are used for Human emotion detection based on Artificial Neuro Fuzzy logic system. In the above paper they have used Gaussian membership function for fuzzy model and width and height of the membership function is adjusted by neural network. They have used artificial neuro fuzzy system for mixed model emotion detection. They have done classification by real range of data. In the above paper based on epochs the results are going to change. For the first experiment there are 22 emotions before training, after training it is 15.4 happiness, 6.48 fear and 8.3 sadness crying.

In our approach each physical parameter is divided into three ranges. The membership function for the middle range is triangular function and extreme two memberships are trapezoidal function to cover full side ranges. In this paper separately result has been analyzed.

Fuzzified physical parameters are used for classification of pure emotions using back propagation algorithm. Total 14 input neurons are used at the input layer; 6 neurons are used at the hidden layer and 6 neurons are used at the output layer based on six different emotions. Threshold value is set to 0.01. Since supervised learning algorithm is used, each emotion has its predefined target. Out of 50 data 35 data are used for training and 15 data are used for testing. If the correct emotion is detected it is true positive. If false emotion is not detected, it is true negative. If correct emotion is detected as negative it is false negative and otherwise it is false positive. This is the approach, by which we can easily identify the sensitivity and specificity of the system. This method is much easier and user friendly for the doctors. The perfectness of the system can be easily identified by sensitivity and specificity data, which is not attempted for the reference paper. We got better result than the reference but the average sensitivity is 56.67% and average specificity is 75.07%, which can be improved further. In the above case each training cannot cover all the emotions. But in our case if number of features improved, sensitivity and specificity can be improved better.

Compare to reference [5] in our paper 14 physical parameters are considered and back propagation algorithm in Artificial Neural network is used as classifier. The output is 56.67% and 75.07% for sensitivity and specificity respectively which is better than the output of 54.5% for arousal and 38% for valance after KNN classification.

In reference [6], [7], [8], [9], [10] multimodal emotion analysis are discussed. In reference [6] output is 70%. In reference [7] output is 70%. In reference [8] output is as 68.5% for valence and 76.4% for arousal. In reference [9] results are 73.59% and 72.98%. In our paper we have used physical parameters and FPGA facial features which are not used in any paper. We have got the result of 85.29% and 81.13% for sensitivity and specificity respectively after Back propagation classification which is better than all the referenced multimodal classification.

V. CONCLUSIONS

In this paper six emotions like fear, anger, surprise, happy, neutral and sad. Facial emotions and physical parameters are considered for the analysis. The combined features are classified by back propagation algorithm. Out of all emotions fear emotion has the more sensitivity and specificity of 97.36% and 91.67% respectively. The

sensitivity and specificity for only physical parameters and facial images are 58.62%, 79.41%, 81.25%, 47.62%.

Declarations

Ethics approval and consent to participate

1. Research committee members of Sathyabama University
2. Sree Jayam Clinical Laboratory for their kind approval of laboratory utilization during experiment.
- Consent for publication

Not Applicable

Availability of data and material

The data used from database and partially from human subjects. 50 human subjects are used for data collection for physical parameters in Sree Jayam Clinical Laboratory, Tambaram, Chennai. The participants are students of age group 23 to 26.

Competing interests

There are no conflicts of interest.

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