

Human emotion Classification based on Fuzzified Physical Parameters

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Abstract- There are six basic emotions (sad, happy, fear, angry, surprise, neutral) which can be classified based on different technologies such as image processing, signal processing etc. Facial Emotion detection, fMRI based emotion classification, EEG based emotion analysis are some of the varieties which can diagnose human emotions. In this paper the human emotion classification is done based on physical parameters. The experimental physical parameters are classified by back Propagation algorithm of Artificial Neural Network classifier after fuzzification of data. It is seen that a significant improvement has happened in value of specificity and sensitivity after fuzzification of data.

Key Words: Artificial Neural Network, Fuzzification, human emotion, Sensitivity, Specificity

I. Introduction

Human Emotion analysis is a very popular topic of interest. If emotion can be classified properly many psychological problems can be detected at the earliest and further complications can be prevented and cured fully. In reality six distinguishable basic emotions exist. Other than these, there are lots of compound emotions present which are difficult to classify properly. The emotion identifications are done by Facial Image Processing, fMRI Image Processing, EEG [1] Signal Processing as well as based on Physical Parameters. But in this work experimental dataset is preprocessed and fuzzified. The fuzzified data is then classified with the help of Back Propagation algorithm. Fuzzification is process where the data boundaries are defined very clearly. 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).
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. Those 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 81 to 91 Hg.
8. Skin Conductance Response (SCR): Three linguistic variables for SCR are Low SCR (HSCR) from 0.85 to 1.5 ms.
9. (LSCR) from 0 to 0.2 ms, Normal SCR (NSCR) from 0.1 to 1 ms and High SCR
10. 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.

11. 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.
12. Respiration Rate (RR): Three linguistic variables for RR are Low RR (LRR) from 5 to 10 breath/minute, Normal RR (NRR) from 7 to 23 breath/minute and High RR (HRR) from 15 to 24 breath/minute.
13. 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.
14. 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.
15. Finger Temperature (FT): Three linguistic variables for FT are Low FT (LFT) from 65 to 75 °F, Normal FT (NFT) from 75 to 85 °F and High FT (HFT) from 80 to 90 °F.

Fuzzification is the first step in the fuzzy inferencing process[5]. This involves a domain transformation where crisp inputs are transformed into fuzzy inputs. Crisp inputs are exact inputs such as temperature, pressure, rpm's, etc. measured by sensors and passed into the system for processing. 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. The following shows the structure of membership functions within a universe of discourse for a crisp input.

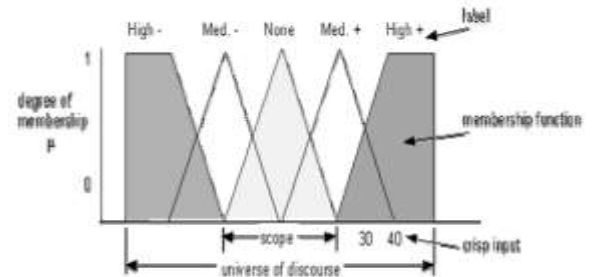


Fig. 2. Membership Function Structure

II. Fuzzification:

The flow diagram used is shown in figure 1.

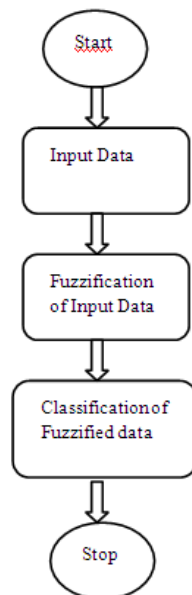


Fig.1. Flow diagram of Physical parameter based emotion analysis

where: degree of membership: degree to which a crisp value is compatible to a membership function, value from 0 to 1, also known as truth value or fuzzy input. Membership function, MF: defines a fuzzy set by mapping crisp values from its domain to the sets associated degree of membership. Crisp inputs: distinct or exact inputs to a certain system variable, usually measured parameters external from the control system, e.g. 6 Volts. Label: descriptive name used to identify a membership function. Scope: or domain, the width of the membership function, the range of concepts, usually numbers, over which a membership function is mapped. Universe of discourse: range of all possible values, or concepts, applicable to a system variable. When designing the number of membership functions for an input variable, labels must initially be determined for the membership functions. The number of labels correspond to the number of regions that the universe should be divided, such that each label describes a region of behavior. A scope must be assigned to each membership function that numerically identifies the

range of input values that correspond to a label. The shape of the membership function should be representative of the variable. However this shape is

Table 1. Representation of an imaginary example of a decision matrix.

		Input Y			
		LOW	NORMAL	HIGH	VERY HIGH
Input X	LOW	Low	High	High	High
	NORMAL	Low	Low	Medium	Medium
	HIGH	Low	Low	Low	Low
	VERY HIGH	Low	Low	Low	Low

III. Artificial Neural Network (ANN)

One type of network sees the nodes as ‘artificial neurons’. These are called artificial neural networks (ANNs). An artificial neuron, as shown in figure 3, 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.

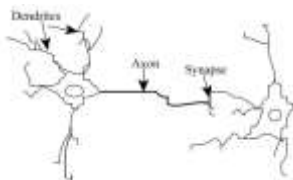


Fig. 3. Natural Neurons

The complexity of real neurons is highly abstracted when modeling artificial neurons, as shown in figure 4. 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.

also restricted by the computing resources available. Complicated shapes require more complex descriptive equations or large lookup tables.

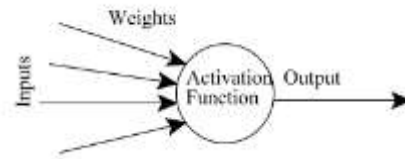


Fig. 4. An Artificial Neuron

IV. The Back Propagation Algorithm

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[6]. 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.

The activation function of the artificial neurons in ANNs implementing the back propagation algorithm is a weighted sum (the sum of the inputs x multiplied by their j_i respective weights w):

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

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:

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

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.

V. Efficiency analysis

The analysis of 50 subjects is carried out. 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?’

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

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.

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

VI. Results & Discussions:

In this paper emotion analysis is done for 50 subjects. Six emotions are taken into consideration. Total number of data considered for classification is 50.

Table 2 Classification result for input non fuzzified data

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 3 Classification result for input fuzzified data

S. No.	Types of Emotions	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)
1	Happy	25	17	6	2
2	Sad	29	15	1	5
3	Fear	30	18	1	1
4	Angry	26	19	5	1
5	Neutral	27	20	3	2
6	Surprise	28	12	7	3

Table 4 Analysis of different emotions for non fuzzified input

S. No.	Types of Emotions	Specificity (in %)	Average Specificity (in %)	Sensitivity (in %)	Average Sensitivity (in %)	Likelihood Ratio (in %)	Average Likelihood (in %)	Positive Predictive value (in %)	Average Positive Predictive Value (in %)	Negative Predictive value (in %)	Average Negative Predictive Value (in %)
1	Happy	44.44	75.07	63.63	56.67	1.13	2.00885	67.74	67.17	42.10	65.55
2	Sad	47.82		66.66		1.2775		60		55	
3	Fear	81.25		79.41		4.2352		90		65	
4	Angry	53.57		90.90		1.9577		60.6		88.23	
5	Neutral	50		84.61		1.6922		64.7		75	
6	Surprise	62.96		65.21		1.7605		60		68	

Table 5 Analysis of different emotions for fuzzified input

S. No.	Types of Emotions	Specificity (in %)	Average Specificity (in %)	Sensitivity (in %)	Average Sensitivity (in %)	Likelihood Ratio (in %)	Average Likelihood (in %)	Positive Predictive value (in %)	Average Positive Predictive Value (in %)	Negative Predictive value (in %)	Average Negative Predictive Value (in %)
1	Happy	73.91	81.94	92.59	92.39	3.5488	8.2937	80.6	87.97	89.47	87.51
2	Sad	93.75		85.29		13.6464		96.66		75	
3	Fear	94.73		96.77		18.3624		96.77		94.73	
4	Angry	79.16		96.29		4.62		83.8		95	
5	Neutral	86.95		93.10		7.134		90		90.9	
6	Surprise	63.15		90.32		2.451		80		80	

Table 6 Comparison of different emotions for fuzzified & non-fuzzified input

S. No.	Input types	Average Sensitivity	Average Specificity	Average Likelihood Ratio	Average Positive predictive value	Average Negative predictive value
1	Non Fuzzified Inputs	75.07	56.67	2.00885	67.17	65.55
2	Fuzzified Inputs	81.94	92.39	8.2937	87.97	87.51

VII. Conclusion

In this paper the comparison between fuzzified input and non fuzzified input is done. It is seen that specificity, sensitivity and Likelihood ratio are improved by respectively.

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