

A Novel Neuro-Fuzzy Model to Detect Human Emotions Using Different Set of Vital Factors with Performance Index Measure

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Abstract—A novel optimization algorithm is proposed for detecting human emotions (responses) using artificial intelligence techniques such as exhaustive search, fuzzy logic and neural networks. Previous models for detecting human emotions have used fourteen measurable physical and physiological input factors to detect twenty two human emotions [1]. This paper presents an optimization method to reduce the number of input factors required to detect a set of emotions. The proposed method utilizes twelve optimization procedures (cases) each one has unique error values, and different input factors. Optimization is sought to reduce the cost and complexity of implementing human emotion detection systems. A performance measure index is used to evaluate the effectiveness of the proposed model. This study shows that using less than half of the factors (6-8 factors) is the most cost effective set of input parameters for the human emotions detection system.

Index Terms—Adaptive Neuro-Fuzzy Inference System, Emotion Detection, Exhaustive Search, Performance measure index.

I. INTRODUCTION

The need for intelligent computing techniques becomes essential especially in human medical research and applications that require rather complex representation, intensive computations, and decision making processes [1,2]. The prime motive for embarking on this work is to optimally detect and identify human emotional responses such as anger, anxiety, disgust contamination, disgust mutilation, embarrassment, fear, fear imminent threat, sadness crying, sadness non crying, sadness anticipatory, sadness acute, affection, amusement, contentment, happiness, joy, antic pleasure visual, antic pleasure imagery, pride and relief, surprise and suspense. The detection of such emotional responses relies mainly on several vital factors such as Heart

Rate (HR), Finger Temperature (FT), Electroencephalography (EEG), Heart Rate Variability (HRV), Respiration Rate (RR), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Nonspecific Skin Conductance Response Rate (nSRR), Pre-Ejection Period (PEP), Oscillatory Resistance (Ros), Skin Conductance Level (SCL), Skin Conductance Response (SCR), Stroke Volume (SV) and Tidal Volume (Vt) [1-3, 9, 10]. Human emotion detection models can be readily used in conjunction with social networks such as Facebook, Twitter, Myspace, LinkedIn, Instagram, and messenger applications, amongst others, by announcing the emotional statuses between communicating parties [1, 20]. Other suitable arenas would include health care applications readily disseminating vital health signs between patients and their care providers [1]. Other areas of applications would include monitoring for security at airports, banks, military facilities, wherein criminal intentions by subjects are detected and identified. Mission-critical applications like space missions and the gaming industry provide other useful venues for application of the proposed emotion detection approach [1-3].

In the original neuro-fuzzy inference models developed by the authors in [1, 2] for human emotion detection, fourteen different factors were used to detect one or more of twenty two different emotions. The 14 factors used in [1] were selected based on their ability to detect the 22 different emotions described in [3]. All of the 14 factors are physiological variables and have direct interaction with the human autonomic nervous system (ANS), as suggested in [3, 14], where the emotions can be correlated to the human ANS. However, the cost and complexity of the system can be very large if all 14 factors are used in a given environment, as exhibited in [1, 2]. Moreover, quite often not all the detectible emotions are required for a given application. For example, security related applications do not utilize the emotions of happiness, relief, joy, and other positive emotions. Hence, it is important to be able to use the most suitable or optimal set of factors required for any given application. This paper is concerned with finding an optimal set of factors (significantly less than 14) for the detection of a subset of emotions.

The optimization approaches addressed in this paper use exhaustive search strategies to account for all possible sets of factors. This approach is supported with a procedure used to determine the dominant factors for each human response (emotion).

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Such exhaustive search technique can readily be skipped in the event that the decision maker is an expert in the field such as in the case of a psychiatric or neuroscience expert. This would, inherently, require an ongoing decision making to be in place. Henceforth, and to avoid extensive dependencies on human interpretations, exhaustive search is considered to be a viable technique in the process. Notably, exhaustive searches normally provide the model involved with huge amounts of data allowing the designer to determine the optimum set of input variables, per emotion, in lieu of the complete 14 vital factors. In the process of conducting exhaustive search for optimal set of vital variables, several statistical parameters can be readily obtained such as the average error (which is the sum of all output values for each emotions for each case of input factors K divided by the number of the output), the most frequent value within the common range, the common value within emotion range, the most dominant factors for each emotion, etc.

For the purpose of this study, MATLAB tool is the applied programming platform where exhaustive search using (n-choose-k factors) is a key component in the design where, $n=14$ input factors, and $k = 2, \dots, 13$. Further, fuzzy logic is used as the representation technique of the input vital factors since each factor includes overlapping ranges of membership functions. Note that there is no crisp value within the range. As such, fuzzy logic will provide a means for representing the data adequately using fuzzy linguistic variables. Whereas neural network provides the training technique to facilitate adaptive learning and cater for minimizing the differences between actual and desired output. This is in addition to the use of data mining procedure which rely on statistical measures to classify the results. The techniques used in this work are designed and implemented using command line and verified leveraging Adaptive Neuro-Fuzzy Inference System (ANFIS) and Fuzzy Inference System (FIS) graphical user interfaces.

II. RELATED WORK

The detection of human emotions has been an area of concern for many researchers for a quite a long time., However, few were able to create an accurate unbiased model. For example, facial expressions algorithms provide indicators regarding human emotional status, although they fail to overcome highly trained organized criminals.

Also, using Electroencephalography (EEG) signal has been proposed [3,4] to provide accurate indicator of certain emotional responses, albeit with excessive and invasive deployment complexity.

Kreibig reported experimental results for (134) medical research subjects on measuring human responses using different physiological factors [3]. The significance of the use of physiological variables stems from the fact that they are too difficult to alter or control by trained criminals to hide certain emotional responses. The author methodology depended on comparing previous researchers' opinions on the correlation between human responses and autonomic nervous activity. Nonetheless, a controversy still exists between a number of researchers working in the field including Fledman-Barrett, Brown and Fee where Fledman-Barrett stipulated that there was little correlation between emotions and autonomic nervous system reactions [3, 11]. Brown, Fee and Stemmler, on the other hand, noted that there was indeed significant correlation

between human emotions and autonomic nervous system activities including heart rate, respiration rate and brain activity [3, 12, 13]. Meanwhile, some researchers take an intermediate position; they believe that there exists some degree of correlation between human emotions and autonomic nervous system reactivity [3, 14]. Table 1 in [3] presents a correlation between human emotions and autonomic nervous system.

Furthermore, brain signals, especially (EEG) signals, are often used to measure human emotions [3, 4]. Medical experts point out that there are differences between physiological actions such as voice or face and conscious feelings (Emotions). This means that facial and voice expressions are not objective since they get interpreted relying on human elements. Therefore, using vital factors (HR, EEG, and SBP) become a must. EEG signals, for instance, are used to recognize human emotions depending on emotional representation, *viz.*, valance, dominance or arousal. However, correct EEG recognition of emotions was about 60% [3, 4 and 15]. New studies [19] reveal that correct EEG recognition of emotions reaches 83.6%.

As such, vital physiological factors have direct influence on human emotional statuses; for instance, respiration rate is usually a continuous process and, in some circumstances,, it changes rapidly indicating the occurrence of a non-healthy situation, physical fatigue or emotions establishment. Therefore, respiration rate measure is essential to define an emotion [5].

The Facial Action Coding System (FACS), first introduced by Ekman and Friesen, is commonly used as an emotional indicator [4, 16-18]. This system uses a judgment procedure that relies on human facial signs. It provides information about the frequency, intensity and duration of facial expression and relies on empirical studies to select the system variables involved; physical or emotional signs. The decision about the type of emotion is usually made by an individual familiar with the particular culture; so it is highly culture-dependent and provides no reliable indication [4, 16-18].

A recent study [9] presents a model to detect stress based on two vital factors namely, heart rate (HR) and galvanic skin response (GSR). This system utilizes fuzzy logic to represent the vital factors. Furthermore, the stress-detection system has an accuracy up to 99.5% during a period of 10 seconds. Moreover, 90% success rates are achievable by decreasing the acquisition period to 3-5 seconds. The proposed stress-detection model is suitable for some real-time applications [9].

Another study [10] provided classification for three emotional states, namely boredom, pain, and surprise based on vital factors which include electrocardiography (ECG), electro dermal activity (EDA), skin temperature (SKT), and photo plethysmography (PPG), and using several machine learning algorithms. The study is conducted using 217 subjects and it led to linear discriminating analysis (LDA) algorithm based on 27 parameters which are extracted from four vital factors [10].

A more comprehensive neuro-fuzzy system was designed [1] to detect twenty two different human emotions using fourteen vital factors. The emotions include eleven positive and eleven negative emotions (anger, anxiety, disgust contamination, disgust mutilation, embarrassment, fear, fear imminent threat, sadness crying, sadness non crying, sadness anticipatory, sadness acute, affection, amusement, contentment, happiness, joy, antic pleasure visual, antic pleasure imagery, pride and

relief, surprise and suspense). The vital factors include Heart Rate (HR), Finger Temperature (FT), Electroencephalography (EEG), Heart Rate Variability (HRV), Respiration Rate (RR), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Nonspecific Skin Conductance Response Rate (nSRR), Pre-Ejection Period (PEP), Oscillatory Resistance (Ros), Skin Conductance Level (SCL), Skin Conductance Response (SCR), Stroke Volume (SV) and Tidal Volume (Vt). These 14 factors by and large include most of the factors that have been investigated in various studies [3, 4, 5, 14, 15, 16, 18, 19]. In this study, and in [1, 2] the authors have built emotion detection models using all 14 factors, which are used the most commonly used positive and negative emotions .

Six different input-output neuro fuzzy inference models to detect human emotions were built and trained using many sets of training data to minimize the error between measured and desired results [1]. The study used the ANFIS-GUI in MATLAB toolbox [1, 8]. Although this study is rather complete, it requires large number of sensors, and often sophisticated measuring device such as for EEG brain wavelets, heart rate variability and blood pressure. Moreover, processing the input data from a relatively large number of input devices/sensors could cause time delays in real time systems [6]. Therefore, an optimization procedure is required to minimize the cost and yet preserve the ability to detect the required emotion with acceptable accuracy. However, it is important to note that the original comprehensive model provides a reliable point of reference for any emotions detection using a reduced set of vital factors.

The model presented in [1] was initially proposed to solve different problems like enhancing the communication between patients and their doctors. The proposed optimization model presented in this paper relies on [1] as the baseline model where the main objective of this paper is to determine an optimal set of vital factors, which is required to identify a certain emotion.

The remainder of this paper is organized as follows. System Design outlines system description in section three, and then analysis and results for selective optimization procedures (input factor cases) are provided in section four. Performance analysis is provided in section five to signify the significance of the proposed optimization model. Conclusions are given in section six.

III. SYSTEM DESIGN

Previous work [1] related to the problem of addressing emotion detection and identification used all fourteen input factors to determine each emotional response. In this context, all fourteen factors had to be used to determine each and every one of twenty-two emotion. Evidently, this is a costly procedure and could suffer performance degradation since this would require a large number of measurements to be validated and used to decide an emotion which is complex in physical realizations.

The objective of this study is to optimize system performance by minimizing the number of input factors, such that the reduced number of factors produces similar results with acceptable and tolerable error values that are ± 0.5 from the nominal values presented in [1]. This would ultimately reduce underlying system complexity and the ensuing implementation cost. The optimization process hinges primarily on artificial

intelligence techniques such as exhaustive search and adaptive neuro-fuzzy inference system in addition to data mining. Following section investigates these techniques and outlines system model operation.

A. Methodology

The three techniques used to find the optimal set of input factors, are illustrated in Figure 1 and further explained below.

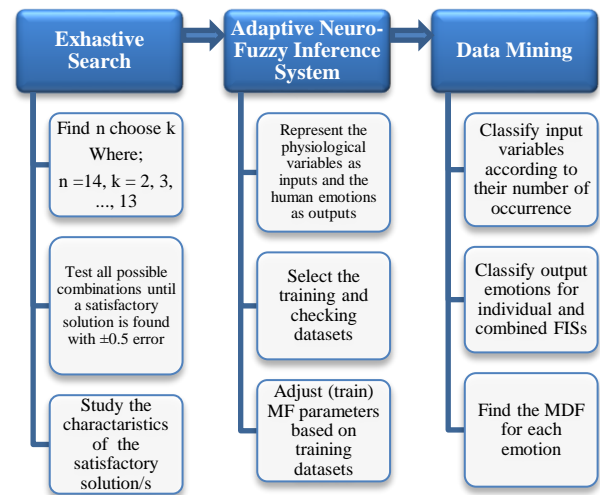


Fig. 1. A brief description of the utilized techniques

1) Exhaustive Search

Exhaustive search is a general, systematic search technique that enumerates all possible candidate solutions without redundancy in order to get the targeted solution/s. Using this method, we will look into all possible combinations of factors, taking any K factors out of the fourteen factors at a time ($2 \leq k < 14$). For example, for $K=2$, we would take the set of factors (F_i, F_j) , where $i \neq j$, and $i=2, \dots, 14, j=2, \dots, 14$ [2, 7, and 8]. The exhaustive search technique is outlined in the following steps:

1. Generate candidate solutions using "n-choose-k" to set all possible combinations where $n = 14$ and $k = 2, 3, 4, \dots, 13$. Each value of "k" defines a case study with a large number of possible combinations. For example for $k = 2$; the candidate solutions are equal to 91 combinations which constitute fuzzy inference systems (FISs) with two distinct human physiological input factors for each FIS and with a selected number of rules containing those factors [2, 7, and 8].
2. Test and investigate the candidate solutions by defining a set of conditions for the possible value of inputs, until a satisfactory solution is found with ± 0.5 error tolerance from emotions' nominal values [2, 7, and 8].
3. Analyze the characteristics of the satisfactory solution/s. If no satisfactory solution is found, announce failure in defining a solution [2, 7, and 8]. Equation 1 illustrates the process of generating all possible combinations.

$$\text{All Candidate Solutions} = \binom{n}{k} = \frac{n!}{(n-k)!k!} \quad (1)$$

where $n=14$, $2 \leq k < 14$.

2) Adaptive Neuro-Fuzzy Inference System (ANFIS)

The basic idea behind the ANFIS technique is simply to provide a method for modeling a FIS to adapt to some data set (input set) to compute the associated membership function parameters that best fit the intended FIS design [7,8]. These parameters differ from one membership (MF) type to another; for example, the Gaussian MF has two parameters; mean and standard deviation [7,8]. The ANFIS technique adjusts the membership function parameters using back propagation or a combined optimization technique consisting of back propagation and least squares algorithms [7,8]. Hence, FIS maps input/output correctly according to the relevant training data. Note that the training process involved ends when an error criterion is achieved or whenever the desired number of epochs is reached. Equation 2 illustrates the Gaussian MF [7,8].

$$\text{Gaussian_MF} = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \quad (2)$$

where c - mean, σ - standard deviation.

A sophisticated iterative process to create all the FIS subcomponents is addressed, where; four main components should be taken into consideration, namely: Fuzzy inputs which correspond to the selected human physiological factors, fuzzy operators AND, OR and NOT, fuzzy rules which are if-then statements formulating the fuzzy logic conditions between inputs and outputs, and fuzzy outputs (human emotions) [7,8]. Each FIS output is defined by an emotion index, emotion name, emotion value, and emotion range [7,8]. For example, the first emotion is anger with a value of 1 and range 0.5-1.5; fear emotion has index 6, value 6 and range 5.5-6.5, and so on. Twenty two human emotions are defined using ANFIS rules, these rules are extracted from [3], a research includes 134 papers which are related to vital factors-emotions relationships.

The model utilizes training data to extract information and consequently adjusts its membership function parameters [7, 8]. This is valid for an actual training and data testing that is like real input data for the intended FIS [7,8]. Testing for data integrity is considered as the second check in the system validation process. To further elaborate on this, let us explore the training and data testing in more detail [7, 8]. The training and data testing used in this study are similar in principle, but data testing provides a more accurate mechanism than training data since training data involves additive noise in the process [7, 8]. Training and testing data are generated using uniform random number generators limited by the boundaries of each vital factor [7, 8]. The randomly generated numbers are formed as a $[N \times M]$ matrix of where N being the number of available human data records (as related to the number of human cases) while M is the number of inputs plus one, e.g. $M=15$. The first 14 columns define crisp input values whereas column 15 represents the output value (1, 2, 3..., 22). In this study, the training data contains 814 records while the test data contains 156 records [1, 2, and 8].

3) Data Mining

Data mining is a process whereby targeted forms of knowledge are extracted from large amount of data leveraging certain patterns or rules that are presented in readable formats [7, 8]. Data mining is commonly used in conjunction with many disciplines like statistics, artificial intelligence, machine learning and database access technologies. In this ensuing study large amounts of data are produced and to extract the targeted information, data is classified into two categories with each one having its own classification pattern [7, 8 and 10].

Classification of physiological input variables:

Vital factors emanating from human response are categorized according to their frequencies and percentages of occurrence for each possible value of input after looking them up from exhaustive search [2]. Here, each case has k -input variables selected out of the fourteen total factors. The classification is done for each possible input variable individually. However, this step is performed prior to designing the FIS system [2].

Classification of human output (emotional) values:

The output data generated from each case of study is huge; since we have 12 case studies which include ($2 \leq k < 14$), for example when $k = 2$, the total number of possible output is $(14 \text{ choose } 2) * (\text{no. of emotions})$ which is equal to 2002, so the classification procedure is accomplished at two levels which include:

Individual FIS

1. The idea, here, is to get fairly the same output values for each case study close enough to outputs measured leveraging the results of the more general model (using all 14 factors) [1,2]. Hence, a group of input sets is generated for each FIS design which includes (66) sets divided into three groups containing (22) elements each [1,2]. These sets contain output values for various emotions after evaluating a selected number of crisp input values into the intended FIS; the selected crisp values are reused from the original non-optimization model input space that have the same value of the output under consideration [2].

2. A range for each output value is defined within (± 0.5) tolerance from established nominal output values, and intersect with them in the corresponding output set (human output value). For example, range1 varies between 0.5-1.5 intersects with output1_set1 which contains the measured output values of emotions using crisp input number one that is related to emotion number one (anger) as defined in [1,2]. These results define the common values between acceptable and measured human emotions values, so a prediction can be made.

Combination of all FISs

Past approaches form the basis for this level of classification. Output values with the same index "refer to the same output

emotion" for all FIS generated in each case of k are combined as the common value within emotion range [2]. After defining these sets, a statistical measure such as average error is determined. Also, the most frequent value within emotion range, its frequency of occurrence, and the corresponding FIS that contains it are computed. Furthermore, the most dominant factors (MDF) related to each emotion are defined and tabulated [2]. These values will facilitate the mapping method to the desired FIS, and, consequently tracking them back to the desired input factors [2].

IV. ANALYSIS AND RESULTS

A. Analysis procedures

The results are generated and analyzed as follows:

1. First, input variables are classified according to their frequency of occurrence and their percentages after finding all possible candidate solutions for the case under consideration (n -choose- k value) [2].
2. Second, use training sets to find the desired output value for each emotion [2].

In the process of analysis, a statistical measurement is used to extract useful information, In addition to a set of unique measures; these include:

1. Common values within emotion range; a range for each emotion is defined with a tolerance of ± 0.5 from the nominal output value and with a step of (0.0001). This step is small enough to extract large set of common values since outputs after evaluation in FIS and training in ANFIS generate small values. Also the FIS index which produces each output is extracted and tabulated in order to identify the inputs (factors) required to detect the emotion indicated by the common value of the output. When the number of common values increases, a reduction of input numbers can be expected with a certain error value [2].
2. Average error for common values for each k factors [2].
3. Most frequent value of any detectable emotion when applying the evaluation sets, and their number of occurrence [2].
4. Most dominant factors for each emotion which helps defining a unique set of input factors for the detectable emotions.

Next we provide several study cases to illustrate the procedures described above.

B. Study Cases

1) Input Factors Analysis

Table 1 illustrates the results for the cases of $k = 2, 3, 4$. For each k , we find the percentage of occurrence for input no.1, 3, 4 in the generated FIS combinations. For $K=4$, there are 1001 possible (non-redundant) combinations; the number/percentage of occurrence of each factor in the 4th position is shown in table

1. For example, SV appears 3 times in the 4th position of the 1001 combination [2].

TABLE I
THE NUMBER AND PERCENTAGE OF OCCURRENCE OF FACTOR 1, 3, AND 4 FOR $K=2, 3, 4$ RESPECTIVELY [2]

n = 14						
Input Factor	k = 2, n choose k = 91 Combinations		k = 3, n choose k = 364 Combinations		K = 4, n choose k = 1001 Combinations	
	No.	%	No.	%	No.	%
EEG	11	12.1	-	-	-	-
HR	12	13.2	-	-	-	-
HRV	11	12.1	1	0.3	-	-
PEP	7	7.7	2	0.5	1	0.1
SV	7	7.7	2	0.5	3	0.3
SBP	8	8.8	12	3.3	7	0.7
DBP	11	12.1	14	3.8	21	2.1
Vt	2	2.2	23	6.3	59	5.9
Ros	7	7.7	33	9.1	92	9.2
RR	7	7.7	53	14.6	125	12.5
SCR	7	7.7	26	7.1	33	3.3
nSRR	1	1.1	60	16.5	158	15.8
SCL	-	-	67	18.4	230	23
FT	-	-	71	19.5	272	27.2

For $k = 2$, the HR physiological input variable is the most frequent input with a percentage of (13.2 %) This means that when we use two input physiological variables out of fourteen according to the proposed optimization algorithm. From the 91 combination we count each physiological variable and in this case HR appears 12 times with a percentage of $(12/91)*100\%=13.2\%$. For $k = 3$ and 4, the FT physiological input variable is the most frequent input with a percentage of (19.5%) and (27.2%) respectively [2].

2) Output Factors Analysis

Each FIS combination among the unique set of (14 choose k), is trained with 200 epochs of training. The total number of FIS combinations for each K is shown in Table 2. Note that each FIS is trained for 200 epochs, and thus, for example, there is a total of 686400 different output values for $K=7$. The results for all k values are summarized in Table 2 [2].

Table 2 shows the average error, a sample of the most frequent value and the number of occurrence for all k values. For example, the average error using $k = 4, 6, 7$ is the lowest, indicating that these values of k are the best choice to use. Also, the frequency of occurrence of emotion 16 is 37 for $k = 4$ i.e., it appeared in 37 different FIS combinations [2].

TABLE II
AVERAGE ERRORS, MOST FREQUENT VALUE FOR ALL K VALUES [2]

Number of factors K	Total number of FIS combinations	Most Frequent Emotion	No. of occurrence	Average Error
2	91	16	4	2.999159
3	364	16	17	2.532723
4	1001	16	37	0.184588
5	2002	18	73	0.563918
6	3003	18	147	0.319814
7	3432	18	167	0.333632
8	3003	20	174	0.57455
9	2002	20	142	0.575186
10	1001	20	99	1.966364
11	364	12	54	2.460691
12	91	20	26	3.119905
13	14	1,2,3,...,22	1 for each emotion	4.3097

V. PERFORMANCE ANALYSIS

A. Performance index measure (PIM)

A performance index measure (PIM) is defined to evaluate the effectiveness of the optimization method. PIM is a measure of the ability to detect given number of emotions at a certain cost, and is defined as follows:

$$PIM = \rho * \tau \quad (3)$$

Where ρ is the emotion detection ratio defined as:

$$\rho = N_i / N \quad (4)$$

N_i is the number of emotions detected using F factors and N is the maximum number of emotions detectable in the system (N=22 in this study).

And τ is the cost effectiveness factor defined as:

$$\tau = T_i / F \quad (5)$$

Where T_i is the time required to process N choose K FIS combinations. Figure 2 shows the performance index measure PIM for different factors F=2, 3, ..., 14.

Note that the PIM is highest when the number of used factors is 6-8, indicating that using very large number of factors is too costly despite the fact that more emotions can be detected, while using too small number of factors detect less number of emotions despite the fact that it has smaller cost. Using 6, 7, or 8 factors we can detect 20 emotions out of 22 ($\rho = 0.91$) with cost effectiveness $\tau = 0.75, 0.84,$ and 0.86 respectively. When 14 factors are used, the rate of emotion detection is 100%; however this rate is reduced by the cost effectiveness factor $\tau = 0.08$ thus making the PMI = 0.08 for F=14.

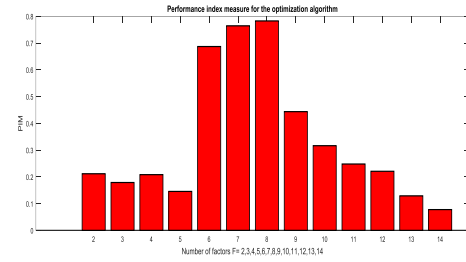


Fig. 2. Performance index measure for the optimization algorithm

B. Average Error

The average error of the detected emotions is another measure of the effectiveness of the number of used factors. Figure 3 shows the average error for each number of factors K [2].

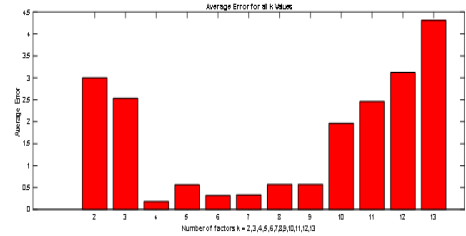


Fig. 3. Average error for all k values

Note that the lowest error value is obtained, as shown in Fig.3, for k=4, 5, 6, 7, 8 and 9.

C. Most Dominant Factors (MDF)

The main objective of this research is to define the optimal set of factors, which are required to detect a certain emotion. For this purpose, we examine the FIS combinations, which are found to produce the output value corresponding to the emotion under consideration with an error margin of ± 0.5 [2]. We then find the dominant factors for each emotion E_i as follows. Let E_i be detected by a set of FIS combinations $\{FIS_i\}$; Each FIS_i has a set of K factors $\{F_i\}$. The K factors in each set is one of the (14 choose K) combinations [2]. The most dominant factors (MDF) are then defined as the intersection between all $\{F_i\}$ [2]. $\{MDF\} = \{F_i\} \cap \{F_j\} \cap \{F_k\} \cap \dots$

Where F_i, F_j, F_k, \dots correspond to FIS combinations i, j, k, ... and include a set of K factors. Note that the number of sets $\{F_i\}$ can range from null (no set is found to produce the emotion) to $\binom{N}{K}$ (the total number of possible combinations). The intersection between all sets $\{F_i\}$ is the optimal set of factors, which must be used to detect emotion E_i [2]. Note that the size of $MDF\ S = |\{MDF\}| \leq K$. If $S < K$, then the remaining factors (K-S) are selected from any of the factors found in any of the FIS combinations $\{F_i\}$. The following example illustrates the process of finding the MDF for K=7 and emotion $E_i=3$ (See table 4). For K=7, there are 3432 FIS combinations [2]. Only two FIS combinations (number 1768 and 1823) produce emotion 3 with 0.107 and 0.051 error margin respectively (the emotion output is 3.1069 and 3.0505) [2].

$\{F_{1768}\} = \{3\ 4\ 5\ 7\ 8\ 10\ 14\}$ and $\{F_{1823}\} = \{3\ 4\ 6\ 7\ 8\ 10\ 14\}$;
 $\{MDF\} = \{F_{1768}\} \cap \{F_{1823}\} = \{3\ 4\ 7\ 8\ 10\ 14\}$.

$S = |\{MDF\}| = 6$; hence, the complete set of factors required to detect emotion 3 requires one more factor, which can be either factor #5 selected from $\{F_{1768}\}$ or factor #6 selected from $\{F_{1823}\}$.

Tables 3 and 4 summarize the results for a set of emotions for $K=4$ and $K=7$. For simplicity purposes, only 3 output values are shown for each emotion and their corresponding FIS indices [2]. The null value in tables 3 and 4 indicates that the emotion is not detectable by the given FIS. Null in the MDF field means that the emotion is not detectable at all using K factors [2]. The MDF can be any of the K factors, as is the case for emotion 5 and $K=4$ [2].

TABLE III
 A SAMPLE OF THREE OUTPUT VALUES FOR FIVE EMOTIONS, FIS INDEX, DOMINANT FACTORS USING $K = 4$ [2]

Emotion default value	Out1 {FIS _i }	Out2 {FIS _i }	Out3 {FIS _i }	Most dominant factors
1, 2, 4	Null	null	Null	Null
3	3.0013 {320}	3.0003 {330}	3 {344}	3 4 10
5	5.4588 {229}	5.0788 {234}	5.4596 {235}	Any four inputs
6	6.2934 {90}	6.2132 {439}	6.1044 {444}	4
7	7 {20}	7.0807 {27}	7 {29}	1
8	7.9119 {27}	7.7884 {79}	7.9139 {85}	Any four inputs
9	9 {31}	9.3753 {34}	9.0121 {98}	13
10	10.402 {11}	10 {12}	10.4022 {15}	1
11	11.016 {73}	11.2487 {89}	10.7354 {100}	Any four inputs
12	12.346 {14}	12.4876 {23}	12.3575 {90}	1
13	13.024 {4}	12.5653 {8}	12.5941 {13}	1
14	13.896 {4}	13.9687 {6}	14.3059 {9}	1 2
15	15.016 {2}	15.4199 {9}	15.4816 {19}	1
16	15.732 {1}	15.7138 {3}	15.6288 {4}	1
17	17.079 {42}	17.0825 {63}	16.9753 {131}	Any four inputs
18	17.999 {7}	18 {12}	18 {16}	1 13
19	19.034 {66}	18.9127 {132}	18.8353 {135}	Any four inputs
20	20.5 {5}	19.6198 {37}	20.3141 {38}	1 3
21	20.598 {36}	20.6588 {37}	21.3599 {47}	1
22	22 {27}	21.596 {36}	21.7544 {48}	Any four inputs

TABLE IV
 A SAMPLE OF THREE OUTPUT VALUES FOR FIVE EMOTIONS, FIS INDEX, DOMINANT FACTORS USING $K = 7$ [2]

Emotion default value	Out1 {FIS _i }	Out2 {FIS _i }	Out3 {FIS _i }	Most dominant factors
1,2	Null	null	null	Null
3	3.1069 {1768}	3.0505 {1823}	null	3 4 7 8 10 14
4	3.9575 {1823}	null	null	3 4 6 7 8 10
5	5 {75}	4.9067 {76}	5.4691 {118}	1 2 3 14
6	5.5902 {849}	5.8383 {878}	5.8192 {880}	1 4 11
7	7.22 {40}	7.2733 {68}	7.2078 {69}	1 2 3 11
8	8.0421 {222}	8.0008 {229}	8.0192 {243}	1 2 4
9	9 {60}	9 {175}	9 {195}	1 2 13
10	9.5616 {226}	10.242 {247}	10.220 {248}	1 2
11	11.001 {89}	11.117 {128}	11.000 {145}	1 2
12	12.049 {10}	12 {20}	12 {32}	1 2 3 4 11
13	12.667 {219}	13.263 {258}	12.974 {259}	1
14	14 {5}	14.045 {8}	14 {11}	1 2 3 4 5
15	15.492 {236}	15.49 {275}	15.089 {574}	1
16	15.504 {66}	15.504 {122}	15.901 {195}	1 3
17	17.139 {541}	17.137 {550}	17.082 {564}	1 3 4
18	17.615 {4}	18 {5}	18 {11}	1 2 3 4
19	19.409 {10}	18.924 {19}	19.064 {20}	1
20	20.5 {4}	19.692 {12}	19.847 {18}	1 2 3 4
21	21.031 {6}	20.996 {10}	20.984 {19}	1 2 3 4
22	21.755 {1}	21.977 {2}	21.534 {5}	1 2 3 4 5

The optimal set of factors can be extended to a number of emotions as well [2]. For example, the factors 1, 2, 3, and 4 are dominant for emotions 12, 14, 18, 20, 21, 22 for $K=7$, indicating that 6 emotions (Affection, Contentment, Antic Pleasure Imagery, Relief, Surprise, and Suspense) can be detected with 7 factors, of which 1, 2, 3, and 4 (Electroencephalography, Heart rate, Heart rate variability, Pre-ejection period) are common for all [2].

With the help of data tabulated as in tables 3 and 4, we can find for each emotion the least number of factors required to detect the emotion. Besides, we can find for a set of emotions the least number of factors required to detect these emotions. Evidently, this process allows the reuse of the measured vital factor as well as the reduction of cost of measurements required to detect the given set of emotions.

Evidently, the total number of input factors required to detect any emotion is a key index to the cost and complexity of the emotion detection system [2]. The number of required input factors is plotted for each emotion in Figures 4 and 5 respectively. Note that for the majority of emotions, the number of dominant factors is less than 4 for $K=4$ and less than 7 for $k=7$ (except for emotions 1, 2, and 3) [2].

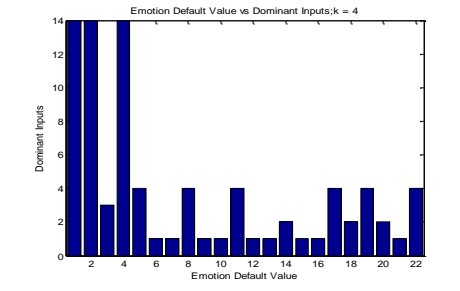


Fig. 4. Emotion default value with the number of dominant inputs using $k = 4$ [2]

Note that in Fig. 4 three emotions (1, 2, 4) cannot be detected using the utilized evaluation set, since they need fourteen inputs to be detected. On the other hand, the remaining emotions can be detected using $k = 4$ with dominant inputs between one to four. Similar observation is given by Fig. 5, for $k = 7$, where only two emotions cannot be detected which are 1 and 2; these emotions require fourteen inputs and the remaining emotions are detected using $k = 7$ with dominant inputs vary between one to seven. Fig. 6 shows the number of detectable emotions for each K factors.

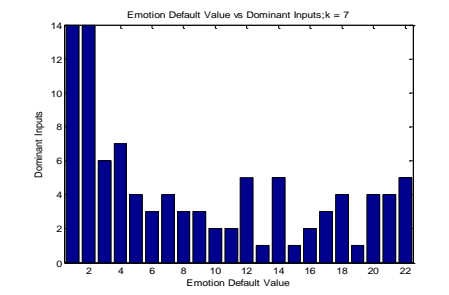


Fig. 5. Emotion default value with the number of dominant inputs using $k = 7$ [2]

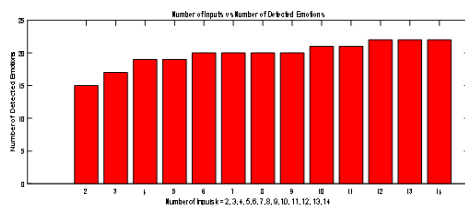


Fig. 6. Number of detected emotions for all k -values [2]

Figure 6 shows that 6 or 7 input factors allow for the detection of 20 emotions out of 22 but with different error rates. Using 4 or 5 inputs allows for the detection of 19 emotions out of 22.

The results summarized in figures 4, 5, and 6 indicate that for the detection of a given emotion, we do not need to use all 14 factors. In fact, using 6 or 7 factors is sufficient for 20 out of 22 emotions. Thus, depending on the application and the emotions involved in the application, the selection of the most dominant factors for these emotions allow for an optimal solution to be found.

VI. CONCLUSION

In this research, we have investigated the possibility of using less number of input physiological factors to detect human emotions. Previous studies have identified fourteen different factors and showed that these factors can be used in a fuzzy neural network system to detect human emotions with relatively high accuracy. In this study, we developed a model to detect the same emotions with sufficient accuracy ($\pm 0/5$) but using a smaller subset of the factors. We have used exhaustive search methods to identify the proper set of input factors, which can be used to identify the same set of emotions. The following conclusions can be made based on the experiments conducted in this study:

- Physiological input variables are classified according to their number of occurrence and so each factor within any case study (any k value) has its own distribution of inputs.
- Large numbers of FIS combinations are generated for each case and each one is used to generate the output emotions with a certain percent depending on how many output value are taken into consideration.
- Almost all emotions are detectable with smaller number of inputs compared with the former work, except for emotion number one and two which are anger and anxiety can be detected only with $12 \leq k \leq 14$ inputs.
- Statistical measure such as average error is evaluated to obtain the relationship between all generated values between all FIS for all k values.
- The performance index measure (PIM) indicates that the best choice of k is between 6 – 10 factors.

The most general conclusion related to this study is that the number of input factors required to detect a given emotion can be reduced and optimized, thus requiring smaller number of measurement devices.

The results generated in this research rely on artificially generated input data using modified random number generators. The authors are currently building a database of real data generated by a combination of virtual reality and physical measurement of physiological variables. The results will be published in a separate publication, where the theoretical models will be validated by physical models.

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