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Emotion Recognition based on Hybrid model of Fuzzy Logic and Aritifical Neural Network

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***Abstract* — The advantage of emotions is that they lead us astray. Just as your car runs more smoothly and requires less energy to go faster and farther when the wheels are in perfect alignment, you perform better when your thoughts, feelings, emotions, goals, and values are in balance. Hence recognising emotions on an accurate basis is more important than it seems. We extend the concept of emotion recognition over the broad range of mammals, as humans possess many unique characteristics but we also share a number of similarities with other animals. These similarities and differences are revealed through our genetic make-up, the ways our bodies are constructed and our behaviour. They help us to understand our place in the animal kingdom by allowing us to work out the evolutionary relationships between ourselves and other animals. This paper presents an adaptive neuro/fuzzy system which can be trained to detect the current emotions from a set of measured responses. Models are built using different types of input/output membership functions and trained by different kinds of input arrays. ANFIS editor in MATLAB is used to build the models**.

Index Terms - Emotions, Adaptive neuro/fuzzy system, ANFIS Editor, MATLAB.

I. Introduction

A. General overview and Challenges

The instant detection of each human's emotions has not been thoroughly studied. The problem is that each person manifests emotions in a manner different from others. So we come across the need to generalise particular ways in which people react and also how their bodies respond accordingly.

The human emotional status is rather intangible, and therefore cannot be directly measured. However, these emotions can be correlated to external and/or internal factors, which are rather tangible things, and hence they can be measured and analyzed. The internal factors come from different parts of the body in several forms such as electroencephalography (EEG), heart rate (HR), heart rate variability (HRV), pre ejection period (PEP), stroke volume (SV), systolic blood pressure (SBP), diastolic blood pressure (DBP), skin conductance response (SCR), tidal volume (VT), oscillatory resistance (ROS), respiration rate (RR), nonspecific skin conductance response rate (nSRR), skin conductance level (SCL), finger temperature (FT), and others.

These factors measurements are provided in wide ranges and often their impacts vary from a person to a person and for different postures for the same person. For example, a given measurement of some factors may relate to a person being happy, while the same measurements may reveal a rather "sad" status for another person. This kind of behaviour lends itself naturally to fuzzy sets and fuzzy logic as 0 & 1/True & False cannot present this kind of data.

In this paper, we will use fuzzy operations to represent the knowledge about each factor. This will enable us to detect the emotion of a person using fuzzy inputs of the various factors. For example, we can use a fuzzy rule such as "IF (Temperature is High) AND (Heart Rate is High) THEN (Person is Excited)." Although fuzzy sets and operations are useful for representing the knowledge base, they fail to model the individual behaviour of each and every person. Obviously, a model that is able to adapt to various categories of human responses would be referred. Consequently, an adaptive learning mechanism is required to adjust the model if we were to cater for the differences in emotions between various humans. This requirement calls for the use of an adaptive learning system such as artificial neural networks (ANN). However, the ANN model does not allow the use of fuzzy sets or rules, which is the more natural way of representing the relation between human emotions and human physical and physiological parameters. ANN uses exact and crisp values for representing the model's input. In order to utilize the benefits of both fuzzy logic and artificial neural networks, we will use the hybrid approach, which combines fuzzy logic and artificial neural networks in a single model.

B. Emotions in animals

Recent work in the area of ethics and animals suggests that it is philosophically legitimate to ascribe emotions to non-human animals. Furthermore, it is sometimes argued that emotionality is a morally relevant psychological state shared by humans and non humans. What is missing from the philosophical literature that makes reference to emotions in non-human animals is an attempt to clarify and defend some particular account of the nature of emotion, and the role that emotions play in a characterization of human nature. Because this is so, the thesis that humans and non-humans share emotions may well be a more difficult case to make than has been recognized thus far.

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Because of the philosophical questions of consciousness and mind that are involved, many scientists have stayed away from examining animal and human emotion, and have instead studied measurable brain functions through neuroscience. So we try to build a system that intakes physiological values and simultaneously predict the corresponding emotions of animals and to compare the results with that of the humans.

II. EMOTION

In psychology and philosophy, emotion is a subjective, conscious experience characterized primarily by psycho-physiological expressions, biological reactions, and mental states. Emotion is often associated and considered reciprocally influential with mood, temperament, personality, disposition, and motivation as well as influenced by hormones and neurotransmitters such as dopamine, noradrenalin, serotonin, oxytocin, cortisol and GABA. Emotion is often the driving force behind motivation; positive or negative. An alternative definition of emotion is a "positive or negative experience that is associated with a particular pattern of physiological activity."

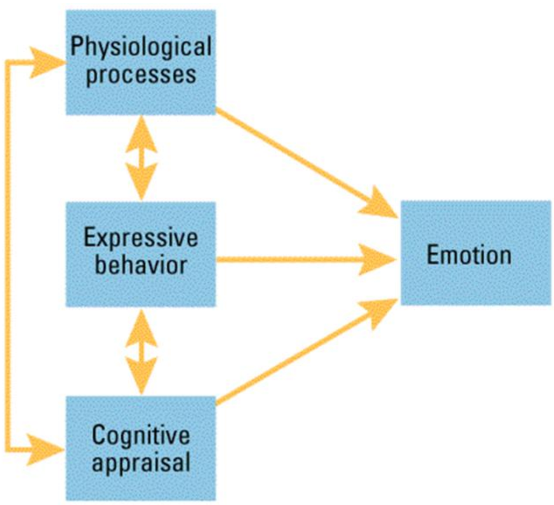

Fig. 1 Components of emotion.

The physiology of emotion is closely linked to arousal of the nervous system with various states and strengths of arousal relating, apparently, to particular emotions. Although those acting primarily on emotion may seem as if they are not thinking, cognition is an important aspect of emotion, particularly the interpretation of events.

In Scherer's components processing model of emotion, five crucial elements of emotion are said to exist. From the component processing perspective, emotion experience is said to require that all of these processes become coordinated and synchronized for a short period of time, driven by appraisal processes. Although the inclusion of cognitive appraisal as one of the elements is slightly controversial, since some theorists make the assumption that emotion and cognition are separate but interacting systems, the component processing model provides a sequence of events that effectively describes the coordination involved during an emotional episode.

- Cognitive appraisal: provides an evaluation of events and objects
- Bodily symptoms: the physiological component of emotional experience
- Action tendencies: a motivational component for the preparation and direction of motor responses
- Expression: facial and vocal expression almost always accompanies an emotional state to communicate reaction and intention of actions
- Feelings: the subjective experience of emotional state once it has occurred

Based on neurological approach, emotion can be distinguished into two classes: "classical" emotions such as love, anger and fear that are evoked by environmental stimuli via distance receptors in the eyes, nose and ears and "homeostatic" (or "primordial") emotions – imperious (attention-demanding) feelings such as pain, hunger and fatigue, evoked by internal body states communicated to the central nervous system by interceptors, that motivate behaviour aimed at maintaining the body's internal milieu at its ideal state.

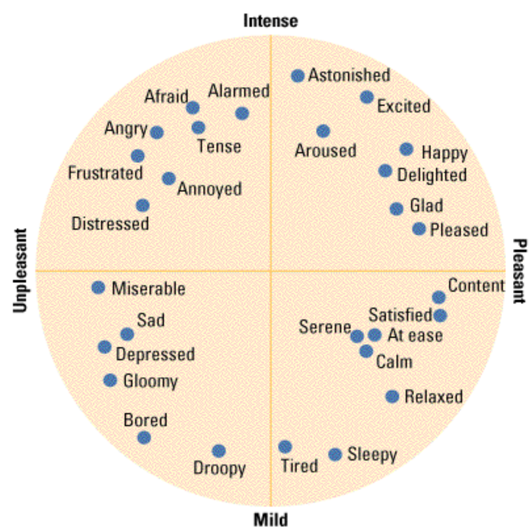

Fig. 2 Russell's Circumplex model.

III. FUZZY LOGIC

Fuzzy logic is a form of many-valued logic; it deals with reasoning that is approximate rather than fixed and exact. Compared to traditional binary sets (where variables may take on true or false values) fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Fuzzy logic has been extended to handle the concept of partial truth, where the truth value may range between completely true and completely false. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions.

In Fig. 3, the meanings of the expressions cold, warm, and hot are represented by functions mapping a temperature scale. A point on that scale has three "truth values"—one for each of the three functions. The vertical line in the image represents a particular temperature that the three arrows (truth values) gauge. Since the red arrow points to zero, this

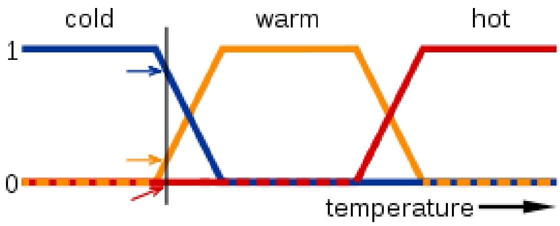

Fig. 3 Fuzzy in temperature scale.

temperature may be interpreted as "not hot". The orange arrow (pointing at 0.2) may describe it as "slightly warm" and the blue arrow (pointing at 0.8) "fairly cold".

IV. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is a relatively crude electronic model based on the neural structure of the brain. The brain basically learns from experience. It is natural proof that some problems that are beyond the scope of current computers are indeed solvable by small energy efficient packages. This brain modelling also promises a less technical way to develop machine solutions. This new approach to computing also provides a more graceful degradation during system overload than its more traditional counterparts.

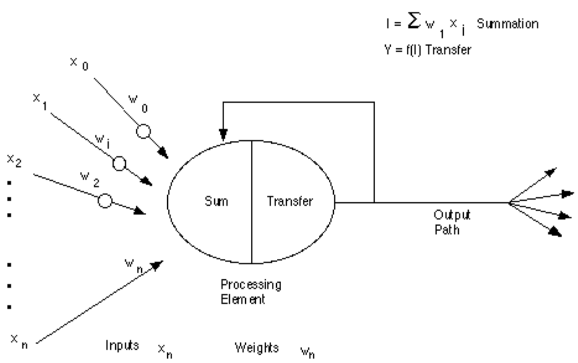

Fig. 4 Representation of artificial neuron.

These artificial neural networks try to replicate only the most basic elements of this complicated, versatile, and powerful organism. They do it in a primitive way. The goal of artificial neural networks is not the grandiose recreation of the brain. On the contrary, neural network researchers are seeking an understanding of nature's capabilities for which people can engineer solutions to problems that have not been solved by traditional computing.

A. ANN vs. Fuzzy logic

Obviously, a model that is able to adapt to various categories of human responses would be preferred. Consequently, an adaptive learning mechanism is required to adjust the model if we were to cater for the differences in emotions between various humans. However, the ANN model does not allow the use of fuzzy sets or rules, which is the more natural way of representing the relation between human emotions and human physical and physiological parameters. ANN uses exact and crisp values for representing the model's input. Fuzzy is based on how brain deals with inexact information while ANN is modelled over physical architecture of the brain.

In order to utilize the benefits of both fuzzy logic and artificial neural networks, we will use the hybrid approach, which combines fuzzy logic and artificial neural networks in a single model. This will be beneficial in such a manner that ANN can provide fuzzy with learning abilities while fuzzy can provide ANN with a structural framework.

B. ANFIS

The acronym ANFIS derives its name from adaptive neuro-fuzzy inference system. Using a given input/output data set, the toolbox function anfis constructs a fuzzy inference system(FIS) whose membership function parameters are tuned using either a back-propagation algorithm alone, or in combination with a least squares type of method. This allows your fuzzy systems to learn from the data they are modelling.

The parameters associated with the membership functions will change through the learning process. The computation of these parameters is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modelling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure. Anfis uses either back-propagation or a combination of least squares estimation and back-propagation for membership function parameter estimation.

The modelling approach used by anfis is similar to many system identification techniques. First, you hypothesize a parameterized model structure (relating inputs to membership functions to rules to outputs to membership functions, and so on). Next, you collect input/output data in a form that will be usable by anfis for training. You can then use anfis to train the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion. In general, this type of modelling works well if the training data presented to anfis for training (estimating) membership function parameters is fully representative of the features of the data that the trained FIS is intended to model. This is not always the case, however. In some cases, data is collected using noisy measurements, and the training data cannot be representative of all the features of the data that will be presented to the model. This is where model validation comes into play.

We use Gaussian membership functions in order to set various input ranges. Gaussian functions arise by applying the exponential function to a general quadratic function. The Gaussian functions are thus those functions whose logarithm is a quadratic function.

V. HUMAN EMOTION ANALYSIS AND DETECTION

Human emotions are intangible things; however there are several factors which can be used to detect them. The factors impact the human emotions and in different ways. The

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amount of information presented by the various factors is enormous, thus drastically increasing the complexity of any model used to correlate the factors to the emotions. In order to simplify the model by reducing the amount of data required to evaluate the model, we make use of fuzzy logic, where the input parameters are quantified with linguistic variables such as low, normal, and high which represent a wide range of input values.

A. Parameters used

Following is a brief description of the factors used in our model and their impact on human emotions.

1. Electroencephalography (EEG): EEG measurements are given in frequency ranges, and can be represented with four linguistic variables, namely alpha, beta, theta and delta with ranges 13–15, 7.5-13, 2.5-8, and <4 Hz respectively.

2. Heart Rate (HR): Three heart rate ranges are identified, and categorized with fuzzy linguistic variable low (LHR) from 20 to 70 bpm, normal (NHR) from 45 to 100 bpm and high (HHR) from 84 to 120 bpm.

3. There are several frequency-domain measures which pertain to HR variability at certain frequency ranges; and these measures are associated with specific physiological processes. HRV has three ranges of frequencies; high from 0.15 to 0.4 Hz, low from 0.04 to 0.15 Hz and very low from 0.003 to 0.04 Hz.

4. Pre-Ejection Period (PEP): PEP is defined as the period between when the ventricular contraction occurs and the semi lunar valves open and blood ejection into the aorta commences. Three linguistic variables are used to implement PEP, namely low (LP) from 0 to 800 ms, normal (NP) from 0 to 1000 ms, and high (HP) from 500 to 1100 ms.

5. Stroke Volume (SV): Stroke volume is defined as the amount of blood pumped by the left ventricle of the heart in one contraction, and its normal range is from 0 ml to 250 ml. Three linguistic variables are used to implement SV, namely low (LSV) from 10 to 144 ml, normal (NSV) from 10 to 250 ml, and high (HSV) from 240 400 ml.

6. Systolic Blood Pressure (SBP): SBP is the maximum value of blood pressure during one breath. Three linguistic variables are used to implement SBP; low from 100 to 121, normal from 110 to 134, and high from 120 to 147.

7. Diastolic Blood Pressure (DBP): DBP is the minimum value of blood pressure during one breath. Three variables are used to implement DBP namely low (LDBP) from 77 to 87, normal (NDBP) from 81 to 91 and high (HDBP) from 81 to 91.

8. Skin Conductance Response (SCR): SCR is the phenomenon that the skin momentarily becomes a better conductor of electricity when either external or internal stimuli occur that are physiologically arousing. Three linguistic variables are used to implement SCR namely low from 0 to 0.2 ms, normal from 0.1 to 1 ms, and high from 0.85 to 1.5 ms.

9. Tidal Volume (Vt): Tidal volume represents the normal volume of air displaced between normal inspiration and expiration when extra effort is not applied. Three linguistic variables are used to implement Vt, namely rapid breath from 100 to 150 ml/breath, quiet breath from 200 to 750 ml/breath and deep breath from 600 to 1200 ml/breath.

10. Oscillatory Resistance (Ros): Ros is the resistance offered by the lungs when the subject is forced to ventilate. Three linguistic variables are used to implement Ros, namely low from 0 to 0.49, normal from 0.4 to 0.88 and high from 0.5 to 1.

11. Respiration Rate (RR): RR is the no. of breaths taken per time interval. Three linguistic variables are used to implement RR namely, low from 5 to 10 breath/min, normal from 7 to 23 breath/min and high from 15 to 24 breath/min.

12. Nonspecific Skin Conductance Response (nSRR): nSRR is used to measure the moisture level of the skin and is implemented with three linguistic variables, low from 0 to 2 per min, normal from 1 to 3 per min and high from 2 to 5 per min.

13. Skin Conductance Level (SCL): SCL measures the electrical conductance of the skin. Three linguistic variables are used to implement SCL namely low from 0 to 2 ms, normal from 2 to 25 ms and high from 20 to 25 ms.

14. Finger Temperature (FT): FT is used to measure the change in blood flow. Three linguistic variables are used to implement FT namely low from 65 to 75°F, normal from 75 to 85°F and high from 80 to 90°F.

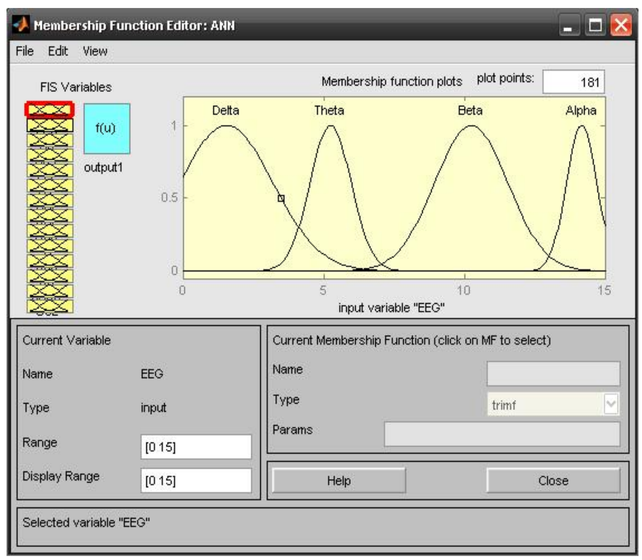

Fig. 5 EEG membership function.

B. Parameters considered in mammals

In mammals, certain parameters need not be considered as they are not so dominant in the estimation of an emotion, like respiration rate, finger temperature and so on. Instead of these parameters, some new one's are recorded, namely, cortisol, prolactin, leptin, ghrelin, epinephrine and non-epinephrine.

1. Cortisol: Cortisol, more formally known as hydrocortisone is a steroid hormone, more specifically a glucocorticoid, produced by the zona fasciculata of the adrenal cortex. It is released in response to stress and a low level of blood glucocorticoid. Its primary functions are to

increase blood sugar through gluconeogenesis, suppress the immune system, and aid with fat, protein, and carbohydrate metabolisms. Two linguistic variables are used to implement cortisol, namely, low from 28 to 30 nmol/24 hr and high from 280 to 490 nmol/24 hr.

2. Prolactin: Prolactin is secreted from the pituitary gland in response to eating, mating, oestrogen treatment, ovulation, and nursing. Prolactin is secreted in a pulsatile fashion in between these events. Prolactin also plays an essential role in: metabolism, regulation of the immune system, and pancreatic development. Two linguistic variables are used to implement prolactin, namely, low from 2.74 to 4.15 µg/L and high from 12.4 to 23.2 µg/L.

3. Leptin: Leptin is an adipokine that plays a key role in regulating energy intake and expenditure, including appetite and hunger, metabolism, and behaviour. It is one of the most important adipose-derived hormones. Leptin functions by binding to the leptin receptor. It is a hormone made by fat tissue that acts on the brain to regulate food intake and body weight. Two linguistic variables are used to implement leptin, namely, low from 1 to 5 ng/dl and high from 7 to 9 ng/dl.

4. Ghrelin: Ghrelin is a amino acid hunger-stimulating peptide and hormone that is produced mainly by P/D1 cells lining the fundus of the human stomach and epsilon cells of the pancreas. Ghrelin levels increase before meals and decrease after meals. It is considered the counterpart of the hormone leptin, produced by adipose tissue, which induces satiation when present at higher levels. In some bariatric procedures, the level of ghrelin is reduced in patients, thus causing satiation before it would normally occur. The intravenous administration of ghrelin to mammals increased food intake by 12–36% over the trial period.

5. Epinephrine: Epinephrine (also known as adrenalin) is a hormone and a neurotransmitter. It is produced in some neurons of the central nervous system, and in the chromaffin cells of the adrenal medulla from the amino acids phenylalanine and tyrosine. This leads to Increase in heart rate, respiratory rate, stimulates glycogenolysis, triggers lipolysis and Muscle contraction.

6. Non-Epinephrine: Non-Epinephrine or non-adrenalin is a catecholamine with multiple roles including those as a hormone and a neurotransmitter. It is the hormone and neurotransmitter most responsible for vigilant concentration. It is used in those with severe hypotension. It does this by increasing vascular tone through α-adrenergic receptor activation. The most important functions of norepinephrine is its role as the neurotransmitter released from the sympathetic neurons to affect the heart. An increase in norepinephrine from the sympathetic nervous system increases the rate of contractions in the heart.

VI. MODEL IMPLEMENTATION

The first step in the implementation process involves defining of set of variables based on input parameters, formulation of rules according to studies and creating output variables for expected results.

Input/output data sets, on which the FIS was not trained, are then presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values. This process is known as model validation and is accomplished with the ANFIS Editor GUI using the so-called testing data set, and its use is described later.

Another type of data set for model can be used for validation in anfis. This other type of validation data set is referred to as the checking data set and this set is used to control the potential for the model over-fitting the data. When checking data is presented to anfis as well as training data, the FIS model is selected to have parameters associated with the minimum checking data model error.

The basic idea behind using a checking data set for model validation is that after a certain point in the training, the model begins over-fitting the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that over-fitting begins, and then the model error for the checking data suddenly increases. In the first example in the following section, two similar data sets are used for checking and training, but the checking data set is corrupted by a small amount of noise. This example illustrates of the use of the ANFIS Editor GUI with checking data to reduce the effect of model over-fitting. In the second example, a training data set that is presented to anfis is sufficiently different than the applied checking data set. By examining the checking error sequence over the training period, it is clear that the checking data set is not good for model validation purposes. This example illustrates the use of the ANFIS Editor GUI to compare data sets.

We use the Sugeno constant and linear output functions. The rule in Sugeno fuzzy model has the form:

If (input 1 = x) and (input 2 = y)
THEN output z = ax + by + c

For the constant Sugeno model, the output level z is constant c, where a = b = 0. The output level z_i of each rule is weighted by firing strength w_i of the rule.

The general structure of the ANFIS model is the same for all models. The models differ in the specifications of the membership functions and the output specifications. However, the general structure remains the same for all.

A. Rules

The correlation between the input and the output variables is done through a set of fuzzy rules. Each rule uses AND/OR connectors to connect various input factors with a particular output emotion. Five of the 22 different rules used in our model are listed below for illustration. Each rule corresponds to one and only one output emotion. For example, rule 1 shows all the input factors which produce the anger emotion; the initial value of the anger emotion is set to 1. In the ANFIS model, rules are also assigned weights. The initial weights for all rules are set to 1.

1. Anger:

If (EEG is Beta) and (HR is HHR) and (HRV is LF) and (PEP is LP) and (SV is LSV) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is HRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is LFT)

2. Anxiety:

If (EEG is not Alpha) and (HR is HHR) and (HRV is VLF) and (SV is NSV) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is HRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is LFT)

3. Disgust contamination:

If (EEG is not Alpha) and (HR is HHR) and (HRV is HF) and (PEP is LP) and (SV is LSV) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is HRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is LFT)

4. Disgust mutilation:

If (EEG is not Alpha) and (HR is LHR) and (PEP is LP) and (SV is NSV) and (SBP is HSBP) and (DBP is HBP) and (SCR is HSCR) and (Vt is RapidL) and (Ros is NRos) and (RR is HRR) and (nSRR is HnSRR) and (SCL is HSCL) and (FT is HFT)

5. Embarrassment:

If (EEG is not Alpha) and (HR is HHR) and (HRV is VLF) and (PEP is LP) and (SBP is HSBP) and (DBP is HBP) and (SCL is HSCL)

B. *Animal Emotions*

Unlike in the case of humans, factors that affect emotions in animals are much lesser and also the measuring of each of these parameters is not as feasible and are quite hard to obtain.

Instead of trying to compare animals and humans, researchers should study the "survival circuits" behind behaviours. Studies in animals can find survival circuits universal to mammals, like fear and hunger.

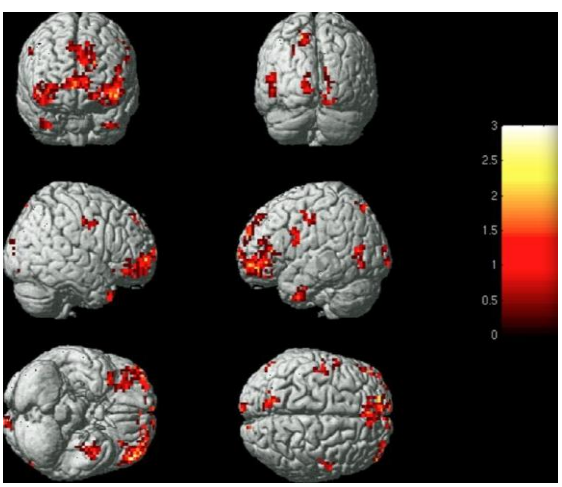

Fig. 6 Brain map of rats.

Survival phenomena are closely associated with emotions. We need to focus on a species' independent way of getting at these key functions. Many different animals have very similar survival circuitry: for example, the brain regions that tell an animal to run away from a threat are the same even if that animal runs on two legs, four legs or takes flight.

These areas are organized similarly in spite of the fact that they control different behavioural responses in different species. These are more related to motivation. The line between emotion and motivation is very thin: when you are in an emotional state you are motivated. This leads to differences in behaviour and how we perceive our own feelings and emotions.

Hence, instead of considering each animal, we take a broad view, by collectively generalising the emotional behaviour of mammals as a whole. Our test subjects were rats, whose active brain map is shown in fig. 6 during emotion variations.

Rules are generalised to be as follows:

1. Angry:

If (EEG is Alpha) and (SBP is HSBP) and (DBP is HDBP) and (Vt is rapid_breath) and (Cortisol is High) and (Adrenaline is High) and (Non_adrenaline is High)

2. Sad:

If (EEG is Theta) and (SBP is LSBP) and (DBP is LDBP) and (Vt is deep_breath) and (Prolactin is High)

3. Hungry:

If (EEG is Theta) and (SBP is LSBP) and (DBP is LDBP) and (Vt is quiet_breath) and (Leptin is High) and (Ghrelin is High)

4. Fear:

If (EEG is Alpha) and (SBP is HSBP) and (DBP is HDBP) and (Vt is rapid_breath) and (Prolactin is High) and (WBC is High) and (Epinephrine is High) and (Non_epinephrine is High) and (Cortisol is High)

VII. RESULT

The concept of human emotion recognition is raised to newer heights in terms of accuracy of the output obtained. Also, multiple emotions can be recorded and displayed using our system, and the same approach has been extended to mammals rather than concentrating solely on humans. This approach is done by means of creating a separate, generalised rule set for basic emotions displayed by a mammal. Thus different emotions corresponding to the values entered can be obtained.

Fig. 7 Rule viewer.

VIII. CONCLUSION

In this paper, we presented a neuro/fuzzy model for the detection of human emotions using fourteen measurable human factors which are known to impact human emotions in varying degrees. The factors are converted into fuzzy variables and used in a set of rules to detect one of twenty two different emotions.

The developed models can be used in social networking such as Facebook and Twitter, health organizations especially for coma, infant or autism patients, security systems like airports and critical places, and gaming industry. The experiments show that the model is sensitive to the choice of input membership functions as well as the output function. The developed system benefits the advancement of security systems, virtual reality and others. The system is also extended to find emotions showcased by mammals by generalizing characteristic emotions displayed by them.

The main hurdle faced by scientists in developing artificial intelligence is the disability in adaptive learning by machines and also emotion recognition. Hence, implementation in the field of Kinematics can further improve the results which will lead the march towards a day where artificial intelligence triumphs over all other fields in modern day science.

Another area of research is prediction of the future mood swings. Further study on the same, can make us achieve the impossible task of taking a peek into the future.

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