A review on human emotions elicitation and association of Physiological signal datasets

A. Inna Reddy[1] and Prof. G. Narsimha[2]

1. *Asst. Professor, Government Degree College, Chanchalguda, Hyderabad*
2. *Professor, Jawaharlal Nehru Technological University, Hyderabad*

ABSTRACT

Emotional state recognition is a crucial task for achieving a new level of Human-Computer Interaction (HCI). Machine Learning applications are penetrating at rapid speed into spheres of everyday life. Recent studies are showing promising results in analyzing physiological signals (EEG, ECG) using Machine Learning for accessing emotional state and its classification. In general, specific emotion is invoked by playing affective videos or sounds. Nevertheless, there is no canonical way for emotional state elucidation. In this study, we present the theories of emotions using discrete model and Valence / Arousal emotion model. The study also emphasized EEG and ECG signals association with human emotions. A series of databases were developed by many researchers to study the classification and correlation of human emotions with physiological signals. The structures of the databases developed by these researchers have variations and each database has oriented in different directions for the sake of elicitation of human emotions.

KEYWORDS

Human Computer Interaction(HCI), EEG, ECG, **Valence / Arousal, HRV,** Physiological signal data Datasets, AMIGOS

1. INTRODUCTION

Emotion is a psycho-physiological state of a human being which describes a person's temperament. Although human emotional experience plays utmost important role in human lives, our scientific knowledge about human emotions has its own limitations. Hence, an ability to detect and recognize ones' emotional state is essential in the improvement of artificial intelligence part of Human Machine Interaction (HMI). Emotion recognition is widely used in medical, defense, lie detection techniques, entertainment, education etc. Various findings from neuroscience, cognitive science and psychology suggest that emotions are important in human intelligence development, social interaction, perception, learning, and so on.

Physiological signals are generated by the body during the functioning of various physiological systems. Hence, physiological signals hold information which can be extracted from these signals to find out the state of the functioning of these physiological systems. The process of extracting information can be very simple as feeling the pulse to find the state of heart beats and it can be complex which may require analysis of the structure of tissue by a sophisticated machine.

1.1Theories of emotions

The origin of emotions has been an interesting concept for philosophers from the ages. Starting with Aristotle, who established the four humors - components of the human body that are responsible for an emotional state. Then, Galen called them "sanguine", "choleric", "melancholic" and "phlegmatic" [1]. From the inception of the twentieth century, physiology as a part of medicine experienced rapid development. Based on research, the most of the scientists agree that three basic emotions (fear, anger, and happiness) are the most distinguishable and significantly differ from each other [2]. However, emotional expressions are much more compound, so more complex multidimensional models were developed to provide a comprehensive representation of human emotions [3]. This section describes two most popular models of human emotional state.

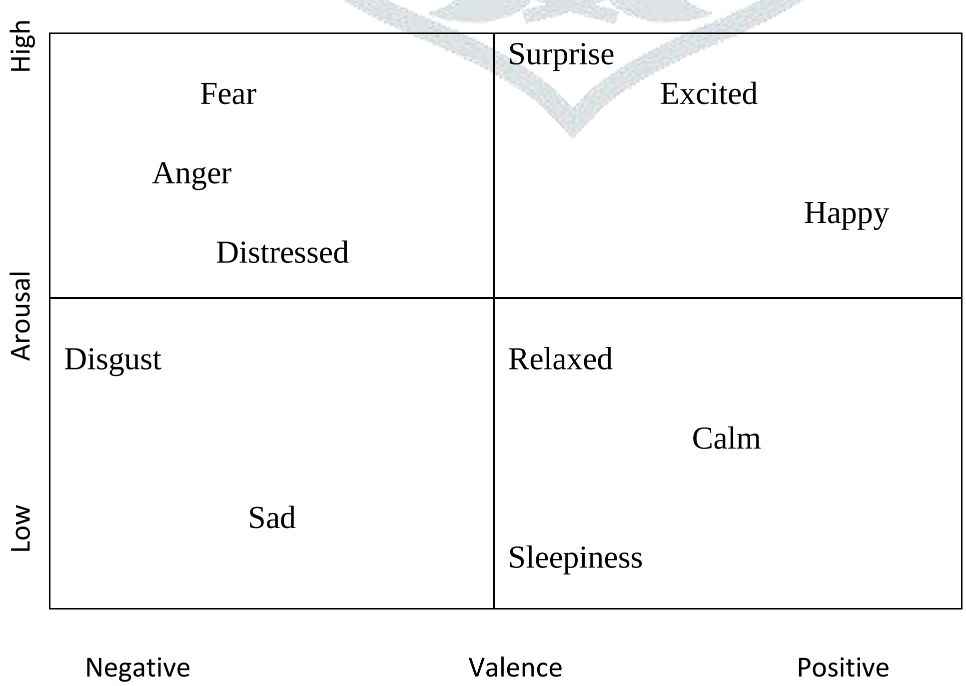
2.1 Discrete Emotion Model

The most well-known emotional paradigm belongs to one of the most authoritative physiologists of 20th century Paul Ekman. During his research in Papua New Guinea, the remarked that some facial expressions of isolated tribe members also manifested in another culture [28], which means that some emotional expressions are common for all human beings. Based on his interpretations he proposed six basic emotions: anger, disgust, fear, happiness, sadness, and surprise. In fact, the more efficient paradigms was developed, described one still considered suitable for emotional state representation.
The major advantage of emotion categorization in a discrete manner is plainness for the majority of people that allows for their extensive use in surveys and questioning. But, they are not suitable for human-computer interaction. It is quite common that Humans tend to name the same emotional state using different words. For example, the words which describe emotions may vary depending on context, cultural background, and personality. This is the reason why we need something more efficient to represent a human emotional state.

1.2 Valence / Arousal Emotion Model

Russel [3] proposed the two-dimensional emotional model in 1980. The basic idea was to divide emotions into two components: valence (or pleasure) and arousal (or activation) as shown in Figure 1.1. Negative values on a valence axis relate to negative emotional state, and positive values relate to a positive state, respectively. Arousal axis describes “power” of emotion or how it is active or passive depending its positive or negative. Origin of the mentioned two axes represents a neutral state.
Whissel proposed to divide the this model into quadrants like in Cartesian plane and assign to them emotions from the discrete paradigm [4] such as disgust or sadness. The fourth quadrant (negative valence, positive arousal) defines positive states with low power; the best example will be relaxation, satisfaction, and calmness. First quadrant, which includes the emotions positive valence, positive arousal, specifies active and positive emotional states like excitement, surprise, happiness, etc. The second quadrant, representing negative valence, positive arousal, corresponds to high-activated negative emotion like anger, fear, distress. The third quadrant, representing negative valence, negative arousal, indicates negative calm states,

Figure 1.1



2. SIGNALS ASSOCIATED WITH EMOTIONS

2.1 Electroencephalography (EEG)

Electroencephalography (EEG) is a signal representation of brain activity. The signal waves hold the valuable information of the state of brain. It is one of the non-invasive techniques for brain imaging which provides electrical potential recording for the surface of the scalp due to the electrical activity of the large collections of neurons in the brain [14]. Non-invasive is a technique in which the body is not attacked or cut open as during surgical investigations or therapeutic surgery. Invasive technique is opposite to non-invasive.

2.1.1 Types of Signals

EEG signals are defined in term of rhythmic and transient and are complex signals as shown in Figure 2.1. The rhythmic activity is scattered into different frequency bands. Different people of different ages may have different amplitude and frequency of EEG signals while they are recorded in different states such as performing a task or relaxing.

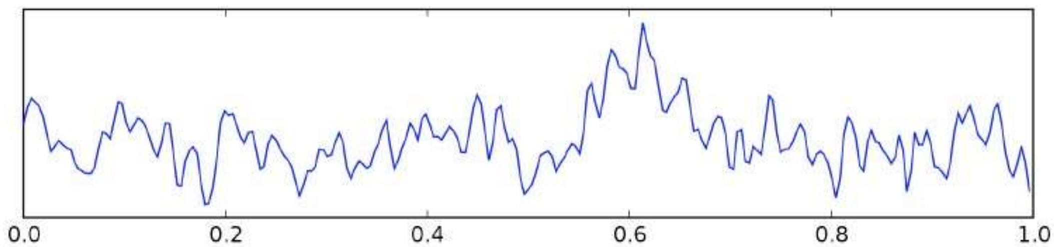


Figure 1.3 – EEG Signals [16]

Figure 2.1

Five types of waves can be identified depending on frequency ranges. They are alpha (α), theta(θ), beta, (β), delta (δ) and gamma (γ) from low to high frequency respectively.

A specific wave is mostly available in specific lobe of cerebral cortex however this is not always true. Different mental states are associated with different waves which is helpful to define one's situation at a specific time as described in the Table 1.

Wave	Frequency(Hz)	Mental State
Delta (δ)	0 – 4	Deep Sleep
Theta (θ)	4 – 8	Drifting Thoughts, Dreams, Creativity
Alpha (α)	8 – 13	Calmness, Relaxation, Abstract Thinking
Beta (β)	13 – 30	Highly Focused, Highly Alertness
Gamma (γ)	> 30	Simultaneous Process, Multi-Tasking

Table 1 – Frequency and Mental States of Waves

Delta Waves (δ)

Delta waves are spread in the frequency range of 0 – 4 Hz. Mental states associated with these waves are deep sleep, coma or hypnosis and sometimes awake. In awake state, it is always considered to be pathological phenomenon. The higher is the amplitude, higher serious is the problem considered. These waves are decreased by the age and are normally present in healthy people in their awake state.

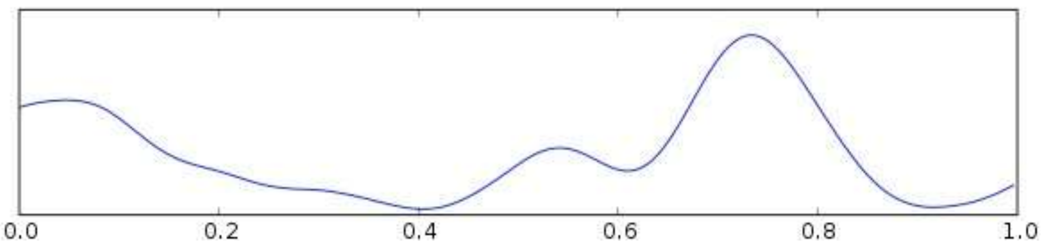


Figure 2.1.1 Delta wave

Theta Waves (θ)

Theta waves are within the frequency range of 4 – 8 Hz. Mental states associated with these waves are drifting thoughts, creative thinking and unconscious materials. These waves appear in central, temporal and parietal parts of head. These waves are normally present in healthy people while they are in deep sleep.

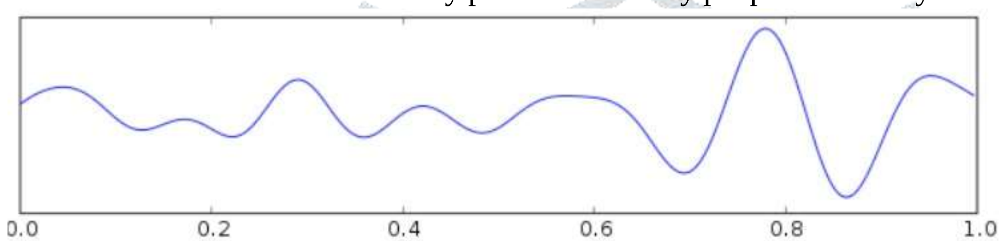


Figure 2.1.2 – Theta Wave [16]

Alpha Waves (α)

Alpha waves are under the frequency range of 8 – 13 Hz. Mental states associated with these waves are relaxed and calm states. These waves appear on back side of head and occipital area of brain. These waves are of high amplitude as compared to others. This can be observed while subject is awake and clam. Sometimes, these waves interfere with μ-rhythm. These waves are normally present in people while they are calm and relax being in awake state.

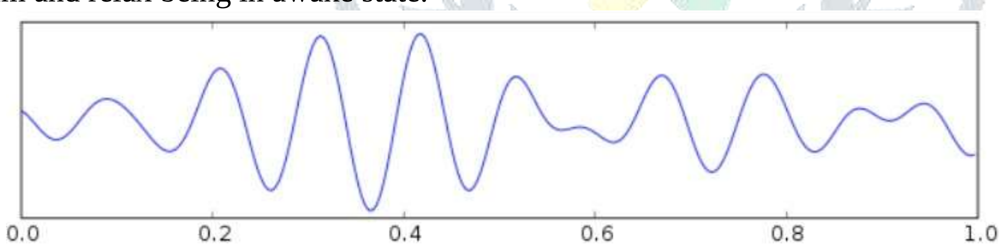


Figure 2.1.3 – Alpha Wave [16]

Beta Waves (β)

Beta waves are under the frequency range of 13 – 30 Hz. Mental states associated with these waves are highly focused and alertness, such as during deep thinking and concentration. Beta waves are having large band of frequency as compared to others. These waves generally appear at central area of brain and front side of head.

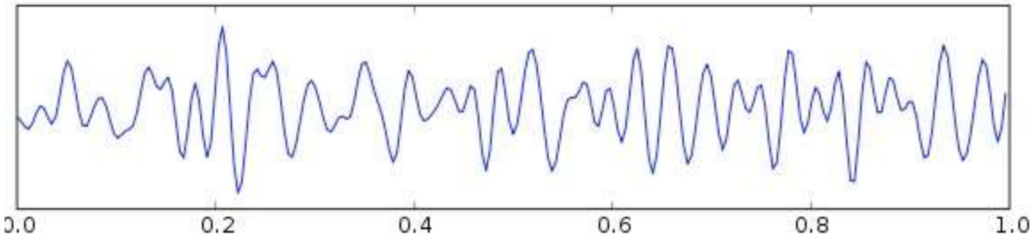


Figure 2.1.4 – Beta Waves [16]

Gamma Waves (γ)

Gamma waves are within the frequency range of 30 Hz. Mental states associated with these are simultaneous work and multi-tasking. These waves are hard to notice due to their very low amplitude. These waves appear in each part of brain.

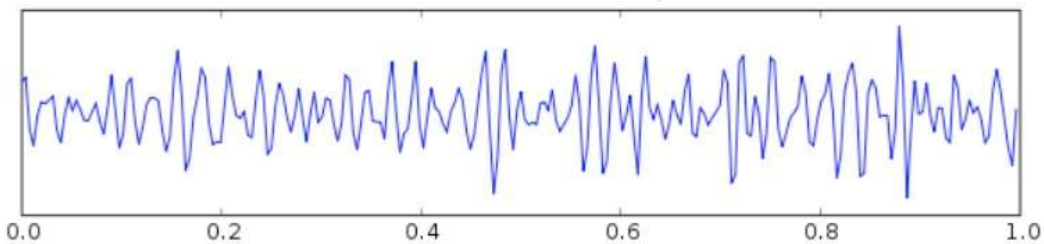


Figure 2.1.5_ Gamma Waves

2.1.2 Electrocardiography(ECG)

Electrocardiography(ECG) is the approach of recording the electrical activity of the heart using electrodes attached to the skin. These electrodes detect the minimal electrical changes on the skin surface that appear from the heart muscle's contraction and relaxation during each heartbeat [47]. Conventional 12-lead ECG includes ten electrodes that are placed on the patient's arms, legs and along the chest. They allow monitoring heart activity from different angles in vertical and horizontal electrical planes. Throughout each heartbeat, a healthy heart has an orderly progression of special events that represent mechanics of cardiac muscle activity. In contemporary cardiology, these events are called P, Q, R, S, T points and are shown in Figure 2.2.

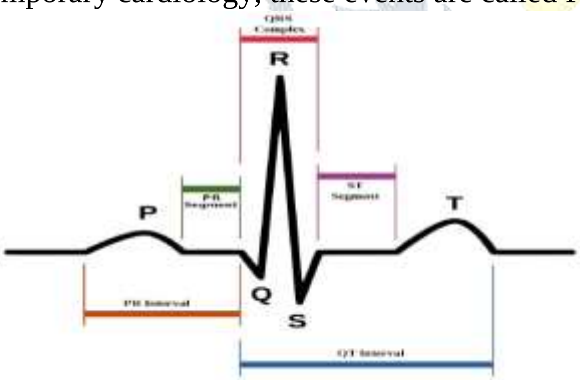


Figure: 2.2

For the experienced doctors, an ECG contains a significant amount of information about the state of the heart and cardiovascular system. Also, an ECG can be used to measure the heart rate variability, the size and position of the heart chambers, the presence of any damage to the heart's muscle cells or conduction system, the effects of cardiac drugs, and the function of implanted pacemakers. Data scientists attempted ECG problems for last two decades [5], however, always faced with a lack of data. Luckily, portable ECG recorders widely arise on the market in recent years, which significantly increased the amount of data. Results were not long in coming, Stanford research group released a paper [7] where they claimed human (doctor) accuracy in various types of arrhythmia detection and reached such performance using data from 30,000 unique patients.

2.1.1 Heart rate variability (HRV)

The time interval between the heartbeats is elicited in HRV. This physiological mark is measured by the length of consecutive interbeat intervals (RR-intervals). Primary methods for tracking heartbeats are ECG, blood pressure, ballistocardiograms (monitoring of barely noticeable body fluctuations caused by heart activity), and the pulse wave signal extracted from a hotoplethysmograph (PPG) [6] (a technique based on an optical sensor for pulse measure, widely spread in modern wearable devices). ECG contains direct information about the cardiac muscle contraction in its waveform , therefore it is considered being the most reliable. For HRV, the analysis performs in time and frequency domains. In case of time domain, the features highlighted are the number of pairs of successive RR-intervals that differ by more than 50 ms, mean, standard deviation and range of RR-intervals and in frequency domain, the high-frequency band (HF) from 0.15 to 0.4 Hz, the low-frequency band (LF) from 0.04 to 0.15 Hz, and the very low-frequency band (VLF) in the range of 0.0033 to 0.04 Hz are extracted using discrete Fourier transform [9] and allow to detect anomalies in the heart functions.

3. EMOTION ELICITATION TECHNIQUES

Emotion elicitation is a vital part of affective science. During the with years of studies in this field, researchers have harmonized that no single sensory domain would be ultimate for emotional invocation. Thus, a wide range of dissimilar techniques were developed. Generally, they contain visual, auditory and even social or environmental effects. Some approaches combine various modalities, like audio + visual by showing affective videos. However, the hottest topic of recent years is Virtual Reality (VR) [8] application for the considered task. The virtual background gives more mobility to the subject allows altering the stimulus to provide higher emotional arousal. In the next sections, all mentioned techniques will be described in more details, with examples of affective databases and their experimental setups.

3.1 Visual Stimuli

International Affective Picture System (IAPS) [10] is the best-known database for affective state studies; it provides pictures to conduct experiments for different physiological research like emotions and attention. It was developed by the National Institute of Mental Health Center for Emotion and Attention at the University of Florida. This database was developed in 2005 and it contained 956 color images varying from everyday items and situations like cats or furniture to very specific, with maimed humans. IAPS has one unique feature that differentiates it from other datasets. All images in it were evaluated in valence and arousal scales. In the process of the collection of the database, subjects' assessments were collected in valence, arousal and dominance dimensions using the earlier described technique called SAM. An experiment was performed as hollows: all images were divided into 16 batches 60 images in each, with 6 seconds for showing a picture and 15 seconds for rating them by the subject. Overall, this experimentation includes 50 men and 50 women. However, The use of IAPS in studies is too wide, making stimulus known to subjects barring from its use in subsequent trials. Thus, datasets analog to IAPS were collected. For instance, Geneva Affective Picture Database (GAPED) contained 730 validated pictures and aimed to increase the availability of visual and emotional stimuli [11]. For extraction of negative emotions, they used photos of spiders, snakes and violent scenes. The Nencki Affective Picture System (NAPS) incorporates even more images (1,356) with high resolution, which are categorized into five groups (landscapes, objects, faces, animals, and humans) [12].

3.2 Audio Stimuli

Audio stimuli are used much less often. Justifiably, mining of audio data requires more effort comparing to images. However, the dataset International Affective Digitized Sounds (IADS) was created **[30],** in comparison with previously collected databases that had an insufficient number of dimensions (separating only positive emotions from negative one), it was validated as well as IAPS in valence / arousal domain. The given database incorporates 111 emotionally evocative sounds for the full range of emotions. Recent studies

[12] shown comparative results of elicitation for further emotional state detection based on physiological signals. The used HRV as a data for emotion recognition and obtained 84.72% on the valence dimension, and 84.26% on the arousal dimension. The same problem was solved by other studies but on the data collected via IAPS [10] or similar dataset provided almost the same results, so audio emotion elicitation is suitable for physiological, affective data collection.

3.3 Videos Stimuli

Video stimuli are the most widely used way for emotion elicitation in laboratory studies [13]. Blend of audio and visual channels provides a more realistic emotional experience which is closer to real life. First trials in the creation of short video for emotion elicitation were made by Philippot [14], also, Gross and Levenson [15]. However, specific clip of segments were able to invoke only robust emotions. Therefore, in consequent research, the researchers attempted to expand the range of emotions that possible to elicit by multimedia stimuli. The Available databases are shown in the table:2

Table 2:

Name	Size and Duration	Emotional labels
HUMAINE [16]	50 clips from 5 seconds to 3 minutes long	Wide range of labels at a global level (emotion-related states, context labels, key events, emotion words, etc.) and frame-by-frame level (intensity, arousal, valence, dominance, predictability, etc.)
FilmStim [17]	70 film excerpts from 1 to 7 minutes long	24 classification criteria: subjective arousal, positive and negative affect, a positive and negative affect scores derived from the Differential Emotions Scale, six emotion discreteness scores and 15 mixed feelings scores
DEAP [18]	120 one-minute music videos	Ratings from an online selfassessment on arousal, valence and dominance and physiological recordings with face video for a subset of 40 music videos
MAHNOB-HCI [67]	20 film excerpts from 35 to 117 seconds long	Emotional keyword, arousal, valence, dominance and predictability combined with facial videos, EEG, audio, gaze and peripheral physiological recordings
EMDB [21]	52 non-auditory film clips of 40 seconds long	Global ratings for the induced arousal, valence, dominance dimensions

VIOLENT SCENES DATASET [20]	25 full-length movies	Annotations include the list of the movie segments containing physical violence according to two different definitions and also include 10 high-level concepts for the visual and audio modalities (presence of blood, fights, gunshots, screams, etc.)
LIRISACCEDE [13]	9,800 excerpts from 8 to 12 seconds long	Rankings for arousal and valence dimensions

A dataset HUMAINE collected by Douglas-Cowie [16] contains several subsets of natural and affected responses. It is not applicable for machine learning task as it has wider range of labels, though well denotes basic principles of affective computing. Shaefer's FilmStim database [17] contains 70 video clips validated by many physiologists for experimental use. It has ten videos for every emotion , they are neutral, tenderness, amusement, sadness, fear, disgust, anger. 24 items of assessment were collected from 364 subjects, which make this dataset validated on the highest number of participants. However, desired the emotional state that expressed by physiological activity leads only up to 10 seconds [Kap11], so in given dataset, a real response is vanished in time because of video length from 1 to 7 minutes. Koelstra built a dataset called DEAP [18], it consist of 120 music video fragments, each minute long and was validated in valence / arousal scale on 14 subjects. Furthermore, physiological signals like EEG, GSR, blood volume pressure, temperature, and respiration. Unfortunately, some of the used videos are under the copyright, another one, collected from YouTube are no longer available. It suggests that such databases have to be based on the open-source content. Soleymani [19]Another created another affective database MAHNOB-HCI,presented in the Table 2. This dataset is multimodal, besides 20 clips extracted from movies, it also contains records of various physiological signals and eye gaze data for applicants. Like n the case of all previous databases, it validated in valence / arousal dimensions. Emotional movie database (EMDB) [21] is a different set of videos for emotions elicitation. The critical feature of this database is that all 54 clips provided without sound. It was done to enhance the capacity of future experiments. Demarty released one specific affective database in 2012 [20]. It called violent scene Dataset, consequently, containing movies with cruel fragments. Because of lopsided thematics of content in given database, only highly aroused negative emotions can be studied. Massachusetts Institute of Technology (MIT) also have their affective database [29]. Using GIF files (short looped videos without sound) from social networks they obtained 2.5M user annotations for 17 discrete emotions. Such broad control group makes this dataset very promising for further research.

In conclusion, the database called LIRIS-ACCEDE, which overcomes the limitations of all predecessors, was released in 2015 by Baveye [13]. 9,800 videos were collected under creative commons licenses, that means no issues with copyrights for public sharing. All videos in a considered database are from 8 to 12 seconds long, which makes it convenient for physiological signal measurements during emotion elicitation. Also, all records are accompanied by valence / arousal values collected via self-assessment

3.4 Other Types of Stimuli

Klaus R. Scherer [22] given the definition of emotion as :"An episode of interrelated, synchronized changes in the states of all or most of the five organismic the evaluation of an external or internal stimulus event as relevant to major concerns of the organism", stimulus for emotion elicitation may be literally any event from the environment. Thus, Healy and Picard from MIT used the real-world driving task to draw drivers into the stressful state [23]. Each of 24 subjects drove at least 50 minutes, while physiological signals like ECG, GSR, and respiration were recorded. Further studies based on collected data [23] showed a correlation between drivers stress level and changes in skin conductivity and heart rate. This research demonstrates how different stimuli can be used for emotion elicitation.

Another alternative way for emotional invocation is using dyadic interaction described by Roberts, Tsai and Coan [24]. The main idea of given technique is to engage interlocutors into such conversation, which maximizes the elicitation of emotion. For instance, contrary emotions were detected during discussions in a controversial field, whereas, positive emotions were obtained in conversations about enjoyable topics. This approach is not suitable for physiological data collection, because it is hard to estimate exact time of real emotional invocation.

Virtual and augmented reality (VR & AR) is new but very promising tools for affective computing. Recent study [8] shows that mentioned technologies can efficiently elicit emotionally and add flexibility to the experimental setup. Adjustability of the virtual environment allows generation of individual stimulus that would provide higher aroused emotional expression.

4. DATASETS OF HUMAN AFFECTIVE STATES

At present, there is no yardstick for emotional state recognition algorithms. However, there are many databases shown in several databases presented in Table 3 are using in research. All these considered datasets are multimodal, that means multiple streams of data were record during each session. DEAP is one of the well-known datasets [18] of EEG signals form emotional state recognition. This dataset also includes several records of peripheral physiological signals like GSR and respiration. However, it is more frequently appears in papers dedicated to research emotional brain activity. Another dataset called DECAF [25] is a Magnetoencephalographybased Multimodal Database for Decoding Affective Physiological Responses. This dataset includes the wider range of signals like ECG, EMG and infra-red video as additional modality and was collected using the same short videos as in the DEAP. The datasets ASCERTAIN [26] and AMIGOS [27] are relatively new and unexplored datasets with both visual and physiological (EEG, ECG, GSR) data streams. Unfortunately, brain activity data of each of them were collected using devices from the public market with dry electrodes, which might provide a signal of lower quality. But still, they are very interesting for further research regarding peripheral philological signal analysis. Currently, a few number of affected state datasets with physiological signals explained by difficulties and costliness of data collection and processing. However, with the advent of inexpensive and accurate wearable sensors, the number of such databases might increase rapidly.

Table 3. Datasets of physiological signals for emotional state recognition [27].

Dataset	Purpose	Modalities	Annotations
DEAP [18]	Implicit affective tagging from EEG and peripheral physiological signals	EEG, GSR, Respiration Amplitude, Skin Temperature, Blood Volume, EMG and Electrooculogram. Visual for 22	Self-assessment of arousal, valence, liking, dominance and familiarity. participants
DECAF [25]	Affect recognition	MEG, Near-infrared facial video, horizontal Electrooculogram, ECG and trapezius-Electromyogram	Self-assessment of valence, arousal and dominance. Continuous annotation of valence and arousal of the stimuli.
ASCERTAIN [26]	Personality and Affect	EEG, ECG, GSR and Visual	Big-Five personality traits, self-assessment of valence and arousal.

AMIGOS [27]	Affect, personality, mood and social context recognition	Audio, Visual, Depth, EEG, GSR and ECG	Big-Five personality traits and PANAS. Self-assessment of valence, arousal, dominance, liking, familiarity and basic emotions. External annotation of valence and arousal.
MAHNOBHCI [19]	Emotion recognition and implicit tagging	Visual, Audio, Eye Gaze, ECG, GSR, Respiration Amplitude, Skin temperature, EEG	Self-assessment of valence, dominance, predictability and emotional keywords. Agreement/disagreement with tags.

5. CONCLUSION

In this paper, we presented a review of various developments in emotion recognition research using physiological signals. The researchers mainly concentrated in the extraction of features from physiological signals like EEG and ECG. We also discussed on the role of various types stimuli like audio, video in elicitation of human emotions.

Different physiological signals possess means advantages over each other. In our research, we got to know that EEG has an upper hand over the other physiological signal. The methodology used for emotion recognition for the various physical signals is the same, only the extraction of features from different datasets is different.

6. REFERENCES

1. Peter F. Merenda. Toward a four-factor theory of temperament and/or personality. Journal of Personality Assessment, 51(3):367–374, 1987. PMID: 16372840.
2. Christine D. Wilson-Mendenhall, Lisa Feldman Barrett, and Lawrence W.Barsalou. Neural evidence that human emotions share core affective properties. Psychological Science, 24(6):947–956, 2013. PMID: 23603916.
3. James Russell. A circumplex model of affect. 39:1161–1178, 12 1980.
4. Cynthia Whissell. Using the revised dictionary of affect in language to quantify the emotional undertones of samples of natural language. Psychological Reports, 105(2):509– 521, 2009. PMID: 19928612.
5. Igor Kononenko. Machine learning for medical diagnosis: history, state of the art and perspective. Artificial Intelligence in Medicine, 23(1):89 – 109, 2001.
6. Sheng Lu, He Zhao, Kihwan Ju, Kunson Shin, Myoungho Lee, Kirk Shelley, and Ki H. Chon. Can photoplethysmography variability serve as an alternative approach to obtain heart rate variability information? Journal of Clinical Monitoring and Computing, 22(1):23–29, Jan 2008
7. Pranav Rajpurkar, Awni Y. Hannun, Masoumeh Haghpanahi, Codie Bourn, and Andrew Y. Ng. Cardiologist-level arrhythmia detection with convolutional neural networks. CoRR, abs/1707.01836, 2017.

8. P-H. Orefice, M. Ammi, M. Hafez, and A. Tapus. Design of an emotion elicitation tool using vr for human-avatar interaction studies. In Jonas Beskow, Christopher Peters, Ginevra Castellano, Carol O'Sullivan, Iolanda Leite, and Stefan Kopp, editors, Intelligent Virtual Agents, pages 335–338, Cham, 2017. Springer International Publishing
9. R. D. Berger, S. Akselrod, D. Gordon, and R. J. Cohen. An efficient algorithm for spectral analysis of heart rate variability. IEEE Transactions on Biomedical Engineering, BME33(9):900–904, Sept 1986.
10. P. J. Lang, M. M. Bradley, and B. N. Cuthbert. International affective picture system (iaps): Technical manual and affective ratings. Technical report, University of Florida, 1999.
11. Elise S. Dan-Glauser and Klaus R. Scherer. The geneva affective picture database (gaped): a new 730-picture database focusing on valence and normative significance. Behavior Research Methods, 43(2):468, Mar 2011.
12. Artur Marchewka, Łukasz ˙ Zurawski, Katarzyna Jednoróg, and Anna Grabowska. The nencki affective picture system (naps): Introduction to a novel, standardized, wide-range, high-quality, realistic picture database. Behavior Research Methods, 46(2):596–610, Jun 2014.
13. Y. Baveye, E. Dellandréa, C. Chamaret, and L. Chen. Liris-accede: A video database for affective content analysis. IEEE Transactions on Affective Computing, 6(1):43–55, Jan 2015.
14. Pierre Philippot. Inducing and assessing differentiated emotion-feeling states in the laboratory. Cognition and Emotion, 7(2):171–193, 1993. PMID: 27102736.
15. James J. Gross and Robert W. Levenson. Emotion elicitation using films. Cognition and Emotion, 9(1):87–108, 1995.
16. Ellen Douglas-Cowie, Cate Cox, Jean-Claude Martin, Laurence Devillers, Roddy Cowie, Ian Sneddon, Margaret McRorie, Catherine Pelachaud, Christopher Peters, Orla Lowry, Anton Batliner, and Florian Hoenig. The humaine database, 10 2011.
17. Alexandre Schaefer, Frédéric Nils, Xavier Sanchez, and Pierre Philippot. Assessing the effectiveness of a large database of emotion-eliciting films: A new tool for emotion researchers. Cognition and Emotion, 24(7):1153–1172, 2010.
18. Sander Koelstra, C. Mühl, Mohammad Soleymani, Jung Seok Lee, Ashkan Yazdani, Touradj Ebrahimi, Thierry Pun, Antinus Nijholt, and Ioannis Patras. Deap: A database for emotion analysis using physiological signals. IEEE transactions on affective computing, 3(1):18–31, 2012. eemcs-eprint- 21368.
19. M. Soleymani, J. Lichtenauer, T. Pun, and M. Pantic. A multimodal database for affect recognition and implicit tagging. IEEE Transactions on Affective Computing, 3(1):42–55, Jan 2012.
20. Claire-Hélène Demarty, Cédric Penet, Guillaume Gravier, and Mohammad Soleymani. A benchmarking campaign for the multimodal detection of violent scenes in movies. In Andrea Fusiello, Vittorio Murino, and Rita Cucchiara, editors, Computer Vision – ECCV 2012. Workshops and Demonstrations, pages 416–425, Berlin, Heidelberg, 2012. Springer Berlin Heidelberg.
21. Sandra Carvalho, Jorge Leite, Santiago Galdo-Álvarez, and Óscar F.Gonçalves. The emotional movie database (emdb): A self-report and psychophysiological study. Applied Psychophysiology and Biofeedback, 37(4):279–294, Dec 2012.
22. Klaus R. Scherer. What are emotions? and how can they be measured? Social Science Information, 44(4):695–729, 2005.
23. J. A. Healey and R. W. Picard. Detecting stress during real-world driving tasks using physiological sensors. IEEE Transactions on Intelligent Transportation Systems, 6(2):156– 166, June 2005.
24. N.A. Roberts, J.L. Tsai, and James Coan. Emotion elicitation using dyadic interaction tasks. pages 106–123, 01 2007.

25. M. K. Abadi, R. Subramanian, S. M. Kia, P. Avesani, I. Patras, and N. Sebe. Decaf: Megbased multimodal database for decoding affective physiological responses. IEEE Transactions on Affective Computing, 6(3):209–222, July 2015.

26. R. Subramanian, J. Wache, M. Abadi, R. Vieriu, S. Winkler, and N. Sebe. Ascertain: Emotion and personality recognition using commercial sensors. IEEE Transactions on Affective Computing, pages 1–1, 2017.

27. Juan Abdon Miranda Correa, Mojtaba Khomami Abadi, Nicu Sebe, and Ioannis Patras. Amigos: A dataset for mood, personality and affect research on individuals and groups. CoRR, abs/1702.02510, 2017.

28. Paul Ekman. Facial expression and emotion. American Psychologist,48(4):384–392, 1993.

29. Brendan Jou, Subhabrata Bhattacharya, and Shih-Fu Chang. Predicting viewer perceived emotions in animated gifs. In Proceedings of the 22Nd ACM International Conference on Multimedia, MM '14, pages 213–216, New York, NY, USA, 2014. ACM.

30. Ryan A Stevenson and Thomas W James. Affective auditory stimuli: Characterization of the international affective digitized sounds (iads) by discrete emotional categories. Behavior Research Methods, 40(1):315–321, 2008.