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Review on Stimuli Presentation for Affect Analysis Based on EEG

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ABSTRACT This work presents a comprehensive review on stimuli presentation, which is an important stage of any emotion elicitation experiment in affect analysis. Due to lack of standard guidelines, the researchers employ their self-devised methods which are not always sufficiently informative — making this area very inconsistent and ambiguous. In addition, an ample study about this stage including how to select, design and present the stimuli has not been reported properly earlier. In this purpose, an inclusive study has been conducted aiming to summarize various aspects of stimuli presentation including type of stimuli, available database, presentation tools, subjective measures, ethical issues and so on. Certainly, among several methods of emotion recognition (e.g., facial expression, speech, gesture and physiological signal), the EEG based emotion recognition works have been considered here due to availability of sufficient number of works, reliability and well-established technology. In total, 137 peer reviewed articles have been studied and the results show that about 83% of emotion elicitations have been performed by employing visual stimuli (mostly pictures and video). Therefore, presentation of visual stimuli has been explored with great emphasis covering laboratory setup, presentation timing, subjective issues, and ethical issues. Finally, an extensive recommendations regarding stimuli presentation has been provided which could guide to conduct the emotion elicitation experiments effectively.

INDEX TERMS Emotion elicitation, EEG based emotion analysis, stimuli classification, stimuli design and presentation.

I. INTRODUCTION

Emotion is a complex mental physiological state which plays an important role in our everyday daily life, like decision making, social interaction, generating perception and so on [1]. Indeed, detailed understanding of emotional states and its associated consequences could be benefited in several ways, which enforce the researchers to comprehend it in various domains of research including neuroscience [2], medicine [62], engineering [4], psychology [9], biology [63], social science [11], economics [12], political science [66] and so on. For instance, in psychology, emotion studies deal with the understanding of human behaviors resulting in physical and psychological changes [59], while in neuroscience emotional studies deal with the neural mechanisms of emotions [2]. Certainly, in computer science, it deals with the study and analysis of emotional responses — termed as affective computing, which got significant attention in recent years. In broad sense, the outline of affective reaction analysis or emotion recognition is to first elicite the emotion by applying predefined stimuli to a group of subjects followed by consequent data acquisition by several means such as facial expression [101], speech [16], gestures [102], physiological parameters [47] and so on. Next, the acquired data are processed to extract several characteristics or features in connection with the applied stimuli. In this context, there are many studies which have been conducted in such data analysis including feature generation, characterization and classification so far. Furthermore, several review works and comparative studies have also been accompanied in these extent; such as, feature generation [78], classification [106] and other concerned reviews [141], highlighting their limitations, effectiveness, recognition accuracies, advantages and disadvantages. Nevertheless, the employed stimulus in any emotion recognition system plays a crucial role in appropriate evocation of target emotion. It generally encompasses design and selection of stimuli and how it has to be applied to the subjects. However, there are no firm guidelines or

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standard procedures addressing these vital issues, leading to discrepancies and inconsistencies in affect studies. Therefore, an inclusive review is very imperative in concern with the role of stimuli in emotion recognition to enrich the affective computing domain.

In this context, to discriminate different emotions, there are two well-known spaces — discrete space, which typically includes six distinct emotions including anger, disgust, fear, happiness, sadness and surprise [162]; dimensional space, which provides higher number of emotions based on latent dimensions. Compared to discrete space, the dimensional space comprising of valence-arousal (V-A) provides better understanding of emotional states [162]. The valence and arousal paradigm ranges from unpleasant to pleasant feeling and activated to de-activated state respectively [124].

Generally, such emotional expressions or reactions are studied by means of verbal (speech/music) [56], non-verbal (facial expression, eye gaze, gestures) [79] and physiological signals [22]. Each of these methods has their own advantages and disadvantages; for example, facial expressions can be masked leading to unstable studies [80], also gestures can be sometimes misapprehended [80]. Among them, emotion recognition based on physiological signals are more reliable, as the changes in these signals cannot be concealed during any emotion arousal and hence are mostly free of any such faults [80].

Signals like heart rate variability (HRV) [140], electrocardiography (ECG) [139], galvanized skin conductance (GSR) [157], electromyogram (EMG) [138], electroencephalogram (EEG) [7], magnetoencephalogram (MEG) [8], functional magnetic resonance imaging (fMRI) [68] displays notable changes during emotional reactions. Indeed, such changes in physiological signals is rooted or controlled by the human brain. Therefore, acquiring signals directly from the brain could offer more detailed information concerned with emotional states unlike other physiological signals [168]. Contextually, there are several means of brain signal acquisition including EEG, MEG, fMRI. Certainly, EEG which records voltage fluctuations at scalp level, has got more attention in emotion recognition due to its non-invasive nature, easily moveable, well established technology and not requiring any highly specialized lab facilities (like MEG, fMRI). In addition, there are ample studies on EEG based emotion recognition which employs various stimuli [185]. These works are adequate to get a broader perception in connection with stimuli design and presentation in affective computing. In this view, this review addresses the fundamental issues to design and present different stimuli for emotion evocation, especially in EEG based emotion recognition in the domain of affective computing.

To the purpose, several reputed databases including PubMed, IEEE Xplore and Web of Science were searched between the earliest return date and December 2018 in English language only. In addition, to obtain a wider context, Google ScholarTM was searched for potentially relevant articles using various keywords such as emotion recognition, emotion analysis, EEG based emotion analysis, psychology+emotion analysis, display+stimuli+setup, visual stimuli, audio stimuli, and so on. The primary objective was on selecting articles which provided information including type of stimuli, stimuli design, way of presentation and participant's information. Finally, around 137 relevant articles were sorted out and reviewed. The articles were scrutinized extensively in the light of choice of stimuli and their design and presentation, extending to associated aspects such as timing, sessions and trials, stimuli repetition, subjective concerns (like age, gender), physical factors (like health, fatigue) and ethical issues. Furthermore, inconsistencies in stimuli design and presentation in the existing works have been explored. Additionally, widely employed stimuli database and stimuli presentation tools have also been listed. Finally, a general conceptual framework in concern with employment of stimuli in emotion recognition has been presented. The recommendations highlighted here have been primarily aimed towards researchers conducting experiments for design and development of emotion recognition systems in affective computing domain.

The rest of the paper has been organized as follows. In Section 2, a background study on EEG based emotion analysis has been outlined. Section 3 includes a short description regarding stimuli along with widely used stimuli datasets and presentation tools. Section 4 presents the review work. Recommendations on presentation have been listed in Section 5 followed by discussion in Section 6. Finally, conclusion has been drawn in Section 7.

II. BACKGROUND STUDY

In this section, an overview on brain and its underlying neural mechanisms in connection with emotion has been briefed. Next, an overview of conventional EEG based emotion recognition technique have also been depicted [18].

A. BRAIN AND EMOTION

The brain, command center of the human nervous system [20], controls main activities such as sensory and motor functions, cognition, emotion processing and so on. It comprises of cerebrum (frontal, temporal, parietal and occipital lobes), cerebellum (grey matter and white matter) and brain stem [21] and these are made up of lots of neurons which generate electrical signals. Such electrical signals show notable change towards any emotional activity which can be captured by electroencephalography (EEG) at scalp level. The EEG signal has a better temporal resolution than spatial resolution. A temporal variation (amplitude, timing) in EEG can be observed during emotion elicitation; for instance, pleasant and unpleasant stimuli results in amplitude enhancement [3]; a negative peak can be seen in case of emotional facial stimuli [5].

Typically, the spectrum of EEG signals is very low; ranging from 0.5 – 100 Hz and is divided into the following sub-bands

TABLE 1. Emotions and corresponding brain regions.

Emotions	Brain Region	Time (ms)
Anger	right frontal	349–431
	right prefrontal cortex	452–467
Disgust	right frontal	138–189
	Frontal	443–478
Fear	left temporal, right frontal	256–306
	right temporal	322–342
Happiness	left frontal, right frontal	138–205
	frontal, temporal, right parietal	244–290
Sadness	prefrontal cortex	138–197
	orbitofrontal, temporal	220–260
	Frontal	279–346
	Temporal	447–474

known as — α (8–15 Hz), β (16–31 Hz), γ (> 32 Hz), δ (<4 Hz) and θ (4–7 Hz) [24]. In literature, most of the studies on emotions and brain can be explained by activation of different brain regions in connection with these sub-bands.

Commonly, the primary regions associated with emotions are frontal, pre-frontal and parietal regions. Greater activation in left frontal region is associated with positive emotions (e.g., joy, happiness); whereas, for negative emotions (e.g., sad, fear, disgust) the right frontal area shows higher activity [16]. The pre-frontal region shows higher activation for neutral emotions, while parietal region is activated for both neutral and negative emotions. In addition, the temporal and occipital region also shows variations towards positive and negative emotions respectively. Such activations in brain regions in connection with emotions persist for certain duration. Based on literature, different emotions, corresponding brain region and timing has been summarized in Table 1 [163].

The emotional evocation in brain is also accompanied by variations in sub-bands [189]. For instance, generally α power variations in cortical area is observed during emotion evocation; while, positive emotions show variations in β and γ in lateral temporal region. Also, the changes in the anterior-right and posterior side of the scalp are mostly indicated by θ and δ for all stimulus types respectively [175].

Furthermore, specific electrode placements have also been identified, which provide a better understanding of the emotional processing in the brain at scalp level. Accordingly, EEG data collected from electrodes FP1, FP2, F3, F4, F7, F8, Fz, C3, C4, T3, T4, and Pz are strongly related to emotions [177]. Also, electrodes from temporal and parietal regions helps to identify distinguishing features for better emotion recognition [178].

B. TRADITIONAL METHOD

A common block diagram of an EEG based emotion recognition system has been illustrated in Fig. 1. As seen, the preprocessing (noise removal, baseline shift, etc.) of the acquired

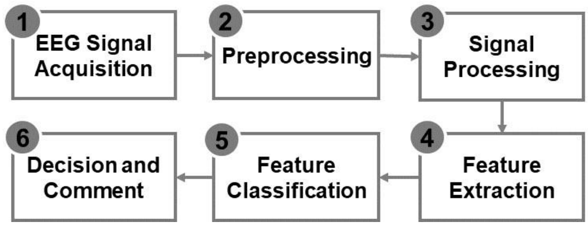

FIGURE 1. Conventional EEG based emotion recognition system.

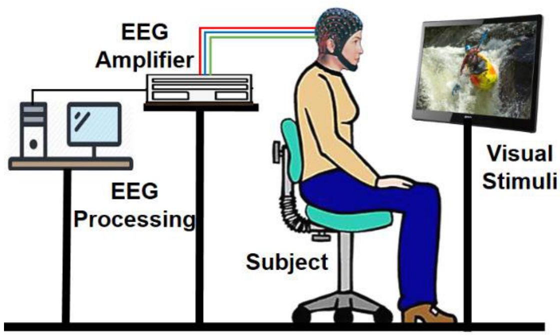

FIGURE 2. Visual stimuli presentation mechanism.

signal is performed, then several features (generated using different signal processing methods) are extracted and classified and finally conclusion are drawn following the objective of the experiments.

As aforementioned, tracking the changes in neuroelectrical activity, observed due to certain emotional events, is the key to measure the human emotion in EEG based emotion recognition systems [186].

Indeed, such neural activations are instigated or stimulated by predefined external means, called stimuli, which could be picture, video, audio, audio-video and others [187]. Particularly, in any emotion elicitation experiment, the stimuli are initially enforced to evoke the desired emotion and simultaneously EEG signals are acquired, as displayed in Fig. 2. For instance, to evoke the happy (or strong positive) emotional state, happy music video/audio clips are used as stimuli. Hence, to evoke a certain emotion, appropriate selection and presentation of stimuli is very imperative in emotion recognition.

III. STIMULI

A stimulus is a thing or event that produces a specific functional reaction in organs which is controlled by brain [70]. Such reactions within an organism differ according to various stimuli, which aids in perceiving the changes in the surroundings. In broad sense, some stimuli can be categorized as relevant to the survival and well-being of an organism, while other are concerned with growth of the organism. In this concern, an "emotional" stimulus is one such category, which creates a perception of understanding of the situation and expressing the required behavioral response accordingly [167]. Hence, correct perception of emotional

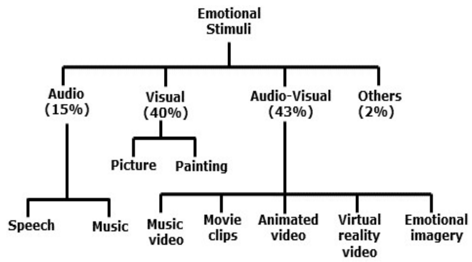

FIGURE 3. Classification of stimuli.

stimuli for a subject is of utmost priority in any study of affect detection. In literature, several kinds of stimuli such as visual (pictures), audio (music/speech) or audio-visual (motion pictures) and others have been employed so far in EEG based emotion recognition which has been de-tailed in the following sub-section.

A. STIMULI CLASSIFICATION

The stimuli employed so far for emotion elicitation can be classified into four broad categories — audio, visual, audio-visual and others as displayed in Fig. 3. Further, the audio stimuli have been applied mainly in two forms — speech and music; whereas, visual stimuli have been conveyed by means of static and abstract pictures. Moreover, audio-visual stimuli, has been largely used in form of movie clips, random emotional videos, animated pictures, virtual reality based videos and emotional imagery. The others category includes stimuli like touch.

Audio stimuli: It refers to an external event that causes an excitation in the auditory system of a person [61]. Such kind of stimuli can be either musical pieces [39] of high emotional content or speech [40]; referring to people talking in a particular language and expressing any desired emotion.

Visual stimuli: These kind of stimuli contain emotionally high pictorial content which causes a subject's visual system to be excited [64]. Such stimuli may be contained in the form of high emotional valued picture [43] or abstract painting portraying specific emotion [67].

Audio-visual stimuli: It stimulates both the visual as well as the auditory systems simultaneously [81]. Such stimuli can either be displayed in form of emotional clips from movies [10], or random musical videos of high emotional content [82]. These clips are usually shown for either shorter or longer duration, sometimes referred to as short or long movie clips respectively. Besides, animated pictures are in focus in emotion elicitation in recent studies [6]. Additionally, virtual reality (VR) based stimuli and emotional imagery have also been employed to evoke emotions. The VR creates the sense of being in the physical world by simulations under controlled laboratory conditions [180]. Such stimuli are provided with 360° view (typically), while the scene updates according to head orientation. The postures of head are also associated with emotions [179]. In this sense, VR creates a more realistic visual stimuli allowing for a stronger emotional arousal. Alternately, emotional imagery refers to conceiving an image within the brain itself, without requiring any external stimulus. It typically depends on capacity of one's brain to visualize real emotion-arousing images. In this case, different sensory inputs, especially audio, are employed describing a situation which assists a subject to envision a visual scene [183]. This state of mind allows a visualization which can be assumed to be a stimulus that finally evokes an emotion.

Others: Other than aforementioned stimuli, few studies used touch as stimuli for emotion analysis. For instance, in Mirror-Touch Synaesthesia (MTS) the user experiences emotional feeling of being touched when they see others being touched in stimuli. Hence, the touch can be considered as stimuli in emotion recognition [105].

The survey reveals that the visual and audio-visual stimuli have been employed more compared to only audio and other type of stimuli as illustrated in Fig. 3 (e.g. audio (15%), visual (40%), audio-visual (43%) and others (2%)). This is due to — a) better stimulation ability [146], b) availability of well defined visual stimuli database, c) compatible and easy accessibility of presentation tools. Therefore, a description over such visual/audio-visual stimuli and available presentation tools has been briefed in the following sections.

B. STIMULI DATABASE

To conduct emotion elicitation through stimuli is always a challenging task, mostly in the selection of appropriate stimuli following the objective of the experiment [188]. In this regard, there are some internationally standard database of visual, audio-visual and audio stimuli which are very often used [78]; such as the International Affective Picture System (IAPS) database, Geneva Affective Pictures Dataset (GAPED), etc. Few such reputed databases are listed in Table 2. Among them IAPS has been widely used due to its standardized stimuli set and relevant information which has been summarized in Table 3. Besides, for audio stimuli the important parameters of the commonly used database International Affective Digitized Sound (IADS) have been listed in Table 4.

IAPS is a set of static pictures defined along the dimensions of valence, arousal and dominance. The image set consists of various pictures depicting mutilations, illness, loss, pollution, puppies, snakes, insects, attack scenes, accidents, contamination and landscape scenes among others. The goal of the IAPS is to develop a large set of standardized and emotionally high content color pictures which will provide a set of stimuli for experimental investigations of emotion and any such cognitive experiments. The development and distribution of this database is under NIMH (National Institute of Mental Health) Center for Emotion and Attention (CSEA) at the University of Florida [170].

In this regard, the materials and equipments used for the development of the IAPS database are illustrated as follows:

TABLE 2. Stimuli database.

Stimuli Type	Stimuli Database	Description	Remarks
Visual	International Picture Affective System (IAPS) [172]	• Around 1182 colored pictures. • Pictures from a wide domain of various emotions • High definition; maximum size: 1024x768 pixels.	• Emotions spread evenly in the Valence, arousal and dominance space.
	Japanese Female Facial Expression Database (JAFFE) [171]	• 213 images of facial expressions (black and white) • Seven kinds of facial expression (six basic and one neutral) depicted by Japanese female models.	• Each image rated on 6 emotion adjectives by 60 Japanese subjects.
	Geneva Affective Picture Database (GAPED) [131]	• Database of 730 colored pictures • Rated in valence arousal space. • Resized and cropped to 640 x 480 pixels.	• Images include human and animal babies as well as nature sceneries and inanimate objects respectively.
	Radboud Faces Database (RaFD) [136]	• Set of pictures of 67 models. • Eight emotional expressions (neutral, angry, sad, fearful, happy, surprised, contemptuous, disgusted). • Colored images cropped and resized to a size of 1024x681 pixels.	• Includes Caucasian males, females and children, both boys and girls, and Moroccan Dutch males.
	Pictures of Facial Affect (POFA) [174]	• Consists of 110 photographs of facial expressions • Wide range of emotions spread along V–A. • All images are black and white.	• No colored images.
	Open Affective Standardized Image Set (OASIS) [28]	• 900 colored images. • Wide range of emotions like happiness, excitement, contentment, sadness, anger, or disgust. • Image size 500x400 pixels.	• Images depict humans, animals, objects, and scenes. • Not subjected to the copyright restrictions that apply to the IAPS.
	Nencki Affective Picture System (NAPS) [83]	• 1356 images (high quality). • Emotions spread across the V–A space. • Images resized/cropped (4:3 (landscape) or 3:4 (portrait)).	• Affective ratings collected from 204 mostly European participants.
	FACES [178]	• 2052 colored images (high quality). • Each face represented with two sets of six facial expressions • Image size 2,835x3,543 pixels	• 154 naturalistic faces of young, middle-aged, and older women and men. • Participants were Caucasian and native German speakers.
	AffectNet[30]	• Over 1 million images. • Both discrete and dimensional emotions considered. • Image size 256x256 pixels.	• Dataset made from internet with search results from six different languages.
Audio-visual	MAHNOB [110]	• 180 sessions of 3h 49m (spontaneous). • Laughter, speech, posed laughter, speech laughter.	• 22 subjects (12 males, 10 females). • Language: English.
	Surrey Audio-Visual Expressed Emotion (SAVEE) [144]	• 480 utterances (acted). • Six basic and neutral emotion.	• 4 male actors. • Language: English.
	eNTERFACE[158]	• 1166 video sequences (induced). • Six basic emotions.	• 42 subjects (34 males, 8 females from 14 different nationalities). • Language: English.
	Interactive Emotional Dyadic Motion Capture (IEMOCAP) [151]	• 12h (acted, spontaneous). • Five emotion categories (happiness, anger, sadness, frustration, and neutral); 3 dimensions (valence, activation, dominance).	• 10 actors (five males, five females). • Language: English.
	Geneva Multimodal Emotion Portrayals (GEMEP) [160]	• Over 7000 portrayals (posed). • 18 affective states (5 discrete emotion classes, anger, fear, joy, relief, sadness).	• 10 professional actors (5 males, 5 females). • Language: French.
	Vera am Mittag German audio-visual emotional speech database (VAM) [152]	• 947 utterances of approximately 12 h (spontaneous). • Three dimensions (valence, arousal and dominance.	• 47 talk show guests. • Language: German.
	Multimedia Human-Machine Communication(MHMC) [124]	• 1680 Sentences of approximately 5 h (posed). • Four emotion categories (happy, sad, anger, neutral).	• 7 actors (both genders). • Language: Chinese.
	Spanish Multimodal Opinion [107]	• 105 videos (spontaneous). • Positive, negative.	• 105 speakers. • Language: Spanish and English.

TABLE 2. ***(Continued.)*** **Stimuli database.**

Audio	International Affective Digitized Sound (IADS) [154]	• 167 sounds. • Spread across the valence, arousal and dominance emotional space.	• 100 participants (approximately 50 male and 50 female) rated the sounds.
	Emotional Oriya Speech Database [135]	• 900 phrases (elicited). • 6 discrete emotions.	• 23 males, 12 females. • Language: Oriya.
	Danish Emotional Speech Database (DES) [173]	• 2 isolated words, 9 sentences, 2 passages (Simulated). • Anger, sadness, surprise, neutral and happiness.	• 4 actors (2 males and 2 female). • Language: Danish.
	Berlin Emotional Database (EMO-DB) [84]	• 10 sentences, 840 utterances (Simulated). • Anger, boredom, disgust, fear, happiness, neutral and sadness.	• 10 speakers (5 males and 5 female). • Language: German.
	Italian Speech Corpus (EMOVO) [85]	• 14 sentences, 588 recordings (Simulated). • 6 discrete emotions and neutral.	• 6 professional actors (3 males and 3 female) • Language: Italian.
	Persian Drama Radio Emotional Corpus (PDREC) [86]	• 748 utterances (Simulated). • 6 discrete emotions including boredom and neutral.	• 33 speakers (15 females and 18 males). • Language: Persian.
	Serbian emotional speech database (GEES) [166]	• 2790 recordings and duration of speech around 3 h. • Neutral, anger, happiness, sadness and fear.	• Six actors (3 females, 3 male). • Language: Serbian.

TABLE 3. **Experimental conditions for IAPS.**

Particulars	Specification
Room size	20ftx30ft
Seating condition	Seated in rows of 90° arcs facing the screen
Screen size	4ftx5ft
Total slides	60
Time frame	26s(get ready (5s)–stimuli(6s)– SAM (15s))

TABLE 4. **Properties of sounds for IADS-2.**

Particulars	Specification
Sound Properties	file format : .wav
	min/max value of the sample
	peak amplitude
	min/max/average value of RMS power
Practice sound	3
Total sound	167
Time frame	26s(preparation (5s)–stimuli(6s)– SAM(15s))

•Selection of a broad sample of contents across the entire affective space.

•All pictures are in color.

•Pictures are easy to resolve, have clear figure and communicate affective quality relatively quickly.

To conduct each rating study of the various images, the experiments were conducted under the conditions stated in Table 3 in which columns one and two refer to the items and their specifications respectively.

In addition to IAPS, the IADS [152] is another widely used audio stimuli for affect analysis. It is a set of well-defined and developed set of normative sound stimuli for use in experiments in concern with affective studies. Similar to IAPS the development and distribution of this database is under NIMH and CSEA at the University of Florida [170] and its the details has been listed in Table 4.

C. STIMULI PRESENTATION TOOLS

The technique and way of how the stimuli is presented is a significant factor in any emotion elicitation experiment [35]. How the stimuli are being shown has an instantaneous effect on the participants' mind leading to changes in the elicitation of the required emotion [17]. In this context, there are several stimuli presentation tools available; which can be incorporated in stimuli presentation phase; few of which have been discussed as follows:

Presentation: It is a stimulus delivery and experiment control program for neuroscience. It provides a range of powerful and flexible stimulus displays while at the same time accurately logging all stimulus and response events [115].

Psychophysics: This tool is a stimulus delivery system of Matlab and GNU Octave functions for vision and neuroscience research. It makes it easy to synthesize and show accurately controlled visual and auditory stimuli and interact with the observer. It is a freely available open source tool [125].

BOLDSync: It provides a user friendly GUI platform for design and presentation of visual, audio as well as multimodal audio-visual stimuli in functional imaging experiments. This toolbox has been developed in MATLAB with the goal of simplifying the process of presenting fMRI stimuli and capturing the responses made by participants [87].

Visage: This is a prototype user interface environment for exploring and analyzing information. It represents an approach to coordinate multiple visualizations, analysis and presentation tools in data-intensive do-mains [119].

Psychtoolbox: This is an interactive toolbox used to synthesize and appropriately display controlled visual and auditory stimuli to the observer. It interfaces between MATLAB and GNU Octave for neuroscience and vision research. Along with allowing the support of video playback and low-latency audio, this toolbox assists in the recording of user responses as well [116].

TABLE 5. **(a) Review of stimuli presentation technique (AUDIO). (b) Review of stimuli presentation technique (PICTURE). (c) Review of stimuli presentation technique (AUDIO-VIDEO).**

Works	Description			Stimuli Format (R–C–W–S–M)¥	Presentation Particulars	Subject			Remarks
	Source	Component	Emotion Space			Gender Male	Gender Female	Age (Year)	
Sawata *et al.*[23]	Self-designed	—	—	X–X–X–15–X	• Classification of favorite music. • 12 channel EEG electrode used; MEG-6116M NIHON KOHDEN	10	—	23	• Female not considered. • Presentation technique not detailed. • 81.4±0.06% accuracy.
Turchet *et al.*[15]	Self-designed	—	Discrete	—	• Subjects seated on chair with headphones. • 40 trials.	9	1	22–44	• For trial session.
						5	5	26–32	• For experiment session.
Thammasan *et al.*[34].	Self-designed	40 pop music clips	V-A	X–X–X–120–16	• Closed eyes and minimal body movement.	15	—	22–30	• Mentally healthy participants.
Paul *et al.*[73]	Self-designed	16 audio clips	Discrete	30–X–X–30–10	• Stimuli presented by headphones. • 7 electrodes used in 10-20 system (F3, F4, Fz, P3, P4, T3, T4).	0	8	22–26	• 4 audio clip for each emotion. • Maximum accuracy 84.5%.
Di *et al.*[72]	IADS	—	V-A	3–X–X–6–15	• Lab environment: Soundproof, tables & chairs placed symmetrically. • Nondirectional dodecahedron sound source (Nor270, Norsonic, Lierskogen, Norway) suspended in the center. • Fatigue monitored. • Second experiment: 24 sound. • Includes four practices before the formal evaluation and a 2m break during the experiment.	44	65	19–28	• First experiment.
						6	10	18–28	• Second experiment.
						—			• Subjects not on drugs; no head injuries, mental, neurological and convulsive disorders. • Female subjects not in menstrual periods.
Liu *et al.*[118]	IADS	—	V-A	1–X–15–30–2–1	• 16 sessions carried out. • Emotiv EPOC device with 14 electrodes used (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4).	9	3	18–27	• Ethical and presentation setup not detailed. • Accuracy 76.51%.
Pereira *et al.*[128]	Self-designed	48 pop/ rock music	—	—	• Volume comfortably adjusted in noise cancelling headphones. • Total 1m presented for each condition, in two 30s blocks.	9	5	24–40	• Evaluate emotional engagement with familiar and unfamiliar music.
Lin *et al.* [137]	Self-designed	16 audio	Discrete	X–X–X–30–15	• Subjects instructed to keep eyes closed. • 16 sound tracks used. • Neuroscan device with 32 electrodes (Fp1, FP2, F7, F3, Fz,F4,F,FT7,FC3,FCz,FC4,FT8,T7,C3,Cz,C4,T8,TP7,CP3,CPz,CP4,TP8,P7,P3,Pz,P4,P8,O1,Oz,O2).	16	10	About 24	• Ethical and stimuli presentation details not provided. • Accuracy 82.29%.
Grimm *et al.* [162]	Self-designed	natural speech	V-A	X–X–X–10–X	• Two speakers; speech segmented into 165 utterances. • Each utterance in German Language.	12	1	24–65	• Wide age group of subjects • Ethical consent details not provided.

¥: Relaxation time/blank screen (in s)–Countdown frames (in s)–White cross presentation/silent period (in s)–Stimuli presented (in s)–SAM rating/rest time (in s); X: Not mentioned.

IV. REVIEW WORK

An extensive review has been performed keeping in mind the major issues concerned with stimuli in emotion elicitation including its type, design and presentation along with subject information and so on. The study and analysis have been summarized in Table 5 (5A: Audio; 5B: Picture; 5C: Audio-Video), in which the first, second and third column refers to type of stimuli, corresponding work and stimuli description respectively; the following columns describe the stimuli presentation technique, subject information and remarks successively. The observation shows that the rules and regulation regarding stimuli presentation, its design and other concerns like how the stimuli has been presented and under what conditions have not been addressed properly [108]. Ambiguities in such information lead to discrepancies in the stimuli presentation. However, an overall framework of presenting a stimulus can be outlined by amalgamating the related studies, which has been depicted in Fig. 4. The whole stimuli presentation time can be divided into three major parts— pre-stimuli (0.5s–3m), stimuli (1s–5m) and post-stimuli (2s–5m).

The pre-stimulus stage refers to specific visual cues presented prior to stimuli onset, to prepare the subject for the experiment. The fluctuations in neural activity during this stage can influence the recognition of various sensory stimuli [191]. It typically includes few seconds of relaxation time or get ready time, which aids in making the subject comfortable in the experimental setup [180] and become conscious about the start of the experiment. This is followed by few seconds of countdown frames and a few seconds of white cross display in a black background to get the attention of the subject. After that, the stimulus is presented following the objective of the experiment. Finally, post-stimuli stage arises where stimulation is reduced by allowing the subject to return to a neutral state of mind [65]. This is significant as it ensures that the emotional arousal of previous stimuli does not affect the subsequent responses. Here, the subject is initially given rest for a while, called as rest time following which self assessment manikin (SAM) ratings have been taken in most of the cases [121].

Other than stimuli, there are certain important issues such as display setup, participant's information and ambient conditions need to be considered in stimuli presentation and reported accordingly. Nevertheless, few studies have not revealed these important factors like, laboratory environment [73], [74], [78] (screen size, ambient conditions, etc.) and the participant information [32], [132]

TABLE 5. *(Continued.)* (a) Review of stimuli presentation technique (AUDIO). (b) Review of stimuli presentation technique (PICTURE). (c) Review of stimuli presentation technique (AUDIO-VIDEO).

Works	Description			Stimuli Format (R–C–W–S–M)¥	Presentation Particulars	Subject			Remarks
	Source	Component	Emotion Space			Gender: Male	Gender: Female	Age (Year)	
Lopez-Gill *et al.*[46].	IAPS,	4 video and 31 Pics	Discrete	—	• Images presented at an interval of 5s. • Video clips shown for 15s. • Emotiv EPOC device with 14 electrodes used (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4).	6	38	20–30	• EEG and Eye Tracking used. • Mind Reading Software Version 1.2. • Maximum accuracy 42.7%.
Peng *et al.*[38]	Emotion6	—	V-A	—	• Emotion6 database has been used. • Contains total 1980 images.	432		—	• M/F ratio not provided. • Ethical and stimuli presentation details not provided.
Yanagisawa *et al.*[69]	IAPS	—	Discrete	25–X–X–25–25	• 8 trials.	21		—	• M/F ratio not mentioned.
Bozhkov *et al.*[75]	IAPS	24 Pics	Discrete	—	• Images presented 3 times in a pseudorandom order. • Trial lasted for 3.5s. • Neuroscan device used with 21 electrodes (FP1, FPz, FP2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3, Pz, P4, P8, O1, Oz, O2).	—	26	—	• No male subjects considered. • Accuracy 88.46%.
Hosseini *et al.*[74]	IAPS	—	Discrete	—	• One block (4 pictures/block); each image shown for 3s. • Consisted of 8 trials. • 10 channel Flexcom Infiniti device used (FP1, FP2, T3, T4, Pz).	15		20–24	• M/F ratio not mentioned. • Accuracy 89.6%.
Gantiva *et al.*[89].	IAPS	24 pics	V-A	5–X–X–6–15	• Lab environment: dimly lit, comfortable desks. • Coloured pictures of size 120 cm.	158	157	18–26	• Subjects with proper vision and mental health considered. • Ethical consent details provided.
Liu *et al.*[90]	IAPS	—	Discrete	3–X–4–10–3	• 8 sessions performed. • Emotiv EPOC device with 14 electrodes used (FC5, F4, F7, AF3).	7	9	20–35	• 4 pictures/session. • Maximum accuracy 85.38%.
Jenke *et al.*[78].	IAPS	160 Pics	Discrete	X–X–X–5–4	• Black screen–4 random pictures for 5s. • Trial ended with neutral picture shown for 4s. • Total 40 trials/subject.	9	7	21—32	• 8 trials of 30s EEG recording for each subject.
Kashihara *et al.*[91]	JAFFE	5 neutral pics; 30 scenery pics	Discrete	X–5—X—1–X	• Inter stimulus gap 0.8 and 1.2s. • Total 40 trials and images converted to gray scale. • Display: 21 inch CRT, positioned at same height as subject. • EGI Inc.'s HydroCel Geodesic Sensor Net (65 channels).	6	6	27	• Subjects' health and vision considered. • Ethical consent properly detailed. • Accuracy 80%.
Valenza *et al.*[71]	IAPS	20 pis	V-A	X–X–X–10–X	• Images displayed on a PC monitor. • Geodesic EEG Systems 300 (Fp1, Fp2, F7, F3, Fz, F4, F8, T7, C3, C4, T8, P7, P3, Pz, P4, P8, O1, O2, Oz).	22		21–24	• M/F ratio not mentioned. • Healthy subjects.
Jatupaiboon *et al.*[103]	GAPED	100 Pics	Discrete	X–X–X–10–5	• Total experiment time is 30m. • Emotiv EPOC device & 14 electrodes used (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4).	6	5	—	• 50 for both positive and negative. • Maximum accuracy 85.41%.
Shams *et al.*[104]	RaFD	8 Pics	Discrete	—	• Data collected for 1m for pictures of children. • Viewing distance: 75 cm. • BMCI model device (C3, C4, F3, F4, P5, P6, T7, T8).	10		5–6	• M/F ratio not mentioned. • Accuracy 96%.
Othman *et al.*[108].	RaFD	—	Discrete	X–X–X–60–X	• Data collected for 40m. • F3 and F4 electrodes used.	5		5	• M/F ratio not mentioned.
Xu *et al.*[112]	Emobrain.	5 pics/ trial	Discrete.	X–X–X–2.5–X	• Experiment done in 3 sessions; 30 trials/session. • Each trial of 5 images displayed for 2.5s; total of 12.5s/block. • F5, F8, AF7, AFz, Fp1, Fp2, Fpz, F7, F6 electrodes.	5		22–28	• M/F not mentioned. • Accuracy 89.3%.
Jin *et al.* [175]	Self-designed	Pics and characters.	—	—	• Subject seated at 105 cm in front of the screen 30 cm high (16.3°) and 48 cm wide. • g.USBamp and g.EEGcap (Guger technologies, Graz, Austria) device used (Fz, Cz, Pz, Oz, F3, F4, P3, P4, P7, P8, O1, O2).	6	4	21–26	• P300 BCI with emotional stimuli and character flash. • Maximum accuracy 93±5.9 %.
Nasehi *et al.*[113]	POFA	60 Pics	Discrete	5–5–1–5–X	• 10 images for each emotion. • Total 16 seconds procedure. • g.MoBIlab EEG acquisition device (FP1, FP2, F3, F4).	6	4	20–42	• No ethical information provided. • Display setup not detailed. • Accuracy 64.78%.
Jack *et al.* [176]	Self-designed	3D photorealistic pics	Cross cultural study based on emotions	—	• Displayed on black background on a 19 inch flat monitor with a resolution of 1024x1280. • Stimuli appeared in the centre, visible till subject responds. • Chin rest ensured, viewing distance (68 cm), images subtending 14.25° (vertical) and 10.08° (horizontal).	6	9	21.3 mean	• Western Caucasian subjects.
						7	8	22.9 mean	• East asian subjects.
Petrantonakis *et al.*[123].	IAPS	40 Pics	V-A	5–5–1–5–20	• Total 36s. • EEG signals acquired from Fp1, Fp2, F3 and F4 position.	9	7	19–32	• Presentation setup not provided. • Ethical details not mentioned. • Average accuracy of 90% obtained.
Zhang *et al.*[120]	IAPS	110 Pics	Discrete	X–X–1–2–X	• Subjects were abstained from making any movements. • AFz, F3, Fz, F4, FC3, FCz, FC4, T7, C3, Cz, C4, T8 electrodes used.	11		—	• M/F ratio not mentioned. • Average accuracy of 93% obtained.
Khosrowabadi *et al.*[134]	IAPS	—	Discrete	X–X–X–60–X	• On 19 inch monitor; 1m away from display. • BIMEC device used (Brainmarker BV, The Netherlands), 8 electrodes used.	26		—	• M/F ratio not mentioned. • Average accuracy of 85% obtained.

TABLE 5. *(Continued.)* **(a) Review of stimuli presentation technique (AUDIO). (b) Review of stimuli presentation technique (PICTURE). (c) Review of stimuli presentation technique (AUDIO-VIDEO).**

Frantzidis *et al.*[132]	IAPS	—	V-A	X–X–1–1–X	• Viewing distance (80cm); in a comfortable armchair. • Used 19 electrodes for EEG acquisition.	14	14	28.2±7.5 (M); 27.1±5.2 (F)	• Ethical approval taken. • Healthy subjects with normal vision considered. • Highest accuracy 85.71%.
Petrantonakis *et al.*[133]	IAPS	60 Pics	Discrete	5–5–1–5–X	• Subjects were abstained from making any movements. • g.MoBIlab EEG acquisition device used (Fp1, Fp2, F3, F4).	9	7	19–32	• 10 pictures/emotion. • Pictures randomly presented. • Average accuracy of 78.28% obtained
Li *et al.*[146].	Self-designed	—	Discrete	—	• Black background; 6x6° viewing angle; horizontal bar (1s). • Two sessions with gap of 10m. • Lab environment: Temp controlled; humidity (40-60%). • Used 62 electrodes for EEG data acquisition.	8	2	25 mean	• Each image presented for 6s. • 12 groups; 5 random pictures/group. • Accuracy 93.0%±6.2%.

¥: *Relaxation time/blank screen (in s)–Countdown frames (in s)–White cross presentation/silent period (in s)–Stimuli presented (in s)–SAM rating/rest time (in s); X: Not mentioned.*

(age, health, gender, etc.); which are substantial for generalizing the way of performing such experiments. In this regard, Petrantonakis and Hadjileontiadis [121] and Jatupaiboon *et al.* [103], performed emotion elicitation experiment while providing details about how the experiment had been conducted; however important details like the laboratory setup and the ambient conditions were not reported. In contrast, Khosrowabadi *et al.* [132], provides the information for laboratory setup but failed to give an insight into the technique for stimuli presentation. In short, most of the works failed to provide substantial information regarding stimuli design and presentation, which leads to an inconsistency in various works related to emotion recognition. Certainly, such issues are very crucial and needs to be addressed properly. Therefore, the important aspects in this regard have been detailed in the next section.

V. RECOMMENDATIONS

Generally, the emotion recognition study entails performing experiments in a laboratory environment, which is usually designed following a specific objective. Indeed, such experimental settings including stimuli design, data acquisition setup, subjective factors and ethical issues are the key factors which has not been reported properly. Certainly, ample knowledge in this regard is very crucial to achieve high valued research findings. Therefore, in this work those key issues have been summarized following rigorous survey; with focus on EEG based emotion analysis. These are highlighted in Table 6 in which the first and second column articulates the major parameters and the related issues respectively and the third and fourth columns emphasize on their shortfalls and corresponding recommendations in that order.

A. AFFECTIVE STIMULI DESIGN AND PRESENTATION

Proper stimuli presentation is a crucial phase in any emotion elicitation related studies as any shortcomings in this stage might affect the overall outcome of the experiments. Therefore, it is important to lay emphasis on not only the type of stimuli used but also the other issues including how it is being presented and to whom. However, the survey shows that the researchers did not follow a specified method of stimuli presentation, instead designed their own procedure. As a result, there is no such standard method or guidelines. Nevertheless, some of the widely used database including IAPS, DEAP [115], NAPS provides certain information regarding how their database have been developed, in which the way of stimuli presentation have been described. Nonetheless, those methods are very specific towards the objective of their respective works and could not cover the broad spectrum of stimuli design.

For instance, IAPS focuses on creation of emotional stimuli of pictures; whereas, DEAP mainly considers video stimuli to generate the EEG database for emotion. Hence, there are firm discrepancies among the methods of stimuli presentation even in the commonly used databases. Indeed, there is a requirement of general guidelines which must cover some of the key issues of stimuli presentation for affective study. Therefore, based on the survey the major issues such as preferred viewing distance, stimuli design, time constraints, etc. have been highlighted in the following sections.

1) PROPER STIMULI PRESENTATION SETUP

In emotion elicitation experiments, stimuli presentation setup is a primary stage which is usually conducted in laboratory environment. Generally, in case of stimulation by visual/audio-visual means, a display unit is placed to present the stimuli to the subjects with specific instructions (see Fig. 2). Certainly, for proper evocation of emotion, the viewing comfortability (especially preferred viewing distance or PVD) must be kept in mind. The concerned factors in PVD, includes screen size, ambient illumination and viewing angle which are correlated as (1) [114].

$$y = -14 + 70x_1 + 2x_2 - 0.0015x_2^2 - 0.46x_3^2 \qquad (1)$$

where, y refers to PVD in mm; x_1 denotes screen size in inch (diagonal measure); x_2 (in lux) and x_3 (in degree) signifies ambient illumination and viewing angle respectively. The screen size influences emotion elicitation, e.g., bigger screen prompts improved subjective emotional arousals [128]. Proper illumination aids in proper stimulation by activation of brain areas associated with emotion [136]. The viewing angle can be adjusted according to the physical comfort of

TABLE 5. *(Continued.)* (a) Review of stimuli presentation technique (AUDIO). (b) Review of stimuli presentation technique (PICTURE). (c) Review of stimuli presentation technique (AUDIO-VIDEO).

Works	Description			Stimuli Format (R–C–W–S–M)¥	Presentation Particulars	Subject			Remarks
	Source	Component	Emotion Space			Gender		Age (Year)	
						Male	Female		
Zhao *et al.*[14]	Self-designed	7 film clips	Discrete	—	• 67—144s per clip; resolution (720 × 576). • Volume controlled using two speakers. • Display: 15 inch LCD. • Viewing distance about 0.6m. • Distraction task–40s rest (eyes open) + 40s rest (eyes closed)–stimuli–SAM rating.	17	20	18–26	• Subjects without psychiatric and neurological disorder. • Refrained from having tobacco or caffeine 24 hours before the experiment.
Becker *et al.*[33]	FilmStim	13 videos	V-A	8–X–2–40 to 360–X	• Display: 21 inch; Viewing distance: about 1m. • One test trial followed by 12 trials. • EGI recording device used.	31	9	36.2±13.9	• Videos in French. • French speaking subjects.
Hu *et al.*[10].	Self-designed	37 film clips	Discrete	—	• Lab controlled illumination; LCD display (22 inch). • Started with 45s rest; Stimuli 30—129s. • NeuSen.W32, Neuracle, China device used with 32 electrodes (Fp1/2, Fz, Cz, C3/4, T3/4, CP1/2, CP5/6, Pz, P3/4, P7/8, Po3/4, PO7/8, Oz, O1/2).	11	9	21–29	• 30 clips for positive- 6 for negative and 1 for neutral. • Highest accuracy 89.8%.
Liu *et al.*[32]	Self-designed	16 Video clips	Discrete	—	• 750x526 resolution, 15 inch LCD screen. • Eyes approx 0.6 m from the screen centre. • Training session—5 min break—testing session. • EMOTIV EPOC device used.	30	—	—	• 8 film clips for each emotion. • Age not specified. • No female subjects. • Highest accuracy 92.26%.
Zheng *et al.*[29]	Self-designed	15 Video	Discrete	15–X–X–240–10	• Experiment performed in 3 sessions and 15 trials • Time between each session was 1 week or longer. • ESI NeuroScan System used; 62 channels used.	7	8	19–28	• 5 video clips of 4 minutes each for each emotion. • Accuracy 69.67% achieved.
Soleymani *et al.* [45].	Self-designed	20 video	V-A	—	• Clips were 34.9 to 117s long. • Biosemi Active II system used with 32 electrodes.	12	16	19–40	• Presentation setup and ethical details not provided.
Zheng *et al.*[65].	Self-designed	Video	Discrete	5–X–X–4–45–15	• Experiments performed twice at the interval of about one week. • Total 30 experiments evaluated. • ESI NeuroScan system used with 62 channel electrodes.	7	8	Mean 23.3	• Subjects informed about the purpose of experiment. • Subjects with normal vision. • Highest accuracy 83.99%.
Lee *et al.*[92]	Film Clip	6 video	Discrete	X–5–30 to 300–60	• Duration of each film is 0.5 to 5m. • 64 channel NeuroScan device used.	21	19	21.4 (M); 21.8 (F)	• Chinese Film Clips. • Abstained from caffeine & tobacco use for 24 hours before testing.
Zheng *et al.*[93]	Self-designed	15 film clips	Discrete	5–X–X–240–45–15	• 5 clips of 4m each. • ESI NeuroScan system used with 62 channel electrodes.	3	2	22–24	• EEG and eye tracking used. • Highest accuracy 73.59%.
Bajaj *et al.*[82]	Self-designed	3 Audio video	Discrete	—	• 5 trials. • BIOPAC EEG recording device used with 16 channels.	4	4	20–35	• Healthy subjects considered. • Ethical details and presentation setup not provided. • Accuracy 91.04%.
Wang *et al.*[94].	Self-designed	Video clips	Discrete	5–X–210–45–X	• . 6 clips/emotion; from Oscar films. • 15s blank screen presented between each clip. • ESI-128 NeuroScan system used with 64 channel electrode cap.	3	3	18–25	• Clips verified by questionnaire from 26 subjects outside participants. • Health monitored. • Maximum accuracy 91.77%.
Nie *et al.* [122]	Self-designed	Video	Discrete	—	• 4m/movie clip (musical, romantic, war, disaster and landscape). • About 12 movie clips/experiment, 6 clips/emotion. • Clips presented randomly; SAM evaluation.	3	3	22	• Healthy and right-handed subjects.
Christie *et al.* [164]	Self-designed	Video clips	Discrete.	—	• Display: 42 inch flat panel. • Viewing distance: 2m; room size 8 x15 feet. • 1m washout clip–2m rest–stimuli. (For 6 stimulus conditions).	16	18	18–26	• Consent taken. • Incentives provided to subjects. • Healthy subjects considered.
Zhu *et al.*[95]	MAHNOB-HCI	Audio visual	V-A	—	• 20 videos used (7 positive and 13 negative).	27		—	• M/F ratio not mentioned. • Well-defined stimuli used.
Li *et al* [181].	Self-designed	73 virtual reality clips	V-A	X–X–5–29 to 668–X	• Display: Oculus Rift CV1 (Oculus VR, Menlo Park, CA) head-mounted display (HMD), 2160x1200 pixels, 110° field of view.	39	56	18–24	• Culture and health of subjects not mentioned. • Ethical consent taken.
Marín-Morales *et al* [182].	Self-designed	4 virtual reality clips	V-A	180–X–X–90–X	• Display: 2D desktop pictures, a 360° panorama IVE, a 3D scenario IVE and a physical environment. • B-Alert x10 (Advanced Brain Monitoring, Inc., USA) device used (Fz, F3, F4, Cz, C3, C4, POz, P3, P4).	24	36	28.9±5.44	• Subjects were physically and mentally healthy. • Laboratory setup detailed.
Liao *et al* [183].	Self-designed	Virtual reality clips	V-A	30–X–10–80–15	• Display: 19-inch widescreen LCD. • 3D models built using Unreal Engine 4.12 • Fp1, Fp2, Fpz electrodes chosen.	13	18	23±2.1	• Subjects were physically and mentally healthy • Ethical consent taken
Onton *et al* [184].	Self-designed	15 guided imagery narratives	V-A	120–X–X–300–X	• Biosemi, Amsterdam device used. • Subjects seated comfortably with eyes closed in a dimly lit room with air-tube fed ear-bud earphones.	13	19	18–38	• Ethical consent taken.
Velikova *et al* [185].	Self-designed	Emotional imagery	V-A	—	• EEG recorded with "Encephalan" amplifier (Medicom MTD, Taganrog, Russia).	10	10	22–51	• Mentally healthy subjects. • Ethical consent taken.
Gemignani *et al* [186].	Self-designed	Imagined stimuli	Discrete	—	• Subjects sat in an armchair in a semi-dark room. • Monopolar EEG electrodes placed bilaterally in frontal (F3–F4), central (C3–C4) and posterior (O1–O2) regions.	2	3	21–30	• Subjects with simple phobia, and otherwise healthy selected. • Ethical consent taken.

TABLE 5. ***(Continued.)*** **(a) Review of stimuli presentation technique (AUDIO). (b) Review of stimuli presentation technique (PICTURE). (c) Review of stimuli presentation technique (AUDIO-VIDEO).**

Zhuang *et al.*[26]	DEAP	40 Music video	V–A	X–2–5–60–X	• Display: 17 inch screen. • Viewing distance: 1m • Stimuli displayed at 800x600 resolution. • 32 channel EEG recorded.	16	16	19–37	• Timing of experiment not mentioned. • Culture of subjects not mentioned.
Ozerdem *et al.*[31].									
Matlovic *et al.*[42]									
Kumar *et al.* [41].									
Kashyap *et al.* [37].									
Atkinson *et al.*[36].									
Vijayan *et al.*[55]									
Sreeshakthy *et al.*[49]									
Candra *et al.*[53].									
Torres-Valencia *et al.*[88]									
Jirayucharoensak *et al.*[96]									
Bastos-Filho *et al.* [114]									

¥: *Relaxation time/blank screen (in s)–Countdown frames (in s)–White cross presentation/silent period (in s)–Stimuli presented (in s)–SAM rating/rest time (in s); X: Not mentioned*

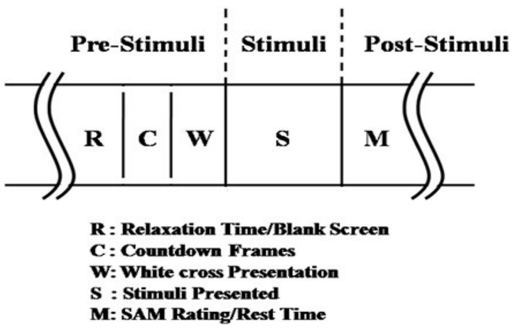

FIGURE 4. **General stimuli presentation technique.**

the subject. In addition, lighting conditions also facilitates visual comfort and play an important role in emotion evocation, like blue light enhances the emotional processes in the brain [48].

2) DISPLAY PROTOCOLS

In experimental design the way of presenting the de-signed/chosen stimuli is another important aspect. It primarily encompasses the overall timing, iteration steps and repetition. Presentation time of stimuli i.e., how long the stimuli is to be shown to the subject is very important, as the brain requires different span of time to process various types of emotions. For instance, Du *et al.* reported that to elicitate happy and sad emotional states require an exposure time of about 10–20ms and 70–200ms respectively [101]. These variations may be due to changes in neural processing pathway (dorsal and ventral) for identifying different visual cues [155]. Besides, the activation of the neural circuits may have an impact on the target emotion. Nevertheless, such duration cannot be confined within a certain time rather a variation can be observed [60]. The following concerns effect the presentation time:

Target emotion: It can be referred to as the emotion which is needed to be elicitated. In literature, the evocation time relies on the nature of target emotion; such as, the required time for elicitation in case of fear, disgust, shame and anger are nearly same, whereas, guilt, joy and sadness needs more time [60].

Timing of experiment: It signifies at what time the experiment has to be conducted which largely effects the overall presentation time. Studies reveal that subjects tend to feel more negative or less positive in the evening as compared to the morning. For example, if the experiment is performed in the evening, the emotion elicitation for excitement and anxiety are less experienced compared to sadness, boredom and anger. Conversely, happiness or low arousal positive emotions like calm, relaxed do not have any effects on the timing of experiment [97].

Sessions and Trials: The emotion elicitation experiments must be conducted in different sessions followed by several trials to avoid discrepancies. Although, the EEG signal is erratic, especially in concern with emotions and cognitive analysis; in a single trial the acquired signal will not be appropriate. Based on our knowledge, there is no specific session or trial numbers for emotion elicitation experiments reported so far. However, as per survey, minimum three sessions with a suitable number of trials in each session (preferably, > 3) has to be considered [25].

Repetition of Stimuli: It refers to the recurrent display of stimuli in emotion elicitation experiments which reduces the neural responses exponentially —known as repetition suppression. This reduction occurs mainly for visually excited neurons, and it depends on the strength of response towards a particular stimulus [123], stimulus contrast, attention and duration of the initial stimulus presentation. Certainly, it reflects in the amplitude variation of the EEG signal [153].

TABLE 6. Drawbacks and recommendations for stimuli presentation in affect analysis.

Major Concerns	Key points	Shortfalls	Recommendations
Affective stimuli design and presentation	Proper stimuli presentation setup	No proper guidelines regarding how to display stimuli to evoke appropriate emotion.	• Ensure comfortability of the subject. • Confirm suitable preferred viewing distance (PVD). • Selection of stimuli according to target emotion.
	Display protocols	Inconsistency in reported studies.	• Stimuli presentation timing: pre-stimuli and post-stimuli timeline should be adequate and consistent throughout the experiment. • Perform experiments in numerous sessions and trials. • Avoid stimuli repetition.
Subjective issues	Subject information	Not listed clearly.	• Large number (at least 32) of subjects. • Maintain sex ratio (1:1) for unbiased emotion analysis. • Consider the age group. • Cultural identity to be noted. • Healthy mental conditions (to check for any psychological distress or depression that might hamper emotion elicitation). • Physical health to be considered and diet, alcohol consumption, caffeine and tobacco intake monitored.
	Fatigue assessment	Mostly ignored.	• Monitor mental and visual fatigue to prevent faulty affect arousal recordings. • Adequate experiment time to prevent fatigue.
	Ethical issues	Not included.	• Consent of the participants. • Approval from concerned ethical committee. • To be aware about the moral implications of the experiment. • Basic medical history. • Keep information privacy and prevent any exploitation of data.

In this context, two major concerns — lag between presentations and stimuli familiarity, should be kept in mind [154]. Review suggests that lag between presentations and repetition has an inverse relation, i.e., sufficient lag reduces repetition suppression [123]. Besides, repetition of familiar stimuli results in decrease in neural response [13]. In addition, how the displayed stimuli have been positioned, i.e., the orientation of the stimuli, also has an impact on the repetition effect. Such changes in orientation reduce the effect of repetition suppression.

Resolution: The resolution of the displayed stimuli creates minor variations in the emotion processing time. The survey suggests that to recognize happiness and surprise, a very short exposure time of about 10-20ms is required; even at low resolutions; whereas, fear and anger requires more time of about 100-250ms even at high resolutions. Sadness and disgust are recognized in between 70-200ms at comparatively lower resolutions [100].

B. SUBJECTIVE ISSUES

The subjective factors such as age, health, gender, cultural background are some key issues in emotion recognition which must be duly considered [59]. Certainly, the number of subjects in such emotion elicitation experiments should also be taken into account to get a desirable result. In parallel, fatigue and ethical issues in concern with the subjects should also be kept in mind. The concerned issues are detailed as follows.

1) SUBJECT INFORMATION

Age: Age is one of the vital factors as it influences the emotional evocation in several ways, mainly in the cognitive abilities, subject's life experiences and brain activities.

Survey reveals that the older adults are less susceptible towards negative emotional stimuli than positive stimuli due to reduced cognitive control [137]. Eventually, the emotional perception also differs along with age owing to life experiences and exposure to different type of objects and situations as well [27]. Such differences can also be seen at the brain level activity; for instance, while viewing emotional stimuli the visual, frontal and limbic brain regions are active for younger subjects whereas older subjects shows similar activation in the parietal, temporal and frontal regions [165].

Generally, such information are not reported properly and in most of the studies, during stimulus rating only young adults are taken into consideration. Certainly, the age related differences that might arise when older adults rate the same stimuli have been ignored. Therefore, in any emotion analysis study, participants from wide span of age groups are highly recommended to generalize the findings, e.g., in designing of stimuli database or physiological signal database, concerned with emotional analysis and so on. Otherwise, specific age group must be highlighted for which the particular experiment will be conducted. In addition, age invariant images must be chosen from a database; for instance, in IAPS, from a set of 504 pictures, approximately two thirds are found to be age independent [147]. Thus it is very important for future emotion oriented research that a useful source for selecting age-matched stimuli is used.

Health: Besides age, health condition, especially mental health of the subject is another key factor [98]; which has not been reported properly. Following this survey, major concerns has been summarized as follows:

•The subjects must maintain a healthy diet before participating in the experiment [159].

•The subjects must not consume food items containing substantial amount of alcohol, caffeine and tobacco, at least 24 hours before the experiment [14].

•Participants with good physical and mental health conditions must be considered [98].

Additionally, in case of female participants, their premenstrual conditions (PMS) should be kept in mind as it causes heightened depression leading to higher level of irritation and anxiety compared to those without PMS [109].

Gender: It is observed that the perception of emotional stimuli may vary according to the gender of the subjects [117]; for instance, males show higher responses to threatening stimuli like violence or aggression; whereas, females show greater neural response towards unpleasant visual stimuli. This gender difference can also be observed in scalp topographies— Males showed higher brain activation (frontal, temporal, pre-frontal and parietal region) against anger, positive and negative emotions, while females show greater responses (limbic, inferior frontal and temporal cortex) towards stimuli depicting disgust [148].

The perception regarding an emotion may be shaped by the society to an extent and that might reflect in the behavior among males and females [44]. In addition, such deviations may also be due to hormonal variations [161]. Hence, to achieve accurate results, such gender differences must be considered during stimuli presentation.

Number: The number of the subjects is also an important factor [18]. Certainly, less number of participants could lead to unbalanced results (see Table 5). Based on survey, EEG based emotion databases, such as SEED [192] and MAHNOB HCI [95], have been constructed using 15 and 30 subjects respectively. However, the widely used database DEAP [37] has been created using 32 subjects, showcasing the reliability of the data. Moreover, since emotion is subjective, more number of participants could provide variability and ensure generalization of the findings/classification results obtained. Also, a greater number of subjects (≥ 32) will be benefitted to study the differences among the groups and aid in providing statistically significant studies.

In parallel, the gender ratio of the participants must be maintained as the degree of elicitation of emotion is gender dependent [127]. Thus, a gender ratio of 1:1 is preferable.

Cultural Bias: Cultural bias, which prompts the preference of one's cultural background, is quite prevalent in emotion processing in connection with stimuli. Generally, subjects show higher emotion evocation when the stimuli belong to their own cultural group [143]. Therefore, to perform a successful emotion elicitation, stimuli must be selected following the cultural backgrounds of the subjects.

2) FATIGUE ASSESSMENT

Fatigue occurs due to prolonged periods of stimulus viewing, which might disrupt the EEG recordings as well the emotional ratings, because the responses and focus to stimuli become less efficient [58]. Besides, mental fatigue causes reduced motivation to perform tasks efficiently and inadvertently which results in disruption of emotion elicitation. Hence, subjects' fatigue conditions should be efficiently examined. It can be monitored from acquired EEG signals in several ways — i) increase in frontal θ or frontal and occipital α activity [99]; ii) rise in power in θ, α, and β [145]; iii) an increase in α activity in the frontal, central, posterior temporal, parietal, and occipital areas, and a dip in β activity in the pre-frontal, inferior frontal, posterior temporal, and occipital regions [57]; iv) $(\alpha+\theta)/\beta$, α/β, $(\alpha+\theta)/(\alpha+\beta)$ and θ/β, are some of the indicators of mental fatigue. With increase in fatigue the values of $(\alpha+\theta)/\beta$, $(\alpha+\theta)/(\alpha+\beta)$ and θ/β significantly increases in the frontal, parietal and occipital regions while α/β increases only in the temporal region [57].

Another vital issue is visual fatigue (discomfort), which is associated with the unpleasant sensation that results as soon as a subject is exposed to any stimulus. Usually, numerous stimuli are being used in emotion elicitation experiments, and to view and rate them could be tiresome [151]. Therefore, careful observation must be done so that the concerned subject is not under any stress leading to fatigue. Certainly, such fatigue can also be detected either by behavioral measure (like changes in the pupil diameter and the number of blinks of the subjects) or subjective measure (like use of fatigue measurement questionnaire) [100]. In this context, use of proper nutrients and presence of intermittent odors before a sustained stimuli viewing task can also be incorporated. In addition, exposure to stimuli based on natural environment reduces both mental and visual fatigue and improves performance [58].

3) ETHICAL ISSUES

Ethical issues should be taken into consideration in affective studies as it involves data collected from human participants along with their personal and behavioral information [166]. Such personal information may include physical and mental health conditions; whereas behavioral data may comprise of numerous subjective traits like reflective or impulsive and so on [54]. Certainly, physiological signal based affective studies, could reveal an individual's innermost features [190]. Such private information can be exploited in a number of ways leading to violation of personal rights. Therefore, an ethical approval is very imperative before data acquisition in this domain. In this context, an ethical consent must be obtained verbally or in written form from the participant. This will prevent harm of the participants and provide protection otherwise. The consent must include the following concerns:

General concerns: These guidelines cover the basic approvals for conducting any experiment with human participants and should be clearly stated or informed. The key points are — i) institutional approval and consent to conduct research; ii) research project details (title, funding and governing institute); iii) details of how the data will be handled including data confidentiality, data distribution and future storage and sharing protocol; iv) details of contact information for further information and also to file a complaint; v) details of how the concerned subjects have been shortlisted and on what basis should be properly described; vi) whether the subjects received incentive/rewards for their participation.

Personal Concerns: These issues are associated with the participants and should be duly answered by them. The main points are — i) proper and clear understanding of the above mentioned general concerns; ii) the option to ask questions regarding the experiment and to get them properly answered; iii) approval to join as a participant in the research; iv) to be aware that participation can be withdrawn at any moment and without stating any reason; v) to provide approval for the recording, handling, usage and storage of personal data and to give consent in either written or verbal form.

Researchers Concerns: These factors are related to specific attributes for researchers in conducting emotion elicitation experiments. The important issues are — i) should handle the data carefully and must not exploit the subject; ii) should abide by the rules governing with studies on human subjects; iii) experiments should be monitored to make humans and machines cooperate in a positive way; iv) should be concerned about the moral implications of the experiment.

VI. DISCUSSION

This review concentrates on emotion elicitation experiment, especially stimuli design and presentation. In this context, important aspects such as the technique, subject and laboratory environment have been detailed. Certainly, various types of stimuli employed so far in this area are categorized and contextually emphasized. Besides, how such stimuli have been applied including subject concerns, laboratory conditions and ethical is-sues have been reviewed and summarized. Several discrepancies regarding aforementioned issues were found in related works, which have been underlined; such as experimental design (display setup, presentation technique), subject concerns (age, gender, health, fatigue monitoring) and others like ethical issues and so on. For instance, Bozhkov *et al.* [75], provides information regarding type of stimuli used and how it had been presented, but missed to give an insight into the laboratory setup. Shams *et al.* [104], provides laboratory information but subject information like sex ratio and age were ignored. Such ambiguity, due to unavailability of any standard guidelines, need to be addressed properly. Therefore, several works were studied to get a general framework for stimuli presentation. Following the goal, few recommendations have been listed with the view that such experiments are very subjective in nature. In this context, stimuli presentation is often used in other research domain like cognitive science, psychology, etc. Therefore, the recommendations are based on not only emotion related studies, but also on various other fields of studies including cognition [51], ergonomics [76], psychology [19], affective recognition [50], neuroscience [77] and behavioral studies [52]. Thus, a concise assessment of stimuli presentation in emotion recognition has been presented.

VII. CONCLUSION

The current trend in affective computing is based on recognizing emotions that are elicitated generally by employing various stimuli in laboratory environment. Although, the stimulus is the key concern in such experiments, there are no such standard guidelines in this regard. Therefore, this review has been conducted aiming to provide information regarding stimuli design and presentation. It includes the type of stimuli used, how to present them and other related concerns like data acquisition, subjective information and ethical is-sues. In the process of thorough review, some shortcomings are sorted and their corresponding recommendations also have been underlined. Besides, classification of stimuli also has been presented, to provide an insight into the wide range of stimuli for emotion elicitation. In addition, well designed platforms for displaying stimuli (presentation tools) have also been reported along with their usability. This review integrates various significant aspects of stimuli presentation, especially for visual/audio-visual stimuli in concern with EEG based emotion recognition systems. Further, the recommendations can also be conceptualized for use in other modalities of emotion elicitation such as facial expressions, gesture, body movements, speech and so on. Thus, this study could provide a general guidance to conduct emotion recognition experiments efficiently and enrich the domain of affective computing.

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