Chapter 7
Psychophysiology in Games

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Abstract Psychophysiology is the study of the relationship between psychology and its physiological manifestations. That relationship is of particular importance for both game design and ultimately gameplaying. Players' psychophysiology offers a gateway towards a better understanding of playing behavior and experience. That knowledge can, in turn, be beneficial for the player as it allows designers to make better games for them; either explicitly by altering the game during play or implicitly during the game design process. This chapter argues for the importance of physiology for the investigation of player affect in games, reviews the current state of the art in sensor technology and outlines the key phases for the application of psychophysiology in games.

Introduction

Computer game players are presented with a wide and rich palette of affective stimuli during game play. Those stimuli vary from simple auditory and visual events (such as sound effects and textures) to complex narrative structures, virtual cinematographic views of the game world and emotively expressive game agents. Player emotional responses may, in turn, cause changes in the player's physiology, reflect on the player's facial expression, posture and speech, and alter the player's attention and focus level. Computer games, opposed to traditional music and video content, are highly interactive media that continuously react to the users' input. This interactivity can naturally accommodate mechanisms for real-time adaptation of game content aimed at adjusting player experience and realizing affective interaction [107].

The study of the relationship between psychology and its physiological manifestations defines the area of *psychophysiology* [15]. Physiology has been extensively

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investigated in relation to affect ([3, 19] among many others) so the relationship between physiology and affect is by now undeniable; the exact mapping, however, is still far from known. What is widely evidenced is that the sympathetic and the parasympathetic components of the autonomic nervous system are involuntary affected by affective stimuli. In general, arousal-intense events cause dynamic changes in both nervous systems: an increase and a decrease of activity, respectively, at the sympathetic and the parasympathetic nervous system. Alternatively, activity at the parasympathetic nervous system is high during relaxing or resting activities. In turn, such nervous system activities cause alterations in one's electrodermal activity, heart rate variability, blood pressure, and pupil dilation [15, 88].

This relation between physiology and affect has been exploited in game research to detect player affect [106]. While some studies have investigated physiological reactions in isolation, researchers often look at the reactions to aspects of the game context [61, 65, 79]. The context of the game during the interaction is a necessary input for appropriately detecting the psychophysiological responses of players. The game context—naturally fused with other input modalities from the player—has been used in several studies to predict different affective states and other dissimilar mental states relevant to playing experience ([71, 83, 86] among others). The fusion of physiology and gameplay or player behavioral metrics has been explored in a small number of studies, typically by analyzing the physiological responses to game events [20, 38, 79] but also using physiological and gameplay statistical features [60, 66]. Other modalities that have been explored extensively but are covered in other parts of this book include facial expressions [4, 14, 36, 49, 111], muscle activation (typically face) [20, 26], body movement and posture [5, 11, 28, 49, 96], speech [7, 43, 45, 47, 97], brain interfaces [1, 81] and eye movement [5].

At the moment of writing there are a few examples of commercial games that utilize physiological input from players. Most notably *Nevermind* (Flying Mollusk 2015) is a biofeedback-enhanced adventure horror game that adapts to the player's stress levels by increasing the level of challenge it provides: the higher the stress the more the challenge. A number of sensors are available for affective interaction with *Nevermind* which include skin conductance and heart activity. *The Journey of Wild Divine* (Wild Divine 2001) is another biofeedback-based game designed to teach relaxation exercises via the player's blood volume pulse and skin conductance. It is also worth noting that AAA game developers such as Valve have already experimented with the player's physiological input for the personalization of games such as *Left 4 Dead* (Valve 2008) [2].

This chapter builds upon the important association between player experience and physiology in games, it provides a quick guide on the sensor technology available, and it outlines the key phases for building effective physiology-based affective interaction in games: annotation, modeling, and adaptation. The chapter explicitly excludes electroencephalography (EEG) from the physiological signals covered; EEG defines the core topic of another chapter of this book.

Why Physiology in Games?

Arguably several modalities of player input are still nowadays *implausible* within commercial-standard game development. Pupillometry and gaze tracking are very sensitive to distance from screen and variations in light and screen luminance, which makes them rather impractical for use in a game application. Camera-based modalities (facial expressions, body posture and eye movement) require a well-lit environment often not present in home settings (e.g. when playing video-games) and they can be seen by some users as privacy hazards (as the user is continuously recorded). Even though highly unobtrusive the majority of the vision-based affect-detection systems currently available cannot operate well in real-time [111]. Speech is a highly accessible, real-time efficient and unobtrusive modality with great potential for gaming applications (see corresponding chapter on speech); however, it is only applicable to either games where speech forms a control modality (as e.g. in conversational games for children [48, 110]) or collaborative games that naturally rely on speech for communication across players (e.g. in collaborative first person shooters). Aside the potential they might have, the appropriateness of facial expression, head pose and speech for emotion recognition in games is questionable since experienced players tend to stay still and speechless while playing games [6]. Further details about affect detection in games via images, videos and speech are given in other chapters of this book.

Recent years have seen a significant volume of studies that explore the interplay between physiology and gameplay by investigating the impact of different gameplay stimuli to dissimilar physiological signals ([29, 58, 59, 65, 68, 78, 90, 95] among others). Such signals are usually obtained through electrocardiography (ECG) [109], photoplethysmography [95, 109], galvanic skin response (GSR) [39–41, 59], respiration [95], EEG [70] and electromyography (EMG).

Existing hardware for EEG, respiration and EMG require the placement of body parts such as the head, the chest or parts of the face to the sensors making those physiological signals rather impractical and highly intrusive for most games. On the contrary, recent sensor technology advancements for the measurement of electrodermal activity (skin conductivity), photoplethysmography (blood volume pulse), heart rate variability and skin temperature have made those physiological signals even more attractive for the study of affect in games. Real-time recordings of these can nowadays be obtained via comfortable wristbands and stored in a personal computer or a mobile device via a wireless connection.

It is evident that we can measure physiological responses to external stimuli via several modalities of player input. Due to space constraints, however, in this chapter we focus primarily on the two most popular, real-time efficient and appropriate signals for affective games: electrodermal activity and heart activity. Before delving into the details of the sensor technology available and the methods for modeling player's affect via physiology we herein outline the key properties of these two core physiological signals and their importance for psychophysiological studies (in games and beyond).

Heart Activity

Heart rate variability (HRV) refers to the physiological phenomenon that causes variation in the time window between consequent heartbeats. HRV and heart rate are derived through the detection of heart beats. The two core methods used to detect heart beats include the electrocardiogram (ECG) and the pulse wave signal derived from a photoplethysmograph (PPG)—also known as blood volume pulse sensor. While ECG is generally considered superior compared to blood volume pulse (as it provides a much clearer signal) it is not practical for affective gaming applications since it requires the use of electrodes placed on a player's chest.

There are numerous studies suggesting that heart rate and HRV are associated with emotional arousal. In particular, the high-frequency (HF) band of HRV activity has been found to decrease with elevated anxiety [44]. On that basis, HRV has been shown to be reduced under reported stress and worry states [13]. Moreover, it has been suggested that the HF band of HRV is mainly driven by respiration and appears to derive mainly from vagal activity [35]. Specifically, the energy of the HF range, representing quicker changes in heart rate, is primarily due to parasympathetic activity of the heart which is decreased during mental or stress load [35]. The multimodal association of heart rate and HRV to emotion and the real-time efficiency of available HRV sensors have made it a very popular measure of emotive activity in games (see [41, 101] among many).

Electrodermal Activity

Electrodermal activity (EDA) is the ability of the human body to cause continuous variation in the electrical characteristics of the skin [12]. EDA is a core bodily response when the sympathetic branch of the autonomic nervous system is activated due to a stimulus. What is unique about the human skin is that is the only organ that responds solely to alterations of the sympathetic nervous system; skin is not affected by activities on the parasympathetic nervous system. Essentially, an external or internal stimulus may activate the sympathetic nervous system, which in turn, activates the glands to release sweat. Sweat yields increased electrical activity which can be detected via electrical potentials between electrodes placed on the skin. These electrodes are usually placed on the fingertips, the toes or the wrist.

The direct relationship between EDA and sympathetic arousal is well researched and evidenced by now. As a result EDA is the most popular method for investigating human psychophysiological phenomena [12] and skin conductivity is currently amongst the most common modalities for measuring emotive responses that are associated to arousal such as stress, frustration and anxiety (see [40, 41, 79, 101] among many). Beyond affect, EDA has also been associated with manifestations of cognitive processes [24].

Sensor Technology

Physiological sensor technology has seen significant advancements over the last decade. The 8-channel *ProComp Infiniti*[1] (see Fig. 7.1c) was among the first hardware devices used broadly for research in psychophysiology in e.g. physical interactive games [101, 108] (blood volume pulse and skin conductance), and racing games [95] (respiration, blood volume pulse, skin conductance, and skin temperature). While providing signals of clinical-standard resolution, the *ProComp Infiniti* device proved to be cumbersome for use in games due to its sensitivity to movements and impractical for broad use due to its cost. In addition, all aforementioned studies report the significant technical challenges faced with the blood volume pulse sensor and its placement. Due to the lack of a grip for appropriate attachment to a finger or ear lobe (see Fig. 7.1c), the BVP sensor yielded noise-enhanced signals that were challenging to process, to extract features from and/or to derive the heart rate and heart rate variability of the player. Some other popular devices for measuring skin conductance and/or heart activity include the Biopac GSR100C [10], the Affectiva's[2] Q Sensor (which is no longer available), the BodyMedia Sensewear [52], the BodyBugg armband and the Nymi band.[3] All above devices, however, have seen very limited use in gaming applications as they (a) do not allow access to real-time data (BodyMedia Sensewear, BodyBugg, Nymi), (b) are highly intrusive (the Boipac device requires the application of conductive gel), (c) they are very sensitive to movement (Q sensor, Biopac), or (d) they are very expensive for broad gaming applications (e.g. Q sensor, ProComp Infiniti).

In recent years physiological sensor technology has delivered a plethora of sensors that—compared to the aforementioned devices—are both more reliable for data collection and more appropriate for gaming applications. A notable example is the IOM biofeedback device which consists of three sensors: two electrodes for skin conductance and one blood volume pulse sensor placed on the subject's fingertips (see Fig. 7.1a). The use of small and accurate commercial apparatus like the IOM biofeedback device in the least intrusive way minimizes (psychological) experiment effects caused by the presence of recording devices and maximizes data reliability. For its real-time efficiency, low cost and good data quality—mainly due to the robust finger grips of the sensors—IOM has been used extensively in several studies for psychophysiology in games (e.g. see [40, 41, 109] among many). Furthermore, IOM is the key sensor for commercial biofeedback games such as *Nevermind* (Flying Mollusk 2015) and *The Journey of Wild Divine* (Wild Divine 2001). Another example of a successful wearable sensor is the Empatica's[4] *Embrace* wristband (see Fig. 7.1b). Embrace is built on the technical know how of the E4

[1] http://thoughttechnology.com/
[2] http://www.affectiva.com
[3] https://www.nymi.com/
[4] http://www.empatica.com/

Fig. 7.1 The key physiological signal sensors and devices discussed in this chapter. (**a**) The IOM device used during the data collection experiment reported in [109]. (**b**) Empatica's *Embrace* wristband. (**c**) The blood volume pulse sensor of the *ProComp Infiniti* device. (**d**) The *Cardiio* application for smartphones

wristband (used e.g. in [41]) and the Q sensor and measures skin conductivity, skin temperature and 3D movement (via an accelerometer and a gyroscope). It is real-time efficient, highly unobtrusive for both home gaming settings and mobile gaming *in the wild* and provides more reliable data compared to earlier wrist-based devices.

Nowadays there are quite a few smartphone/tablet software applications that are able to support camera-based pulse detection (contact-less physiological measurement) such as the *Strees Check* app for Android by Azumio; however, access to real-time HRV data is not available to the user in most of these apps (if not all). We particularly note the heart rate *Cardiio* app[5] (see Fig. 7.1d) which is build on early studies on face-based pulse detection [76]. Cardiio approximates heart rate through the face's light reflection which is affected by the amount of blood

[5]http://www.cardiio.com/

available on a face. A heart beat increases the amount of blood into one's face which results in lower levels of light reflection. Measurement accuracy for all these mobile applications is very close (e.g. up to a 3 beat per minute difference) to a clinical pulse oximeter; however, the data is reliable only when the mobile's or the tablet's camera is used in a well-lit environment.

For an extensive discussion on available physiological sensors and their corresponding strengths and weaknesses the interested reader may refer to [88].

Annotating Physiology with Psychological Labels

The question of how to best annotate affect has been a milestone challenge for affective computing. Appropriate methods and tools addressing that question can provide better estimations of the ground truth which, in turn, may lead to more efficient affect detection and more reliable models of affect. Affect annotation becomes even more challenging within games due to their fast-paced and rich affective interaction.

Manually annotating emotion in games is a challenge in its own right both with respect to the human annotators involved and the annotation protocol chosen. On one hand, the human annotators need to be skilled enough to be able to approximate the perceived affect well and, therefore, eliminate subjective biases introduced to the annotation data. On the other hand, there are many open questions left for the designer of the annotation study when it comes to the annotation tools and protocols used. Will the person experiencing the emotion (first person) or others (third-person) do the labeling? How well trained (or experienced) should the annotators be and how will the training be done? Will the labeling of emotion involve states (discrete representation) or does it involve the use of emotion intensity or affect dimensions (continuous representation)? When it comes to time, should it be done in real-time or offline, in discrete time periods or continuously? Should the annotators be asked to *rate* the affect in an absolute fashion or, instead, *rank* it in a relative fashion? Answers to the above questions yield different data annotation protocols and, inevitably, data quality, validity and reliability.

Representing both time and emotion as a continuous function has been one of the dominant annotation practices within affective computing over the last 15 years. Continuous labeling *with respect to emotion* appears to be advantageous compared to discrete states labeling for several reasons. The states that occur in naturalistic data hardly fit word labels or linguistic expressions with fuzzy boundaries. Further, when states are used it is not trivial to capture variations in emotion intensity and, as a result, earlier studies have shown that inter-rater agreement tends to be rather low [21]. The dominant approach in continuous annotation is the use of Russell's two-dimensional (arousal-valence) circumplex model of affect [84]. Valence refers to how pleasurable (positive) or unpleasurable (negative) the emotion is whereas arousal refers to how intense (active) or lethargic (inactive) that emotion is.

Continuous labeling *with respect to time* has been popularized due to the existence of tools such as FeelTrace (and its variant GTrace [22]) which is a freely available software that allows real-time emotional annotation of video content [23], the continuous measurement system [67] which has also been used for annotating videos, and EmuJoy [69] which is designed for the annotation of music content. The real-time continuous annotation process, however, appears to require a higher amount of cognitive load compared to e.g. offline and discrete annotation protocols. Such cognitive load often results in low inter-rater agreement and unreliable data annotation [27, 57].

The most direct way to annotate an emotion in games is to ask the players themselves about their playing experience and build a model based on these annotations. Subjective emotion annotation can be based on either players free-response during play (think aloud protocols) or on forced data retrieved through questionnaires. Alternatively, experts or external observers may annotate the playing experience in a similar fashion. Third-person emotion annotation entails the identification of particular affective states by user experience and game design experts. The annotation is usually based on the triangulation of multiple modalities of player and game input such as the players head pose, in-game behaviour and game context [87].

Annotations (either self-reports or third-person) can be classified as rating (scalar), class and preference. In rating, annotators are asked to answer questionnaire items given in a rating/scaling form (as in [59])—such as the affective aspects of the Game Experience Questionnaire [75]—which labels affective states with a scalar value (or a vector of values). In a class-based format subjects are asked to pick an affective state from a particular representation which could vary from a simple boolean question (was that game level frustrating or not? is this a sad facial expression?) to an affective state selection from e.g. the Geneva Emotion Wheel [8]. Finally, subjects are able to provide answers in a rank-based (preference) format, in which they are asked to compare an affective experience in two or more variants/sessions of the game ([99] among others) (was that level more engaging that this level? Which facial expression looks happier?). A plethora of recent studies in the area of affective annotation in games (and beyond) [40, 63, 95, 98, 103–105] have shown the supremacy of rank-based emotion annotation over rating and class-based annotation.

Models of Psychophysiology in Games

In this section we outline the key phases of modeling physiological responses which are labeled with affect annotations—i.e. deriving the mapping between player affect and its physiological manifestations—and the challenges games pose to each one of these phases. The phases we describe follow the core affect detection steps [17] and include signal processing, feature extraction and selection, and modeling.

Physiological Signal Processing

Physiological signals are unidimensional time series, the quality and reliability of which is dependent on the sensor technology available and the experiment protocol followed. In that regard the signals are subject to standard preprocessing and noise removal methods. Popular techniques include wavelet transform thresholding and least mean square adaptive filters [37].

Games pose additional challenges when it comes to data collection via physiological signals. First, particular sensors such as EEG or electrocardiogram can be highly intrusive which, in turn, affects the quality of play and data gathered. Second, the interaction in games is fast-paced and rich causing rapid body movements and quick alterations in emotive states. Finally, there are so many factors contributing to player experience (and affecting it) that not even the most carefully designed controlled experiment can eliminate the potential effects manifested through a player's physiology. For an extensive overview of techniques for data preprocessing on physiological signals one may refer to [16].

Feature Extraction

Once data is denoised any feature extraction mechanism is applicable to the signals. Examples of feature extraction methods include standard ad-hoc (manual) feature extraction such as average and standard deviation values of the signal, principal component analysis and Fisher's linear discriminant analysis. Focusing on the particularity of skin conductance as a signal for feature extraction it is worth noting that the trough-to-peak analysis of galvanic skin response can be subject to superpositioning of phasic and tonic activity. This necessitates the subtraction of baseline measures or other forms of signal correction [12]. It has been suggested that even with such corrections one may still confound phasic and tonic skin conductance [9] which is undesirable in games as they predominantly activate skin conductance via particular in-game events. To address this issue, features of a player's skin conductance can be extracted using continuous decomposition analysis [9]. The method allows for the decomposition of phasic and tonic electrodermal activity and has been applied for stress detection in games [40].

Physiological feature extraction is naturally enriched through the game context. To this end important game events can be used to determine the response time window that features can be extracted from. A number of studies have been adopting this event-based feature extraction approach for variant psychological signals [40, 50, 61, 79, 80].

Because of the rich affective interaction and the availability of multitude types and amounts of emotion elicitors, physiological signals derived from games are rather complex to extract relevant features from. While standard methods used in affective computing might suffice evidence in the literature has shown that methods such as sequence mining [61] and deep learning [62] yield richer representations of affect manifestations in games. In the study of Martinez and Yannakakis [61] frequent subsequent physiological manifestations are fused with in game events to provide relevant features for affect modeling. In the study of Martinez et al. [62], deep learning can derive more complex temporal signal features that yield higher affect model accuracies compared to standard (ad-hoc) designed features.

Feature Selection

Once features are extracted the subset of the most relevant features for a particular affective state or emotion dimension (e.g. arousal) need to be derived from the set of features available. It is desired that the affective model constructed is dependent on a minimal number of features that yield the highest prediction accuracy. The primary reasons for minimizing the feature subset are improvements of model expressiveness (interpretability) and reduction of computational effort in training and real-time performance. Therefore, feature selection is utilized to find the feature subset that yields that most accurate affective model and save computational effort of exhaustive search on all possible feature combinations. The quality of the predictive model constructed (see next subsection) depends critically on the set of input data features chosen. The resulting set of physiological features define the input to the affect model. Studies within affective games have so far primarily used sequential forward selection, sequential backward selection and genetic search-based feature selection [60, 99].

Modeling Psychophysiology

A model of a player's psychophysiology predicts some aspect of the experience of a player in general, a type of player or a particular player would have in some game situation. If data recorded includes a scalar representation of affect, or classes and annotated labels of user states, any of a large number of machine learning (regression and classification) algorithms can be used to build affective models. Available methods include neural networks, Bayesian networks, decision trees, support vector machines and standard linear regression. On the other hand, if the ground truth of player experience is given in a pairwise preference (rank) format (e.g. game version X is more frustrating than game version Y) standard supervised learning techniques are inapplicable, as the problem becomes one of *preference learning* [33, 99]. Available preference learning approaches include linear discriminant analysis, decision trees, artificial neural networks (shallow and deep architectures) and support vector machines. A number of such methods are currently included in the open-access Preference Learning Toolbox[6] [32].

Adapting the Game to Affect Models

For affective interaction to be realized the game logic needs to adapt to the current state of the game-player interaction. Whether agent behavior or parameterized game content, a mapping is required linking a user's affective state to the game context. That mapping is essentially the outcome of the emotion modeling phase described above. Any search algorithm (varying from local and global search to metaheuristic and exhaustive search) is applicable for searching in the parameterised search space and finding particular game states (context) that are appropriate for a particular affective state of a specific player. For example, one can envisage the optimization of agent behavior attributes for maximizing engagement, frustration or empathy towards a player [51]. As another example, the study of Shaker et al. [86] presents the application of exhaustive search for generating *Super Mario Bros* (Nintendo 1985) levels that are maximally frustrating, engaging or challenging for any player.

There are a number of elements (i.e. game content) from the game world that an adaptive process can alter in order to drive the player to particular affective patterns. Game content may include every aspect of the game design such as game rules [91], reward systems, lighting [25, 31], camera profiles [109], maps [93], levels [86], tracks [92, 94], story plot points [34, 82], sound [55, 56] and music [30]. Even behavioral patterns of NPCs such as their navigation meshes, their parameterized action space and their animations can be viewed as content. The adaptive process in this case is referred to as *procedural content generation* (PCG) which is the generation of game content via the use of algorithmic means. According to the taxonomy presented in [94] game content can be *necessary* (e.g. game rules) or *optional* (e.g. trees in a level or flying birds on the background). Further, PCG can be either *offline* or *online*, *random* or based on a *parameterised space*, *stochastic* or *deterministic* and finally it can be either *constructive* (i.e. content is generated once) or *generate-and-test* (i.e. content is generated and tested). The experience-driven PCG framework [107] views game content as an indirect building block of player affect and proposes adaptive mechanisms for synthesizing personalised game experiences.

A critical question once an adaptation mechanism is designed is how often particular attributes should be adjusted. The frequency can vary from simple predetermined or dynamic time windows [102] but adaptation can also be activated every time a new level [86] or a new game [100] starts, or even after a set of critical player actions—such as in *Façade* [64]. The time window of adaptation is heavily dependent on the game under examination and the desires of the game designer.

[6] http://sourceforge.net/projects/pl-toolbox/

Regardless of the time window adopted, adaptation needs to be interwoven well with design if is to be successful.

Psychophysiology Beyond Games

In this section we argue for the broad impact of psychophysiological research and we identify and briefly survey two primary application domains: education (via intelligent tutoring systems) and health. While games have been used extensively in both of these domains simpler modes of human computer interaction (such as mere simulations of virtual agents or tutors) are more common.

Intelligent Tutoring Systems

Confusion, anxiety and frustration are cognitive and affective states with a direct impact on students' learning process and outcome [74, 85]. Consequently, affect detection has become increasingly important in the intelligent tutoring systems (ITS) community [83]. The core idea is to enhance the learning capacity of a student and the learning experience (via e.g. minimizing frustration) through a virtual (intelligent) tutor that is capable of detecting the affective state of the student and reacting to it. Research in ITS has mostly focused on the detection phase [18], evaluating dissimilar methods to model student confusion [36, 42], frustration [20, 65] and attention [77]. An example of game-based virtual tutors that react to automatically detected affect can be found in [83]. Even when tutoring systems are not realized through games, one can argue that a learning activity via interaction with a virtual tutor and a learning activity through a game-based scenario yield similar psychophysiological patterns. As a consequence, the methodology covered throughout this chapter is directly relevant for the study of intelligent tutoring systems.

Health Technologies

Nowadays, a significant part of the world's population is afflicted by depression and anxiety-related disorders, which are directly connected to emotion and moods. Affect detection can be the key for the diagnosis and computer-based treatment of such mental health issues. Post-traumatic stress disorder (PTSD) has attracted a lot of attention within the affective computing literature. Holmgaard et al. [40, 41] have conducted representative research in this area. They designed and developed a game-based tool for treating PTSD based on stress inoculation and exposure therapy techniques. Physiological signals such as galvanic skin response and HRV were recorded from patients. Those signals would be processed to derive stress profiles for the patient based on his skin conductance manifestations of stress on particular in-game auditory and visual events. Those stress profiles can be used both as a diagnostic and as an assistive tool for PTSD (see more details in the games for health chapter of this book).

Another application of affect detection to health technologies is related to syndromes such as autism that involve difficulties processing or expressing emotions. There has been a large body of studies in affective computing research towards developing tools to help parents, teachers and carers of children with autism [46, 54, 72]. These tools detect the affective state of children and communicate it to themselves or others, enhancing communication.

An additional application of psychophysiology to health technologies has been explored in relation to tele-medicine. In this particular domain, emotion is not at the core of the treated illness but it is regarded as an important element of the communication between the patient and the doctor. Detecting the affective state of the patient can help the doctor to better diagnose or simply better interact with the patient. This enhanced communication can improve the patient's satisfaction and lead to a faster recovery. Lisetti et al. [53] developed such a system, in which the affective state of the patient was predicted from her physiological signals and directly communicated to the doctor.

Limitations of Physiology

As already mentioned, most existing hardware for physiological recording require the contact of body parts (e.g. head, chest or fingertips) to sensors making physiological signals such as EEG and respiration rather impractical and highly intrusive. Furthermore some sensors are still very costly for a broad use in gaming. As seen in section "Sensor Technology", however, recent advances in sensor technology have resulted in low-cost unobtrusive biofeedback devices appropriate for gaming applications (such as the IOM and the *Embrace* wristband). In addition, contact-less heart activity detection applications such as *Cardiio* offer a promising future for physiology-based gaming.

Another point of concern for the use of physiology-based game interaction is the effect of signal habituation. Habituation is the learning process of the autonomic nervous system when exposed to a particular stimulus several times. According to Solokov [89] the nervous system creates a representation (model) of the stimulus which is updated each time the stimulus is presented. The closer the expected representation (model) comes to the actual stimulus the lower the affect to bodily responses, which in turn yield physiological habituation. Habituation is of particular relation to game-related research and connected to learnability in games. The design of a successful game-based affective interaction approach should be able to provide dissimilar stimuli or control for habituation.

Physiological responses are affected by numerous factors including mood, physical movement, physical state, age, blood sugar levels, caffeine consumption, and drug use. To eliminate as many subjectivity biases as possible one needs to record the physiological state of a subject during a short resting period prior to any gameplay session. Baseline recordings from that period shall be used to both offset the signals prior to affect modeling and calibrate any resulting affect models during the interaction [73].

Conclusions

This chapter explored the potential of psychophysiology in gaming applications and argued for the importance of physiology for achieving affective interaction and enhanced player experience. Putting an emphasis on heart and electrodermal activity we surveyed the current state of the art in sensor technology and outlined the key phases of physiology-based affect detection and modeling. We also discussed the evident potential of psychophysiology (through games or other applications) in domains such as intelligent tutoring systems and health. Existing studies in the literature, available sensor technology and a plethora of commercial-standard games that incorporate psychophysiological processes as game affordances suggest that physiology is an important means for realizing affective interaction in games with a great potential for further research and development.

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