Physiological Sensing of Emotion

Jennifer Healey

Abstract

Physiological changes have long been associated with emotion. Although the relative role of cognitive versus physiological processes in emotion has been debated, it is acknowledged that in almost all cases, measurable physiological changes co-occur with emotion, for example: changes in heart rate, sweat level, muscle tension, breathing rate, facial expression and electrical activity in the brain. By sensing these changes we can hope to build computer systems that can automatically recognize emotion by recognizing patterns in these sensor signals that capture physiological responses. This chapter will give a detailed introduction to measuring physiological signals that reflect affect (emotion) with a focus on measuring cardiac activity and skin conductance. The discussion will include why these signals are important for measuring emotional activity, how they are most commonly measured, which features are most often extracted for use in recognition algorithms and the trade-offs between signal quality and wearability and convenience for different sensing systems.

Keywords/key phrases: physiological, emotion, heart rate variability, galvanic skin response, signals, sensing

1 paragraph definition for the glossary:

Physiological: in general, physiology is a branch of biology that deals with the functions of activities of life. With respect to affective computing, physiological affect in general refers to responses that come from the body, more especially those associated with the autonomic nervous systems. Although brain activity is in essence physiological, the field of neurophysiology provides a more specific view of brain function and the term "physiological" is usually used to refer to other types of bodily responses.

Emotion: A term used colloquially to reflect a wide range of affective responses (feelings, mood, disposition, etc.). In emotion theory, emotions are generally perceived as short term affective responses and are often perceived as both "basic" versus "social/moral/higher-order" emotions, where the first category is more often tied with primary physiological responses.

Heart Rate Variability: A term used to describe how successive heart beats differ from one another (e.g. how the lengths of the intervals between successive heart beats vary). The term heart rate variability is used to describe a number of metrics, some of which are calculated in the time domain and others of which are calculated in the frequency domain.

Galvanic Skin Response: (also commonly referred to as electrodermal activity (EDR) or Skin Conductance) is a commonly measured physiological metric that measures a person's sweat levels by measuring the conductance of the skin. The skin is normally an insulator, but sweat is ionic and conducts electricity so that when a person starts sweating their skin conductivity increases. This phenomena is most often measured by placing two electrodes on two adjacent fingers and measuring the voltage in response to a small injection current that runs between the two electrodes across the skin of the palm of the hand where many of the most emotionally reactive sweat glands are found.

Signals: A signal is a time varying response that communicates information about phenomena. In the context of physiological affective computing, a signal is usually a two dimensional time-voltage signal, measured from some part of the body. For example, a skin conductance signal conveys information about how a person's sweat level changes over time and a heart rate signal conveys information about how a person's heart rate changes over time.

Sensing: using a physical instrument to detect a physical stimulus. In affective computing, sensing is used to capture information that can be used by a computer to incorporate into algorithms, for example to sense skin conductance, a GSR sensor is used and to sense heart rate a heart rate sensor (ECG, BVP) is used.

1. Emotion and Physiology

Emotion has long been presumed to have a physiological component, although the primacy and extent of that component is often debated. Research on affective computing has primarily focused on detecting changes in variables such as heart rate and skin conductance as well as changes in muscle activity, respiration, skin temperature and other variables. Various methods can be employed to monitor physiological signals for the purpose of emotion detection. These methods often vary in the degree of invasiveness required and have associated differences in signal fidelity and the kinds of features that can be reliably extracted from the signals. Some methods are more "wearable" and therefore more suited for monitoring "in the wild" whereas other methods are more awkward or sensitive and should be restricted to use in controlled settings. This chapter presents an overview of why we might want to measure physiological signals and gives a detailed description of monitoring heart rate and skin conductance variables.

Since ancient times, it has been speculated that emotion has a physiological component. In ancient China it was believed that emotions resided in the physical body and that excess emotion could cause damage to a person's life energy and affect the function of vital organs. In ancient Greece, the physician Hippocrates theorized the body was comprised of four "humours" which were described as: yellow bile, black bile, phlegm and blood. These humors were thought to be essential to a person's physiology and responsible for health and that emotion and behaviours were caused by the action or imbalance of these humours. An excess of one of the fluids would result in a temperament that was choleric, melancholic, phlegmatic or sanguine, respectively. Aristotle also had a physiological view of emotions and viewed them as "passions" that could be compared to physical states like changes in appetite. Many of these ideas still pervade our thinking and directly influence modern emotion theorists, for example, Hans Eysenck cited the idea of temperament as a mixture of "humours" as a primary inspiration for defining dimensions of personality such as Neuroticism and Extraversion in his factor analysis method (Eysenck, 1947)

In modern times, the first theorist to put forth a physiological theory of emotion was William James (James, 1893). James viewed the physical response as primary to the feeling of an emotion: we feel happy because we laugh or smile; we feel fear because our hair stands on end and our hands go cold; and we feel grief when we cry uncontrollably. James believed that a stimulus would first

trigger activity in the autonomic nervous system which would then produce an emotional response in the brain. At about the same time Carl Lange proposed a similar theory, so the view of emotion as a being primarily a physiological reaction became known as the James-Lange theory of emotion. William James was also one of the first researchers to list the specific patterns of response that corresponded to specific emotions, for example, he described anger as ``increased blood flow to hands, increased heart rate, snarling and increases involuntary nervous system arousal'' and fear as ``a high arousal state, in which a person has a decrease in voluntary muscle activity, a greater number of involuntary muscular contractions and a decrease of circulation in the peripheral blood vessels.'' Around this same time period, Charles Darwin also began cataloging specific patterns of observable physiological response in both animals and people. In particular, he studied fear reactions and used different responses to help classify different species. He also speculated on how these repeated, identifiable patterns of physical expressions could aid an organism's survival (Darwin, 1872).

The description of a set of physiological patterns corresponding to unique emotional states as put forth by James and Darwin is the theoretical basis for using physiological pattern recognition to recognize emotion in affective computing. While the descriptions of James and Darwin make sense to human readers, computer algorithms need more mathematically quantifiable metrics to use as features. As a result, affective computing researcher use electronic sensors and digital recording devices to calculate such features as heart rate acceleration and skin conductivity metrics to classify emotion (Ekman, Levenson, & Friesen, 1983) (Levenson, 1992).

It should also be noted that all of nuances of emotion may not be reflected physiological signals. One of the greatest critics of the James Lange theory of emotion was the neurologist Walter Cannon who argued that autonomic patterns were too slow and non-specific to be unique to each emotion and that emotion therefore had to be primarily a cognitive event (Cannon, 1927). Cannon was famous for coining the term "fight or flight" reaction, and in his view, the sympathetic nervous system simply prepared the organism to take some sort of action and which action to take "fight" or "flight" was determined by cognitive processes. In Cannon's view an organism always struggled to maintain physical homeostasis and emotion such as "distress" were experienced when an organism was thrown off balance and was trying to recover. Cannon thought that the physical reactions of the organism as it returned to homeostasis were too gross to be the emotion itself and that any sense of emotional "feeling" associated with these physical changes had to be primarily cognitive, otherwise "anger", "fear" and "excitement" should all "feel" the same (Cannon, 1927).

5

The psychologist Stanley Schachter proposed a compromise between the two views saying that emotion is both cognitive and physiological in his "two-factor" theory of emotion (Schachter, 1964). In his experiments, Schachter attempted to artificially creating the physical "state" of an emotion in absence of an actual emotional prime by injecting subjects with epinephrine. He then sought to determine if from purely physical state changes the subject would be able to correctly identify or "feel" the emotion as he imagined much be the case in James theory where the physical effect "was" the emotion. He found overall that subjects could not clearly identify an emotion from the physical state changes he induced. In another experiment, he injected some subjects with epinephrine and then exposed them to situations that would induce either anger or happiness. He found that the subjects given epinephrine reported feeling "more" of both types of induced emotion: the positive and the negative. In conclusion, Schachter determined physiology was part of the emotional experience, but that emotions were the result of a two factors, physiological changes and cognitive interpretation of those changes.

While Schachter's experiments are informative, they do not entirely explain the complex nature of the interactions between cognitive and physiological responses in emotion. One criticism is that the injection of epinephrine is too coarse a physiological prime to elicit particular emotional feelings. In more recent work for example, psychologist Robert Zajonc showed that by putting subjects' facial muscles in the position of a smile, they reported feeling happy (Zajonc, 1994). In the end, it may be that Cannon's intuition about ANS activation alone being too gross to solely distinguish nuanced emotions might be true and that a wider range of systems such as facial muscles and neurochemical reactions need to be considered within the scope of physiological responses that need to be recorded to distinguish between emotions.

Measuring physiological signals is the first step towards creating a system that can automatically recognize physiological patterns associated with emotion. In the widest view, all bodily changes could be considered physiological signals including changes in the brain activity, changes in facial expression, changes in vocal patterns and changes in body chemistry; however the primary focus of this chapter will be measuring continuous physiological signals that can be sensed from the surface of the skin and that reflect autonomic nervous system activity. In particular this chapter discusses various methods for measuring features of cardiac activity (heart rate, heart rate variability, and blood volume pressure), features of galvanic skin response (specifically skin conductivity), surface electromyography (EMG) and respiration through chest cavity expansion (as opposed to gas

exchange). The methods typically used to detect these signals are introduced and the trade-offs of different monitoring methods, such as wearability and signal fidelity, are discussed.

2. Measuring Cardiac Activity

Cardiac activity has been studied extensively by the medical community. The heart is a major muscle and its activity can be easily measured by monitoring either electrical changes on the surface of the skin or by measuring pulse signals at various locations on the body. In affective computing, heart rate and heart rate variability have been used a measures of overall physical activation and effort (Aasman, Mulder, & Mulder, 1987) (Itoh, Takeda, & Nakamura, 1995) and changes in heart rate have been used to mediate computer human interaction (Kamath & Fallen, 1998) and have been reported as indicators of fear (Levenson, 1992), panic (Hofmann & Barlow, 1996), anger (Levenson, 1992) (Kahneman, 1973) and appreciation (McCraty, Atkinsom, & Tiller, 1995).

2.1 The Effects of a Heart Beat
The beating of the heart is not a subtle event. When the heart pumps blood, major physiological changes occur. The process of a heart beat begins when the two upper, smaller chambers of the heart, the atria, depolarize, pumping blood into the larger ventricles; then the ventricles depolarize, pumping blood into the rest of the body. The heart beat is controlled by the body's own electrical signal and the polarizations of heart chambers results in electrical changes that can be detected on the surface of the skin. The recording of these surface electrical signals is an electrocardiogram, an example of which can be seen in Figure 1. The beating of the heart also causes blood to be pushed out into the peripheral blood vessels which causes them to swell. The result of this effect is the pulse and an example of a pulse trace can be seen in Figure 2.

2.2 Electrocardiogram
An electrocardiogram (ECG) is a trace of electrical activity captured from the surface of the skin. The inflection points of the time-voltage signal indicate the various polarizations of the heart over the beat. The first inflection point is the "P" wave, indicating atrial depolarization. The next three inflection points are labeled "Q," "R" and "S" and the triangular complex they form is called the "QRS" complex. This complex represents ventricular depolarization and is dominated by the large "R" wave. Finally a "T" and potentially in some cases a "U" inflection point indicates ventricular

repolarization (Goldberger, 2006) . The electrocardiograph has many uses in the medical community but is particularly interesting for researchers in affective computing because the most precise non-invasive measurement of heart rate can be found by measuring the distance between successive "R" waves as shown in Figure 1 (b).
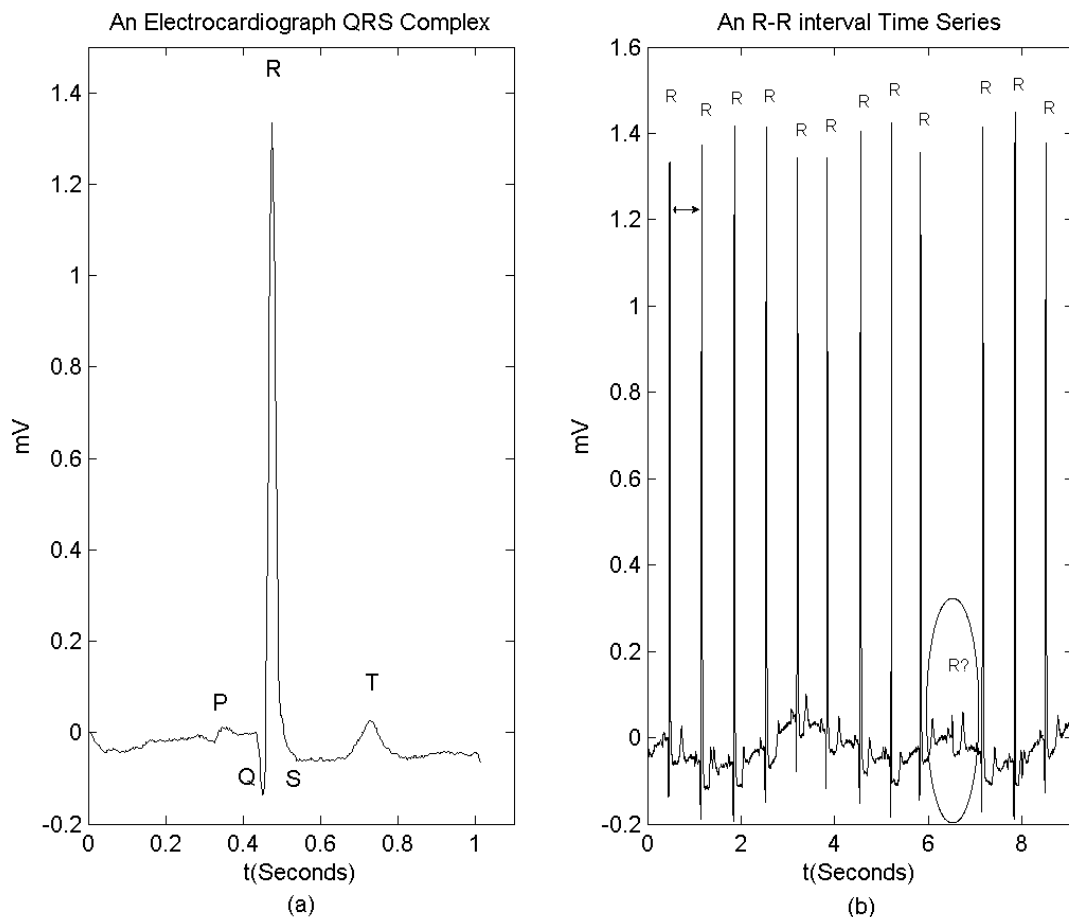

Figure 1. (a) An example of the P, Q, R, S and T waves in a single heart beat recorded from an ECG. (b) An example of an ambulatory ECG time series. The distance between successive R wave peaks is the "R-R" interval. This recording shows a suspicious gap in the R-R interval time series, perhaps due to a missed or dropped sample by the recording device or some other error, or perhaps a heartbeat was skipped. Such outliers can have a large impact on short term heart rate and heart rate variability metrics.

The distance between R waves is inversely proportional to the instantaneous heart rate. If an R wave fails to be correctly recorded, or is in fact missing, this particularly interesting for researchers in affective computing because the most precise non-invasive measurement of heart rate can be found by measuring the distance between successive"R" waves as shown in Figure 1 (b). The

8

distance between R waves is inversely proportional to the instantaneous heart rate. If an R wave fails to be correctly recorded, or is in fact missing, this causes a large gap in the R-R time series and a very low instantaneous heart rate. Some signal processing algorithms will ignore such anomalous beats whereas others will divide the interval in two equal parts to correct for the "missing" beat. Inserting a "missing" beat will introduce artifacts into metrics of heart rate variability, but may give a more robust estimate of average heart rate. One drawback to using an ECG to measure heart rate is that the measurement requires electrode skin contact, which can be uncomfortable. In fact for the best quality signal, such as is used for medical diagnosis, the person wearing the device must have excess hair removed from the adhesion sites, have his or her skin cleaned with alcohol and abraded. In most ECGs, gel is applied to the

electrodes and the electrodes are embedded in an adhesive patch that keeps the electrode-skin contact secure. These adhesive patches need to be changed daily and are often irritating to the skin. An alternative to using gel is to rely on the body's natural sweat to act as a conductive layer between the skin and the electrode; however, this is less reliable than gel and produces a poorer quality signal. Pressure can also be used to keep the electrodes in place instead of adhesives, but this is also less reliable and in some cases even more uncomfortable for the wearer.

2.3 Photoplethysmograph

A photoplethysmograph (PPG) sensor can be used to measure blood volume pulse in peripheral vessels as an alternative to ECG, for example a pulse oximeter is a PPG sensor that also measure blood oxygenation. With every heartbeat, blood is pumped through the blood vessels, which produces an engorgement of the vessels. This change is most pronounced in peripheral vessels such as those in the fingers and in the earlobe. By placing a device that emits light near one of these peripheral vessels the amount of blood in the vessel can be monitored by looking at the amount of light reflected by the vessel over time using a PPG sensor. As blood fills the vessel, more light is reflected back to the sensor. The more blood that is present in the vessel, the higher the reflectance reading. A series of heart beats will result in a light reflectance pattern similar to the one in Figure 2. By detecting the peaks and valleys of this signal, a heart rate time series can be extracted. In some cases, if the subject is stationary, it is also possible to get a measure of the vasoconstriction (vessel constriction) of peripheral blood vessels by looking at the envelope of the signal. Vasoconstriction is a defensive reaction (Kahneman, 1973) in which peripheral blood vessels constrict. This phenomena increases in response to pain, hunger, fear and rage and decreases in response to quiet relaxation and may also be a valuable signal indicating affect (Frija,

9

1986). Figure 2 shows an example of a reflectance PPG reading of a blood volume pulse signal with increasing vasoconstriction.
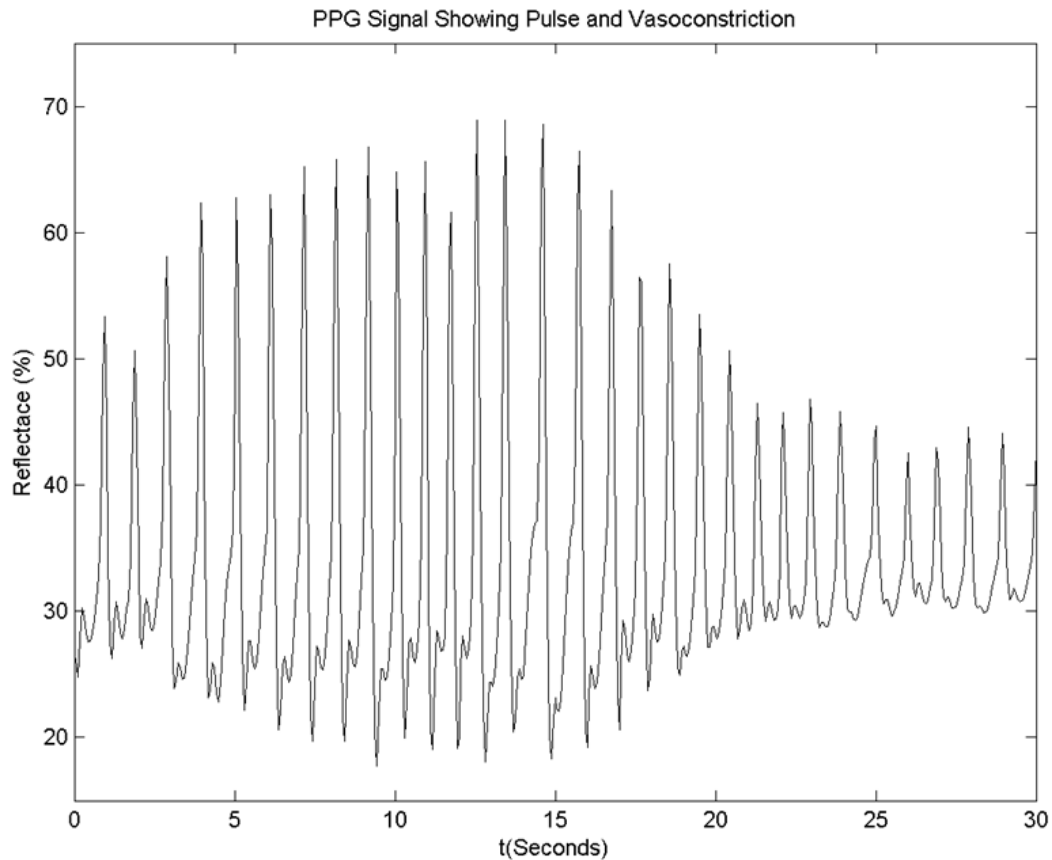

Figure 2. An example of blood volume pulse recorded by a PPG sensor showing vasoconstriction as can be seen by the narrowing of the envelope of the signal.

The PPG sensor can be placed anywhere on the body where the capillaries are close to the surface of the skin, but peripheral locations such as the fingers are recommended for studying emotional responses (Thought Technology, 1994). PPG sensors require no gels or adhesives; however the reading is very sensitive to variations in placement and to motion artifacts. For example, if the light sensor is moved with respect to the blood vessel, the envelope of the signal will change or the signal might be lost entirely. This can happen if the sensor slips from an ear clip placement of if the sensor is bumped during normal daily activities using a finger placement. If a finger placement is used, it should be noted that the signal will also strongly attenuate if the wearer lifts their hand up, as blood flow to the extremity will be diminished.

Recently, new non-contact technologies have been developed to measure the photoplethysmographic effect using a webcam and visible light sources (red, green and blue color sensors) in conjunction with blind source separation techniques (Poh, McDuff, & Picard, 2010). These techniques have been shown to correlate PPG and visible sensor results, particularly from the green sensor and have been shown to accurately estimate mean heart rate for many users, however this signal does not exactly replicate the details of standard PPG signals and requires the user to remain facing the camera.

2.4 Heart Rate and Heart Rate Variability

Two of features most commonly used in affective computing research are heart rate and heart rate variability. Heart rate gives an excellent view into autonomic nervous system (ANS) activity because it is controlled by both the sympathetic and parasympathetic nervous systems. The sympathetic nervous system accelerates heart rate and can be viewed as the part of the ANS that is related to "stress" or activation. The parasympathetic nervous system is responsible for recovering heart rate from sympathetic activation (decelerating heart rate) and can be viewed as the system responsible for "relaxation" or rest and healing. Since the third component of the ANS, the enteric nervous system that governs the gastro-intestinal tract, is difficult to monitor non-invasively, heart rate can be viewed as an excellent window into as much of the ANS.

An increase in heart rate indicates an overall increase in sympathetic nervous system activity and a decrease in heart rate indicates that the parasympathetic nervous system is recovering the person to a relaxation state. Many different features can be extracted from periods of acceleration and deceleration, for example, the mean difference over baseline, the amount of time spent in acceleration vs. deceleration and the magnitude or slope of the acceleration or deceleration.

Heart rate variability (HRV) has also been used as a measure of affect. The term heart rate variability is used to describe a number of metrics, some of which are calculated in the time domain and others of which are calculated in the frequency domain. An HRV metric can be as simple as the measure of the standard deviation of the length of time between successive heart beatswithin a certain time window (also called "the recording epoch") (Berntson, et al., 1997). Simple robust metrics like this one are often best for use with short time windows since the amount of information available in the window is limited (van Ravenswaaij-Arts, Kollee, Hopman, Stoelinga, & van Geijn,

11

1993). Other metrics of HRV include calculating the difference between the maximum and the minimum normal R-R interval lengths in the window limited (van Ravenswaaij-Arts, Kollee, Hopman, Stoelinga, & van Geijn, 1993); the percent differences between successive normal R-R intervals that exceed 50 msec (pNN50) and the root mean square successive difference (RMSSD) (Kamath & Fallen, 1998).

As digital recording devices and signal processing algorithms have come into more common usage, short-term power spectral density analysis of the heart rate has become more popular as a method for assessing heart rate variability. Since it is known that the parasympathetic nervous system is able to modulate heart rate effectively at all frequencies between 0.04 and 0.5 Hz, whereas the sympathetic system modulates heart rate with significant gain only below 0.1Hz (Berntson, et al., 1997) (Akselrod, Gordon, Ubel, Shannon, & Cohen, 1981) , the relative strengths of the sympathetic and parasympathetic influence on HRV can be discriminated in the spectral domain. This ratio is often referred to as the sympathovagal balance. There are many different ways to calculate this balance, each with various merits. More specific metrics, for example narrower and lower frequency bands, usually require longer time windows of heart beats to obtain the detailed information necessary to fill specific bands with enough data points to be meaningful.

One simple sympathovagal ratio calculation is to take the energy in the low frequency band (0.04-0.1Hz) and divide by the total energy in the (0.04-0.5Hz) band which gives the ratio of sympathetic to all heart rate activity. Other researchers suggest comparing low frequency energy to different combinations of low, medium and high frequency energy (Kamath & Fallen, 1998) (van Ravenswaaij-Arts, Kollee, Hopman, Stoelinga, & van Geijn, 1993) (Akselrod, Gordon, Ubel, Shannon, & Cohen, 1981) (Aasman, Mulder, & Mulder, 1987) (Itoh, Takeda, & Nakamura, 1995). Another spectral feature that is of interest to affective computing researchers is the 0.1Hz peak of the HR spectrum which has been associated with sympathetic tone and mental stress (Nickel, Nachreiner, & von Ossietzky, 2003) although other researchers have found that an increase in the 0.1Hz spectrum can occur with practiced relaxed breathing (McCraty, Atkinsom, & Tiller, 1995).

Each HRV metric is differently robust to noise, outliers and irregular beats and the precision with which it can distinguish sympathetic vs. parasympathetic activity. In addition to choosing the appropriate metric, researchers must also chose the appropriate time window for the heart rate series over which she or he wishes to calculate the metric. The choice of metric will largely be determined by which variables are of interest and the quality of the heart rate time series that can be

12

derived from the cardiac signal. In general, a time window of five minutes or more is recommended; assuming a resting heart rate of 60 bpm, this generates a sample size of 300 beats from which to estimate variability statistics. As with all statistics, in general, the more samples you have the better your estimate. In particular with heart rate variability, it should be considered that heart rate varies naturally over the breath cycle, accelerating following inhalation and decelerating after exhalation. Taking a longer time window, allows multiple heart rate samples from all parts of the breath cycle to be incorporated into the estimate.

2.5 Other Factors

Emotion is not the only factor that affects heart rate and heart rate variability and these also need to be taken into account when interpreting heart rate features. Other factors that affect heart rate include age, posture, level of physical conditioning, breathing frequency (van Ravenswaaij-Arts, Kollee, Hopman, Stoelinga, & van Geijn, 1993) and circadian cycle (Berntson, et al., 1997). As age increases, heart rate variability decreases. For example, infants have a high sympathetic activity but this decreases quickly between ages 5 and 10 (van Ravenswaaij-Arts, Kollee, Hopman, Stoelinga, & van Geijn, 1993). In the case of certain diseases such as congestive heart failure, heart rate variability goes to near zero and the heart beats like a metronome. When pooling data between subjects, especially subjects of different ages and physical conditions, these differences need to be considered, in addition to potentially excluding participants who have pacemakers or who are taking medication to control heart rate. Physical activity, talking, and posture (sitting vs. standing vs. laying down) also all affect heart rate and HRV (van Ravenswaaij-Arts, Kollee, Hopman, Stoelinga, & van Geijn, 1993) (Picard & Healey, 1997). This should be considered in monitoring HRV "in the wild" as it can confound affective signals and in planning experiments that may involve different activities, postures or posture transitions.

A non-physiological factor that needs to be considered is also the quality of the heart rate signal. Many factors can affect how well the measured heart rate actually reflects the true heart rate. One factor is the measurement method. The ECG can give a much more accurate instantaneous heart rate and is the preferred signal calculating heart rate variability; this is mainly because the sharp R waves of the ECG give a much clearer picture of when the heart beats than do the more gentle slopes of the PPG signal. However, no beat detection is perfect and if the underlying signal was not sampled at the appropriate rate, R waves can be entirely missed by some digital recordings. Alternatively there can be irregular "ectopic" heart beats that can confound some algorithms. When

a beat is perceived to be "missed" some algorithms might divide the long interval in half, which can introduce artifacts into the heart rate variability metric.

Finally, when estimating the spectral statistics of HRV, the affective computing researcher should be aware that this method assumes that the statistics of the heart rate time series over which the power spectrum are stationary (relatively unchanging circumstances). This assumption is more likely to be true for resting subjects in hospitals than it is for active subjects going about the activities of daily living. It is generally assumed that longer time windows will give more accurate HRV estimates because there will be more data points in each spectral bin, however this is only true if the stationarity assumption is not violated. Windows as short as 30 seconds have been used on ECGs that are free of missed beats and motion artifacts (Kamath & Fallen, 1998) (van Ravenswaaij-Arts, Kollee, Hopman, Stoelinga, & van Geijn, 1993).

4. Skin Conductance

Skin conductance, also commonly referred to as Galvanic Skin Response (GSR) or electrodermal activity (EDR), is another commonly used measure of affect. Skin conductance is used to indirectly measure the amount of sweat in a person's sweat glands since the skin is normally an insulator and its conductivity changes in response to ionic sweat filling the sweat glands. Sweat gland activity is an indicator of sympathetic activation and GSR is a robust non-invasive way to measure this activation (Caccioppo, Berntson, Larsen, Poehlmann, & Ito, 2000). GSR was first famously used by Karl Jung Karl to identify "negative complexes" in word association tests (Jung & Montague, 1969) and is an key component in "lie detector" tests; tests which actually measure the emotional stress associated with lying rather than untrue facts (Marston, 1938). In laboratory studies to measure affect (Ekman, Levenson, & Friesen, 1983) (Levenson, 1992) (Winton, Putnam, & Krauss, 1984), skin conductivity response has been found to vary linearly with the emotional aspect of arousal (Lang, 1995) and skin conductance measurements have been used to differentiate between states such as anger and fear (Ax, 1953) and between states of conflict and no conflict (Kahneman, 1973). Skin conductance has also been used as a measure of stress in studies on anticipatory anxiety and stress during task performance (Boucsein, 1992).

Skin conductance can be measured anywhere on the body, however, the most emotionally reactive sweat glands are concentrated on the palms of the hands and on the soles of the feet (Boucsein,

1992). In laboratory studies, the most common placement for electrodes is on the lower segment of the middle and index finger of the dominant hand. A low conductivity gel is usually used between the skin and the electrodes to ensure good contact and better signal quality. To measure conductance, a small current is injected into the skin and the resulting change of voltage is measured (Dawson, Schell, & Fillon, 1990) (Healey J. , 2011). Using the standard placement, the electrical path of the current passes through the palm as it travels from the base of one finger to the other. By constantly measuring the change in voltage across the electrodes, the continuously changing conductance of the skin can be measured.

For ambulatory studies, alternative placements are sometimes used since hand placement is often found to be inconvenient by participants and signal quality from hand placements can be compromised by hand motion and activities that deposit or remove residue from the surface of the palms such as hand washing or eating. Additionally, since hands are frequently in use during daily life, there is a high chance that electrodes can become dislodged during the day. Therefore many ambulatory skin conductivity sensors measure conductivity on the wrist, arm or leg (BodyMedia, Q Sensor, Basis). Some research systems have also included measuring skin conductivity through clothing or jewelry (Picard & Healey, 1997) (Healey J. , GSR Sock: A New e-Textile Sensor Prototype, 2011).

An example of the time varying skin conductance response is shown in Figure 3. In this figure an audio stimulus (a 20 millisecond white noise burst) was played as a prime to elicit "orienting responses" (also known as startle responses) during the test. We recorded ground truth for the audio prime using a microphone trace. The microphone trace was overlaid on the figure at the mean value of "3" as a reference for interpreting the signal. Examples of seven orienting responses are labeled in the figure.   The first major response, 1, occurs at the beginning of the experiment and was not stimulated by an audio burst. It was likely caused by the computer making a small "click" at the beginning of the audio-player program, but because this ground truth was not recorded we would say that this response is "unstimulated" meaning simply that we did not intentionally stimulate it. The second reaction, 2, is stimulated by the first sound burst, and responses 3, 5, and 7 are stimulated by the successive sound bursts. A second "unstimulated" response occurs between 5 and 7.

An orienting response is usually measured at the upwards inflection point and is assigned an amplitude that extends to the next local maximum. This amplitude is indicated in Figure 3 by the
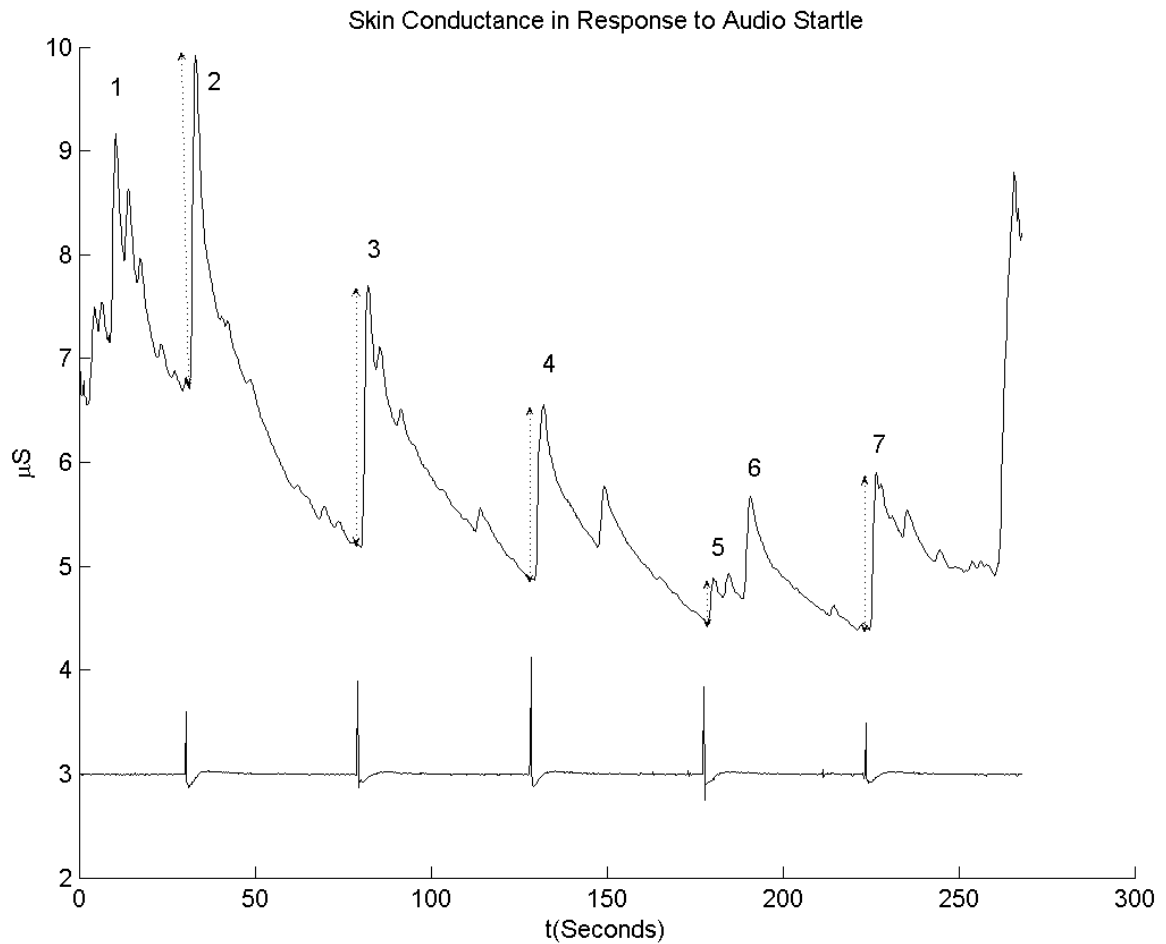
Figure 3 An example of a skin conductance signal showing characteristic orienting responses in response to an audio stimulus. The microphone signal used to record ground truth for the stimulus is superimposed (at 3mS) to show the relationship between stimulus and response.

and skin conductance response, there many other physiological signals have been considered in affective computing research including: electroencephalogram (EEG), electromyogram (EMG), blood pressure and respiration, among others. This section gives a brief overview of these measures and how they are used by affective computing researchers.

5.1. Electroencephalography

The electroencephalogram (EEG) measures electrical activity of the brain by placing electrodes on the surface of the head. The study of EEG is a vast topic and has been extensively studied in the field of neuroscience (see Chapter X by Muhl et al., this volume), however the electrical signals from the brain that an EEG reads are also physiological signals and should be mentioned here in

that context. Recently there has been a widening body of literature (Coan & Allen, 2004) (Davidson, 2004) asymmetries in the pre-frontal cortex (PFC) seem to represent how different emotions, such as anger are processed and how PFC may be acting as a moderator or a mediator between physiological response and cognitive processing. For the first time we may begin to see and model how the "mind" and the "body" work together in processing emotion and gain greater insights into the duality that James and Cannon debated.

From the perspective of physiological signal processing of affective signals, most researchers tend to gravitate towards EEG because it is one of the most non-invasive and accessible tools for getting some sense of brain activity, even if other metrics such as fMRI are far more accurate. A full electroencephalogram incorporates over 128 electrodes; however simpler metrics using two or four channels are used in bio-feedback practice (Thought Technology, 1994). In laboratory experiments, full EEG has been shown to distinguish between positive and negative emotional valence (Davidson, 1994) and different arousal levels (Leventhal, 1990). EEG can also be used to detect the orienting response by detecting ``alpha blocking." In this phenomenon, alpha waves (8-13 Hz) become extinguished and beta waves (14-26Hz) become dominant when the person experiences a startling event (Leventhal, 1990) . In the past, EEG has been less favored as a measure of emotion detection because the full EEG was challenging to both apply and interpret and the reduced electrode sets were considered unreliable. The EEG also reacts to changes in light and sound and it is sensitive to both motion and muscle activity, so it is sometimes difficult to interpret outside of controlled laboratory conditions. During normal waking activity, it has been hypothesized that EEG could only be used as a crude measure of arousal (Leventhal, 1990), but perhaps new discoveries such as the asymmetry properties may change this view.

5.2. Electromyography

The electromyogram (EMG) measures muscle activity by detecting surface voltages that occur when a muscle is contracted. In affective computing, the EMG is used to measure muscle activation, for example EMG has been used on facial muscles to study facial expression (Levenson, Ekman, & Friesen, 1990), on the body to study affective gestures (Marrin & Picard, 1998), and has been used as both an indicator of emotional valence (Lang, 1995)and emotional arousal (Caccioppo, Berntson, Larsen, Poehlmann, & Ito, 2000) (Cacioppo & Tassinary, 1990). EMG can be used as a wearable substitute for affective changes that are often usually detected by computer vision from a

17

camera that is looking at a subject. The main difficulty is that EMG electrodes need both adhesives and gels under normal use and when placed on the face they can be seen which may cause unwanted negative social attention.

Similar to both the ECG and the EEG, the EMG works by detecting electrical signals on the surface of the skin. In a typical configuration, three electrodes are used for this measurement, two placed along the axis of the muscle of interest and a third electrode placed off axis to act as a ground. The EMG signal is actually a very high frequency signal, but in most common usages, the signal is low-pass filtered to reflect the aggregate muscle activity and is sampled at 10-20Hz.

5.3. Blood Pressure

Blood pressure is used as a metric for overall health and general emotional stress. In affective computing research, blood pressure has been found to correlate with increases in emotional stress (Selye, 1956) and with the repression of emotional responses (Innes, Millar, & Valentine, 1959) (Gross, 2002) (Harris, 2001). The main challenges with blood pressure as a metric for use in affective computing are that it is difficult to measure continuously, and the measurement itself requires constricting a blood vessel to measure pressure, which can be noticeable and might cause the user discomfort. Continuous ambulatory blood pressure monitoring systems have been used in medical practice (Pickering, Shimbo, & Haas, 2006), but these can be perceived as cumbersome. Smaller, more portable systems that measure blood pressure from peripheral blood vessels exist, (Finapres, 2013) but they may cause damage to these smaller vessels with long term use.

5.4 Respiration

Respiration is an interesting physiological signal to consider for affective computing; both as a signal in its own right and as a signal to consider in conjunction with other measures such as cardiac activity, due to the strong influence of respiration on heart rate. Respiration is most accurately recorded by measuring the gas exchange of the lungs; however, this method is excessively cumbersome and inhibits natural activities. Because of this, an approximate measure of respiratory activity, such as chest cavity expansion, is often recorded instead. Chest cavity expansion can be

18

measured by a strap sensor that incorporates a strain gauge, a Hall Effect sensor or capacitance sensor.

Both physical activity and emotional arousal are reported to cause faster and deeper respiration, while peaceful rest and relaxation are reported to lead to slower and shallower respiration (Frija, 1986). Sudden, intense or startling stimuli can cause a momentary cessation of respiration and negative emotions have been reported to cause irregularity in respiration patterns (Frija, 1986). The respiration signal can also be used to assess physical activities such as talking, laughing, sneezing and coughing (Picard & Healey, 1997).

6. Conclusions

Physiological sensing is an important tool for affective computing researchers. While the extent to which emotion is a cognitive versus physiological processes is still unresolved, there is wide agreement that physiological responses at least in some way reflect emotional state. Physiological monitoring offers a continuous, discreet method for computer systems to get information about a person's emotional state. Physiological signals have been used successfully to differentiate between different levels of stress (86-97%), (Healey & Picard, Detecting Stress During Real-World Driving Tasks Using Physiological Sensors, 2005) (van den Broek, Janssen, Westerink, & Healey, 2009) different categories of emotion in the laboratory (70-91%) (van den Broek, Janssen, Westerink, & Healey, 2009) and in the wild (Healey, Nachman, Subramanian, Shahabdeen, & Morris, 2010) (Healey J. , ACII, 2011) (van den Broek, Janssen, Westerink, & Healey, 2009).

There are many challenges to recognizing emotion from physiology. One of the most basic challenges is one that pervades all of affective computing: the challenge of correctly labelling the data with an emotion descriptor. In a laboratory, emotions can be acted or primed (e.g. the subject can be scared, frustrated, rewarded, be made to laugh, etc.) and while acting may not result in a purely authentic response and primes might not always be successful, at least the start time of the attempted emotion is known. This greatly facilitates windowing the continuous physiological data for analysis. In the wild, the onset of an emotion is often unclear, especially because the subject may be unaware of the natural "prime" occurring because they are caught up in the emotion itself. And not only does the participant have to notice the onset, they have to record the time precisely. Often in end of day interviews participants can remember being upset "during a meeting" but the exact onset is often imprecise which makes the data difficult to window (Healey, Nachman, Subramanian, Shahabdeen, & Morris, 2010). This causes noise in the windowing of the data.

19

Another challenge is subject self-perception of emotion. Everyone has their own personal experience of emotion and while emotion theorists have worked hard to try to identify universal commonalities of emotion, subject often self-describe emotions in colloquial terms that are hard to classify, for example a participant might say that they felt "happy to be out of that meeting," and if given a forced choice of basic emotions (e.g. anger, sadness, fear, joy, surprise or disgust) the participant might describe this emotion as "joy" when actually their emotion might more accurately be described as "relief" which in emotion theory is would be considered a negative value for "fear" but it is not likely that ordinary people would describe it this way. People also tend to report as emotion feelings such as "boredom, anxiety, fatigue, loneliness and hunger" that fall outside of what is traditionally studied in emotion research. When dealing with subject self-report, the best solution is either to educate the participants about the particular emotion types you, as the researcher, are interested in studying (Healey J. , ACII, 2011) or consider building algorithms for these non-emotion categories that seem to be of interest for people to record.

A different type of challenge is the many to one mapping between non-emotional and emotional influences on physiology (Cacioppo & Tassinary, 1990). If a physiological change occurs, there is no guarantee that an emotion generated the change and conversely non-emotional changes can occur during emotional episodes and add their effect to the physiological response. For example a person who is quite calm and relaxed could suddenly sneeze which would cause a dramatic rise in instantaneous heart rate, blood pressure, and galvanic skin response. Physiologically the person is startled by the experience, but to what extent is this an affective change? A sneeze does not likely impact mood as dramatically as it does physiology. Similarly, if a person gets up from their desk and walks down the hallway, they will have a physiological activation but not necessarily a change of emotion. An accelerometer can be used to capture the occurrence of motion so that these episodes can be excluded from affective analysis, but is very difficult to extract affective signals in the presence of motion. The main reasons for this are that humans are not identical; nor are they linear, time-invariant systems. Heart rate does not increase linearly with effort or emotion even for an individual person, and heart rate increases differently in response to both effort and emotion across individuals. There is currently no method for accurately predicting an individual's physiological response due to motion, so it is even more difficult to attempt to "subtract it off" from the emotional signal. There is also no known method for doing source separation between emotional and non-emotional responses.

A less fundamental challenge is the challenge of recording sufficient physiological data for analysis. Currently high quality recording devices are both expensive and inconvenient to wear.

This often limits the number of subjects that can be run in a study and the length of time the subjects are willing to wear the sensors. As a result affective physiological data sets tend to be small and are often not shared which makes collecting large sample sizes for collective and individual models difficult (Healey J. , 2012).

This chapter has presented different ways of measuring some of the most commonly used physiological metrics in affective computing and has presented the advantages of using different methods to record these signals. The goal of this chapter has been to impart a basic understanding of physiological mechanisms behind some of the most popular features reported in the literature and to introduce different sensing methods so that researchers can make informed decisions as to which method is best for their experiment or application. With the materials presented in this chapter, a practitioner in affective computing research can be better equipped to incorporate physiological sensing methods into her or his research methods. As sensing methods improve in popularity and wearability and our access to context information grows, affective physiological signal processing may soon start to move into the realm of big data, which could lead to a breakthrough in the field. If enough participants were able to own and wear sensors at all times and would be willing to allow context data to be collected from their phones, we might finally be able have a large collection of physiological signals with high confidence affect labels (Healey J. , 2012). Data could be labeled with both subject self-report, and context information such as time of day, weather, activity and who they were with to make an assessment of affective state. Even friends could contribute labels for each other's data. With sufficiently large ground truth data sets, we will likely be able to develop better contextually aware algorithms for individuals and like groups even if the sensor data is noisier. These algorithms will enable affective computing in a private, personal and continuous way and allow our devices to both know us better and be able to more effectively communicate on our behalf with the world around us.

Bibliography

Aasman, J., Mulder, G., & Mulder, L. (1987). Operator effort and the measurement of heart rate variability. *Human Factors, 29*(2), 161-170.

Akselrod, S., Gordon, D., Ubel, F. A., Shannon, D. C., & Cohen, R. J. (1981). Power spectrum analysis of heart rate fluctuation: a quantitative probe of beat-to-beat cardiovascular control. *Science*, 220-2.

Ax, A. F. (1953, September 1). The physiological differentiation between fear and anger in humans. *Psychosomatic Medicine, 15*(5), 433-442.

Berntson, G. C., Bigger, J. T., Eckberg, D. L., Grossman, P., Kaufmann, P. G., Malik, M., . . . van der Molen, M. W. (1997). Heart rate variability: origins, methods, and interpretive caveats. *Psychophysiology*, 623-48.

Boucsein, W. (1992). *Electrodermal Activity.* New York, NY: Plenum Press.

Caccioppo, J. T., Berntson, G. G., Larsen, J. T., Poehlmann, K. M., & Ito, T. A. (2000). The Psychophysiology of Emotion. In M. Lewis, & J. M. Haviland, *Handbook of Emotions* (pp. 173-191). New York: The Guilford Press.

Cacioppo, J. T., & Tassinary, L. G. (1990). *Principles of psychophysiology: Physical, social, and inferential elements.* New York: Cambridge University Press.

Cannon, W. B. (1927). The James-Lange theory of emotion: A critical examination and an alternative theory. *American Journal of Psychology, 39*, 10-124.

Coan, J. A., & Allen, J. B. (2004, October). Frontal EEG as a moderator and mediator of emotion. *Biological psychology, 67*(1-2), 7-50.

Damasio, A. R. (1994). *Descartes error: emotion, reason and the human brain.* New York, NY: Gosset Putnam Press.

Darwin, C. (1872). *The Expression of Emotion in Man and Animals.* London, UK: John Murray.

Davidson, R. J. (1994). Asymmetric brain function, affective style and psychopathology: The role of early experience and plasticity. *Development and Psychopathology*, 741-758.

Davidson, R. J. (2004). What does the prefrontal cortex "do" in affect: perspectives on frontal EEG asymmetry research. *Biological Psychology*, 219–233.

Dawson, M., Schell, A., & Fillon, D. (1990). The electrodermal system. In J. T. Cacioppo, & L. G. Tassinary, *Principles of psychophysiology* (pp. 295–324). New York: Cambridge University Press.

Ekman, P., Levenson, R. W., & Friesen, W. V. (1983, September 16). Autonomic Nervous System Activity Distinguishes among Emotions. *Science, 221*(4616), 1208-1210.

Eysenck, H. J. (1947). *Dimensions of Personality.* London, UK: Routledge and Kegan.

Finapres. (2013, August 1). *Portapres Product Page*. Retrieved from http://www.finapres.com/site/page/2/9/Portapres/

Frija, N. (1986). *The Emotions.* Cambridge: Cambridge University Press.

22

Goldberger, A. (2006). *Clinical Electrocardiography: A Simplified Approach.* Philadelphia, PA USA: Mosby Elsevier.

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology, 39*, 281–291.

Groves, P. M., & Thompson, R. F. (1970, September). Habituation: A dual process theory. *Psychological Review, 77*(5), 419-450.

Harris, C. R. (2001). Cardiovascular responses of embarrassment and effects of emotional suppression in a social setting. *Journal of Personality and Social Psychology, 81*, 886–897.

Healey, J. (2011). GSR Sock: A New e-Textile Sensor Prototype. *Fifteenth Annual International Symposium on Wearable Computers* (pp. 113-114). San Francisco, CA USA: IEEE.

Healey, J. (2011). Recording Affect in the Field: Towards Methods and Metrics for Improving Ground Truth Labels. *Affective Computing and Intelligent Interaction* (pp. 107-116). Memphis, TN, USA: Springer.

Healey, J. (2012, December 8). *Towards Creating a Standardized Data Set for Mobile Emotion Context Awareness.* Retrieved from NIPS 2012 Workshop Machine Learning Approaches to Mobile Context Awareness: goo.gl/VQl29x

Healey, J., & Picard, R. W. (2005). Detecting Stress During Real-World Driving Tasks Using Physiological Sensors. *Transactions on Intelligent Transportation Systems, 6*(2), 156-166.

Healey, J., Nachman, L., Subramanian, S., Shahabdeen, J., & Morris, M. (2010). Out of the Lab and into the Fray: Towards Modeling Emotion in Everyday Life. *Pervasive*, (pp. 156-173). Helsinki, Finland.

Hofmann, S. G., & Barlow, D. H. (1996). Ambulatory psychophysiological monitoring: A potentially useful tool when treating panic relapse. *Cognitive and Behavioral Practice, 3*, 53-61.

Innes, G., Millar, W. M., & Valentine, M. (1959). Emotion and Blood Pressure. *The British Journal of Psychiatry, 105*, 840-851.

Itoh, H., Takeda, K., & Nakamura, K. (1995, August 4). Young borderline hypertensives and hyperreactive to mental arithmetic stress: spectral analysis of r-r intervals. *Journal of the Autonomic Nervous System, 54*(2), 155-162.

James, W. (1893). *The Principles of Psychology.* Cambridge, MA, USA: Harvard University Press.
23

Jung, C. G., & Montague, D. E. (1969). *Studies in Word Association: experiments in the diagnosis of psychopathological conditions carried out at the Psychiatric Clinic of the University of Zurich under the direction of C. G. Jung.* New York: Routledge and K. Paul.

Kahneman, D. (1973). Arousal and Attention. In D. Kahneman, *Attention and Effort* (pp. 28-49). Englewood Cliffs, NJ: Prentice-Hall.

Kamath, M. V., & Fallen, E. L. (1998). Heart Rate Variability: Indicators of user state as an aid to human computer interaction. *SIGCHI Conference on Human Factors in Computing Systems* (pp. 480-487). Los Angeles, CA, USA: ACM.

Lang, P. J. (1995). The emotion probe: studies of motivation and attention. *American Psychologist, 50*(5), 372-385.

Levenson, R. W. (1992). Autonomic nervous system differences among emotions. *Psychological Science, 3*(1), 23-27.

Levenson, R. W., Ekman, P., & Friesen, W. V. (1990). Voluntary facial action generates emotion-specific autonomic nervous system activity. *Psychophysiology, 27*(4), 363–384.

Leventhal, C. F. (1990). *Introduction to physiological psychology.* Englewood Cliffs, NJ: Prentice Hall.

Marrin, T., & Picard, R. W. (1998). Analysis of Affective Musical Expression with the Conductor's Jacket. *XII Colloquium for Musical Informatics* (pp. 61-64). Gorizia, Italy: Press. Page.

Marston, W. M. (1938). *The Lie Detector Test.* New York: R. R. Smith.

McCraty, R., Atkinsom, M., & Tiller, W. (1995). The effects of emotions on short term power spectrum spectrum analysis of heart rate variability. *American Journal of Cardiology, 76*, 1089-1093.

Nickel, P., Nachreiner, F., & von Ossietzky, C. (2003). Sensitivity and diagnosticity of the 0.1-Hz component of heart rate variability as an indicator of mental workload. *Human Factors, 45*(4), 575-90.

Picard, R. W., & Healey, J. (1997). Affective Wearables. *1st International Symposium on Wearable Computers.* Washington, DC, USA: IEEE.

Pickering, T. G., Shimbo, D., & Haas, D. (2006). Ambulatory Blood-Pressure Monitoring. *New England Journal of Medicine, 354*, 2368-2374.

Poh, M.-Z., McDuff, D. J., & Picard, R. W. (2010). Noncontact, automated cardiac pulse measurements using video imaging and blind source separation. *Optics Express*, 10762-74.

Schachter, S. (1964). The interaction of cognitive and physiological determinants of emotional state. In L. Berkowitz, *Advances in Experimental Social Psychology* (pp. 49–79). New York: Academic Press.

Selye, H. (1956). *The stress of life*. New York: McGraw-Hill.

Thought Technology. (1994). ProComp User's Manual Software Version 1.41. Quebec, Canada: Thought Technology Ltd.

van den Broek, E., Janssen, J. H., Westerink, J., & Healey, J. A. (2009). Prerequsites for affective signal processing (ASP). *International Conference on Bio-inspired Systems and Signal Processing* (pp. 426-433). Porto, Portugal: Springer.

van Ravenswaaij-Arts, C., Kollee, L. A., Hopman, J. C., Stoelinga, G. B., & van Geijn, H. P. (1993). Heart Rate Variability. *Annals of Internal Medicine*, 436-47.

Winton, W. M., Putnam, L. E., & Krauss, R. M. (1984). Facial and autonomic manifestations of the dimensional structure of emotion. *Journal of Experimental Social Psychology*, 195-216.

Zajonc, R. B. (1994). Evidence for non-conscious emotions. In P. Ekman, & R. J. Davidson, *The nature of emotion: Fundamental questions* (pp. 293-297). New York: Oxford University Press.