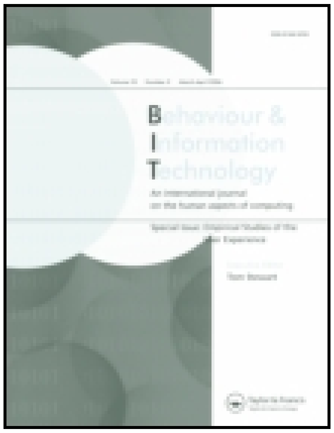

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Beyond cognition and affect: sensing the unconscious

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In the past decade, research on human–computer interaction has embraced psychophysiological user interfaces that enhance awareness of computers about conscious cognitive and affective states of users and increase their adaptive capabilities. Still, human experience is not limited to the levels of cognition and affect but extends further into the realm of universal instincts and innate behaviours that form the collective unconscious. Patterns of instinctual traits shape archetypes that represent images of the unconscious. This study investigated whether seven various archetypal experiences of users lead to recognisable patterns of physiological responses. More specifically, the potential of predicting the archetypal experiences by a computer from physiological data collected with wearable sensors was evaluated. The subjects were stimulated to feel the archetypal experiences and conscious emotions by means of film clips. The physiological data included measurements of cardiovascular and electrodermal activities. Statistical analysis indicated a significant relationship between the archetypes portrayed in the videos and the physiological responses. Data mining methods enabled us to create between-subject prediction models that were capable of classifying four archetypes with an accuracy of up to 57.1%. Further analysis suggested that classification performance could be improved up to 70.3% in the case of seven archetypes by using within-subject models.

Keywords: affective computing; psychology; archetypes; modelling; unconscious

1. Introduction

One of the main goals and motivations in human–computer interaction (HCI) research is to allow people to interact with computer systems in a natural way. For this reason, the current research agenda in the field of HCI includes the investigation of specific communication capabilities and modalities, which supplement and expand more mature HCI interfaces, such as pointing or touch-based input devices. One of the closely studied interaction modalities is the real-time physiological data of users. This modality serves as a foundation for physiological computing, which is a mode of HCI where physiological data provide an input for a computer system (Fairclough 2009). Physiological computing aims to measure user activity at cognitive (Duric *et al.* 2002) and affective (Picard 2000) levels by analysing psychophysiological measurements, such as brain activity and skin conductance. Thus, unlike traditional interactions paradigms, it does not demand users to provide explicit input. The advantages of psychophysiological user interfaces, such as increased adaptive capability, effortless and, extended communication bandwidth, have attracted the attention of HCI researchers (Hudlicka 2003, Pantic and Rothkrantz 2003, Mandryk *et al.* 2006, Fairclough 2009) and have stimulated investigations associated with computer systems that can recognise and simulate human cognitive and affective states (Scheirer *et al.* 2002, Lin *et al.* 2014, McDuff *et al.* 2012). Potential applications of physiological computing include the real-time assessment of mental workload (e.g. in the aviation industry (Wilson and Russell 2007)) and the recognition of particular affective states (e.g. in tutoring and training (Mao and Li 2009)).

HCI research has made considerable progress moving from simple interfaces based on the physical level of user activity to more advanced interaction paradigms empowered by physiological computing that take into account cognitive and affective states of users. In spite of these advances, user experience beyond the levels of cognition and affect, in the domain of ancestral instincts and inborn behaviours, is not well understood and remains a largely unexplored area of HCI with only a few exceptions (McLoone 2010, Ivonin *et al.* 2013). Meanwhile, research in psychology (Bargh *et al.* 2001, Bargh and Morsella 2008) and recently in neuroscience (van Gaal and Lamme 2012) has provided growing evidence that factors defining human experience are not limited to physical, cognitive, and affective levels. It is important to clarify that we refer here to conscious cognitive and affective states that have been the primary focus of investigation in affective and physiological computing. These states are characterised by the fact that awareness about them directly appears in consciousness of individuals.

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On the other hand, there are higher order cognitive and affective processes to which individuals may have little or no direct introspective access (Wilson and Bar-Anan 2008). This fact seems surprising and controversial, but the experimental findings suggest that people are not very well aware of and not able to report on their cognitive processes (Nisbett and Wilson 1977). Thus, a considerable part of human experience is tied to a deeper level of psyche, which due to unavailability for conscious awareness is conceptualised as the unconscious (Wilson and Bar-Anan 2008). Since the phenomenon of the unconscious is still to be fully understood by the scientific community, there has not yet been an established definition developed. In order to avoid ambiguity and confusion, the unconscious mental processes have been operationally defined by Bargh and Morsella 'in terms of a lack of awareness of the influences or effects of a triggering stimulus and not of the triggering stimulus itself' (Bargh and Morsella 2008, p. 3). This definition emphasises the important distinction between unconscious and subliminal by resolving the common confusion about these two phenomena. People outside psychological science often equate the unconscious with processing of stimuli which are too weak or short to enter the conscious awareness and, therefore, are referred to as subliminal. In fact, unconscious information processing is not necessarily associated with presentations of subliminal stimuli and runs continuously as a parallel background process in the human mind (Rauterberg 2010).

Carl Jung, a Swiss psychologist and psychiatrist, developed the concept of the unconscious further and proposed a theoretical framework of the psyche that included three levels (Sally 1994): consciousness; the personal unconscious; and the collective unconscious. Consciousness is the external layer of the psyche consisting of those thoughts and emotions that are available for one's conscious recollection. The personal unconscious represents a repository for all of an individual's feelings, memories, knowledge, and thoughts that are not conscious at a given moment of time. They may be retrieved from the personal unconscious with a varying degree of difficulty that depends on how actively they are being repressed. The term 'collective' reflects the fact that this part of the unconscious is universal and has contents and modes of behaviour that are similar in all individuals (Jung 1981). The collective unconscious does not develop individually but is inherited and accommodates innate behaviour patterns for survival and reproduction. Some researchers (Faber and Mayer 2009) expressed an opinion that contents of the collective unconscious could also be learned by collective exposure to culture and the media that reproduces these archetypes consciously or subconsciously in their narrative structures.

Jung described the content of the collective unconscious as archetypes or pre-existent forms. Archetypes 'are seen as prototypical categories of objects, people, and situations that have been in existence across evolutionary time and across cultures' (Sally 1994, p. 291). Some examples of archetypes are: anima (the female aspect of the male psyche), mother, sky father, and wise old man (Nunn 1998). According to Jung, there is a distinction between archetypal representations and archetypes themselves. While representation is simply what someone experiences when a concept of, for instance, sky father occurs in one's mind, archetypes themselves are different (Nunn 1998). Jung regarded archetypes as a fundamentally unobservable configuration whose existence can be established empirically in a variety of forms (Jung 1981). For instance, the archetype of mother may manifest itself in infinitely many forms and, yet, the one common characteristic of the 'mother-idea' always remains intact (Nunn 1998). When an archetype becomes activated and is experienced with associated feelings and thoughts, it will result in a complex within the personal unconscious (Sally 1994). According to Jung, a complex within the personal unconscious is an independently organised conglomeration of emotions and ideas that are specific to an individual and are products of interactions among a number of archetypes (Jung 1981, Sally 1994). In the context of this study, the unconscious experience related to particular archetypes will be referred to as the archetypal experience.

One of the first studies that made an attempt to explore the phenomenon of archetypes from an empirical perspective was conducted by Rosen *et al.* (1991). In that experiment, the association between archetypal symbols and their meanings was tested based on the assumption that people have a collective unconscious memory. The experimental findings indicated that although the participants had little or no knowledge about the meaning of the archetypal symbols, their collective unconscious (archetypal) memory improved learning and recall of archetypal symbols. Sotirova-Kohli *et al.* (2011) replicated these results in a similar experiment where a set of Chinese Kanji symbols fulfilled the role of the archetypal symbols in the study described above. According to the data reported by the authors, the meaning of Chinese symbols seemed to be embedded in the archetypal memory of the subjects. Another study that adopted the empirical approach in exploration of the impact of the archetypal appearances on affective responses of people was performed by Maloney (1999). The results suggested that archetypal themes could determine emotional responses in the participants. One of the latest experiments that considered the unconscious knowledge about archetypal symbols was reported by Bradshaw and Storm (2013). The design of their study essentially followed the one introduced by Rosen *et al.* (1991), but at the same time accounted for several limitations. Their findings also seemed to reproduce the earlier observations.

The concept of archetypes has been applied to explain how people respond to other people in personality psychology (Faber and Mayer 2009). It also found applications in development of story characters and different kinds of media (Faber and Mayer 2009). Moreover, it received substantial attention in the research on advertising and marketing

(Walle 1986, Caldwell *et al.* 2010, Megehee and Spake 2012, Woodside *et al.* 2012).

Although people do not have direct introspective access to unconscious processes in their minds, the unconscious influences their behaviours, experiences, and memories (Bargh and Morsella 2008). Interestingly, the unconscious experience can be indirectly assessed by the methods developed in psychophysiology (Miller 1992), which are similar to measurements employed in physiological computing. Therefore, in theory, it may be possible to observe the unconscious experiences of individuals through measures of their physiological signals. This opportunity seems interesting and attractive because it would enable us to complement the capability of sensing human experience in the domain of conscious affective and cognitive states with an additional facility for interpreting the archetypal experiences. Overall, it would mean that psychophysiological interfaces and applications could benefit from more detailed information about human experience. As the problem of digitisation and transmission of human experience is essential in many application areas (see (Lahlou 2010) for an elaborate discussion), it seems that a technique for more detailed and deeper capture of human experience will not be excessive. Let us consider some potential applications. First, a technique for capturing the implicit experience of users with new products or systems could efficiently complement questionnaires and provide a new view at how the users feel about using a system. Next, different kinds of lifelogging techniques promoted by the community known as Quantified Self (Rivera-Pelayo *et al.* 2012) could be enriched with additional information about the unconscious experience of people. The members of this community are interested in self-knowledge and self-improvement through self-tracking with wearable computers. A tool for unobtrusive tracking of the unconscious experience will likely be attractive for this community. Finally, we are confident that practitioners will come up with other interesting applications.

The major goal of this study was to evaluate the feasibility of sensing and distinguishing various archetypal experiences of individuals based on the analysis of physiological signals, such as heart rate (HR) or skin conductance. For the achievement of our research goal, an experiment was designed where a range of archetypal experiences and explicit (conscious) emotions were elicited in individuals, and their physiological data were measured in real-time with wearable sensors. In this article, emotion is defined as 'an episode of interrelated, synchronised changes in the states of all or most of the five organismic subsystems in response to the evaluation of an external or internal stimulus event as relevant to major concerns of the organism' based on the work of Scherer (2005). Scherer (2005) named the following organismic subsystems: information processing, support, executive, action, and monitor. We also asked the subjects to provide conscious self-reports about their feelings. The archetypal experiences and explicit emotions were induced by means of film clips. After the experimental session, a set of relevant features was extracted from the physiological signals and a statistical analysis of both physiological and self-reports' data was conducted. Then, several standard data mining techniques were applied to the features in order to obtain prediction models that allow for a meaningful classification of subjects' psychological states in accordance with each of the archetypes and the explicit emotions. Finally, we analysed the findings obtained, proposed an approach to improve classification accuracy, and performed its initial verification.

2. Materials and methods

2.1. Stimuli

As our goal in this study was to explore the relationship between archetypal experiences of people and activations of the autonomic nervous system (ANS), it was necessary to develop a method for elicitation of these pre-existent forms of apperception in our subjects. While the state of the art still lacks an established method for the elicitation of archetypal experiences, it seems reasonable to follow the approach taken by researchers in the field of affective computing. This approach also prevailed in the first studies which considered the problem of recognising archetypes from physiological data (Ivonin *et al.* 2013). The essence of the aforementioned approach is to expose participants of a study to manually selected audio–visual material. It is, therefore, a passive method of elicitation. Unlike the approaches involving confederate interaction procedures, this method may not provide psychological responses of high intensity, but it ensures high degree of standardisation (Rottenberg *et al.* 2007).

Although much of the research in emotion recognition utilised affective pictures and sounds from two databases (Bradley and Lang 1999, Lang *et al.* 2008) for elicitation of affective states, it seems that video could be a better medium for presentation of stimuli. Film clips are powerful in capture of individuals' attention because of their dynamic display that includes both visual and auditory modalities (Gross and Levenson 1995). Moreover, in comparison with still pictures and sounds, film clips have the ability to elicit more intensive emotional responses that lead to activations in cognitive, experiential, central physiological, peripheral physiological, and behavioural systems (Rottenberg *et al.* 2007). In accordance with this argument, some recent studies in affective computing, for instance (Soleymani *et al.* 2011), relied on film clips for induction of emotional states. Eventually, film clips were chosen as a method of eliciting archetypal experiences in our participants because they proved their effectiveness in the induction of emotions and it was not clear which type of media would work best for archetypes. For this reason, we assumed film clips are also likely to influence psychological processes in the psyche that are related to the collective unconscious.

We included seven common archetypes in our study that were selected based on their appearance in the work of Jung (1981) and others (Walle 1986, Campbell 2008, Faber and Mayer 2009, Munteanu *et al.* 2010). These archetypes were: anima; hero initiation; hero departure; hero rebirth; hero return; mentor; and shadow. Four out of the seven archetypes were closely related. They represented important stages of the hero's journey, which was described by Campbell (2008). Campbell identified a prototypical journey that a hero undertakes in a general narrative and divided it into several stages. The archetype of mentor is found in the research of Campbell as well and signifies a character that supports the hero in acquiring knowledge and power. The archetype of anima represents the female aspect of the male psyche, and the archetype of shadow constitutes qualities of the personality that the conscious ego tends to reject. More information about the archetypes can be found in Chang *et al.* (2013a).

Next, we needed film clips embodying these archetypes that would be demonstrated to the participants in the experiment. It was decided to have three clips taken from different sources to present each of the archetypes because, in this case, we ensured that computational intelligence algorithms would perform recognition of the archetypes and not the film clips. Similar to the previous studies that employed films (Gross and Levenson 1995), we obtained our clips by editing fragments of full-length commercial movies. The selection of the fragments was guided by our experience gained from the collaboration with The Archive for Research in Archetypal Symbolism (ARAS) that took place approximately one year ago. ARAS is an organisation that, since the early 1930s, has been collecting and annotating mythological, ritualistic, and symbolic images from all over the world (Gronning *et al.* 2007). It does not seem appropriate to select stimuli for induction of the archetypal experiences based on their visual or audio properties. Instead, the film clips were edited based on their symbolic qualities. Symbols play an important role in connecting the internal psychological phenomena and the external physical world (Varela *et al.* 1992). The symbolic approach is also well-aligned with the work of Jung who identified similar symbolic representations of archetypes across cultures and epochs of human history. The outcome of the selection is given in Table 1. In this table, we provided information that is necessary to obtain exactly the same film clips as were used in this study. Unfortunately, we cannot share the film clips themselves because they were extracted from commercial movies protected by copyright.

Besides archetypal experiences we wanted our subjects to feel explicit emotions as well. There were three main reasons for this. First, we needed a possibility to benchmark our findings against the state of the art in affective computing. Second, it was interesting to compare the results of recognition for archetypal experiences and explicit emotions. Third, it was necessary to analyse the differences in self-reports of the participants in order to confirm they were not consciously aware of the archetypes. Similar to archetypal experiences, explicit emotions were elicited with film clips. Emotions or feelings are commonly represented in affective computing with the dimensional model (Russell 1980). This model projects emotions in the affective space with two or three dimensions. In the case of two dimensions, an emotional state in the affective space is characterised by values of arousal and valence. The dimension of arousal ranges from calm to aroused states, while the dimension of valence ranges from negative to positive states (Ivonin *et al.* 2012). For this study, we did not want to choose too many explicit emotions, but at the same time, the number of emotions should be sufficient to uniformly cover the two-dimensional affective space. Therefore, five emotional states were chosen. Four of them were located in each of the quadrants of the affective space, and the fifth was situated close to the origin. In accordance with their location, we tagged these emotional states as active-pleasant, active-unpleasant, passive-pleasant, passive-unpleasant, and neutral. The film clips for elicitation of these explicit emotional states were identified based on the previous studies in affect induction and recognition. The work of Gross and Levenson (1995) and Soleymani *et al.* (2011) provides guidance with regard to application of video in emotion research and even proposes sets of film clips that can be readily used as emotional stimuli. Unfortunately, we could not always use the recommended clips from the pilot study. We learned that some of the clips taken from old movies do not emotionally engage people because they are perceived as old-fashioned. In the same manner as for the archetypes, three film clips were selected for every explicit emotion. Therefore, in total, we had 15 affective film clips that are listed in the second part of Table 1. Again, the clips could not be shared due to the copyright restrictions, but the data in Table 1 should be sufficient to create videos identical to the ones used in our experiment.

2.2. *Experimental design*

Our experiment was conducted at the usability laboratory of the Polytechnic University of Catalonia. The laboratory was divided into two rooms. The inner room was set up for the presentation of video clips on a large screen and accommodated subjects during the study. It had a comfortable couch located at the distance of three metres in front of the screen and was equipped with surveillance cameras for observation of the participants. The video clips were projected on the screen with a video projector. Sound was delivered via wireless headphones. The wall between the inner and the outer room had windows made of tinted glass and, therefore, the subjects located in the inner room could not see the researchers who administered a session of the experiment. The outer room had a computer that was used for managing playback of the film clips and a screen connected to the surveillance cameras. The monitoring of activations in the ANS of the participants was performed with wireless sensors manufactured by Shimmer (Burns *et al.* 2010).

Table 1. Sources of the film clips.

Film clip	Movie	Length	Start	End
	Archetypal experiences			
Anima (1)	*American Beauty* (1999)	122	0:16:15	0:17:17
Anima (2)	*Maléna* (2000)	109	0:19:18	0:20:20
Anima (3)	*Perfume: The Story of a Murderer* (2006)	147	0:18:03	0:18:18
			0:21:20	0:22:15
Hero departure (1)	*V for Vendetta* (2005)	132	0:41:55	0:43:03
Hero departure (2)	*Braveheart* (1995)	177	0:10:10	0:10:46
			0:14:13	0:14:43
Hero departure (3)	*The Lord of the Rings: The Fellowship of the Ring* (2001)	178	2:21:12	2:21:47
			2:22:37	2:23:06
			2:23:10	2:23:16
Hero initiation (1)	*V for Vendetta* (2005)	132	1:23:29	1:24:34
Hero initiation (2)	*Braveheart* (1995)	177	2:07:39	2:08:37
			2:08:47	2:08:58
Hero initiation (3)	*The Matrix* (1999)	136	2:02:25	2:03:25
Hero rebirth (1)	*V for Vendetta* (2005)	132	1:24:59	1:26:00
Hero rebirth (2)	*Braveheart* (1995)	177	2:15:39	2:16:15
			2:17:35	2:18:01
Hero rebirth (3)	*The Matrix* (1999)	136	2:04:35	2:05:45
Hero return (1)	*V for Vendetta* (2005)	132	2:02:40	2:03:04
			2:03:22	2:04:06
Hero return (2)	*Braveheart* (1995)	177	2:48:56	2:49:08
			2:49:11	2:49:53
			2:49:54	2:50:09
Hero return (3)	*The Matrix Revolutions* (2003)	129	1:53:40	1:53:47
			1:54:02	1:54:05
			1:54:33	1:54:50
			1:55:24	1:55:39
			1:56:02	1:56:29
Mentor (1)	*The Lord of the Rings: The Fellowship of the Ring* (2001)	178	2:03:05	2:04:10
Mentor (2)	*The King's Speech* (2010)	118	1:42:13	1:42:44
			1:42:58	1:43:18
			1:45:33	1:45:52
Mentor (3)	*The Lion King* (1994)	89	0:24:38	0:25:05
			0:25:29	0:26:06
Shadow (1)	*The Lord of the Rings: The Two Towers* (2002)	179	1:35:19	1:36:20
Shadow (2)	*Fight Club* (1999)	139	1:48:24	1:49:32
Shadow (3)	*The Dark Knight* (2008)	152	1:24:22	1:25:30
	Explicit emotions			
Active-pleasant (1)	*Mr. Bean* ((*season 1, episode 1*) 1990)	24	0:06:10	0:07:13
Active-pleasant (2)	Funny cats (YouTube 2008)	1:39	0:00:00	0:01:01
Active-pleasant (3)	Funny clip with mice and a dog (MrBallonRond 2012)	15:02	0:04:11	0:04:44
			0:10:08	0:10:36
Active-unpleasant (1)	*Hannibal* (2001)	131	1:44:50	1:45:50
Active-unpleasant (2)	*American History X* (1998)	119	1:52:07	1:53:10
Active-unpleasant (3)	*The Silence of the Lambs* (1991)	118	1:39:38	1:40:40
Neutral (1)	*Coral Sea Dreaming: Awaken* (2010)	87	0:08:01	0:09:01
Neutral (2)	*Coral Sea Dreaming: Awaken* (2010)	87	0:04:31	0:05:31
Neutral (3)	*Coral Sea Dreaming: Awaken* (2010)	87	0:38:48	0:39:48
Passive-pleasant (1)	*The Lion King* (1994)	89	0:47:51	0:48:52
Passive-pleasant (2)	*Mr. Bean's Holiday* (2007)	90	1:17:19	1:18:19
Passive-pleasant (3)	*Love Actually* (2003)	135	0:10:17	0:11:21
Passive-unpleasant (1)	*The Thin Red Line* (1998)	170	1:07:08	1:08:09
Passive-unpleasant (2)	*Forrest Gump* (1994)	142	2:05:55	2:07:04
Passive-unpleasant (3)	*Up* (2009)	96	0:10:22	0:11:26

Note: The film clips for each archetype and explicit emotion were extracted from the movies specified in the table. The length of the movies (in minutes) is specified in the third column. The clips consist of one or more fragments that were cut from the movies at the times specified in the two last columns. The time format is hours:minutes:seconds.

These portable sensors enabled us to measure physiological signals of the subjects' bodies in a real-time manner. Since physiological signals, such as HR and skin conductance, are affected by the ANS, they provide an indirect evaluation of activities in the ANS. The sensors wirelessly streamed the physiological data over Bluetooth protocol to a tablet computer running Android operating system. We developed an app[1] for the Android platform that established a connection with the sensors and performed collection and visualisation of the physiological data. This app monitored the order and the timing of presenting the video clips as well as provided instructions to the researchers regarding which clip to play and when to start the playback. Our study followed a design in which every subject was exposed to the same pool of media stimuli. The order of presentation of the stimuli was randomly chosen by the app for each participant. In future, we plan to extend the functionality of this app and make it a fully featured instrument for the evaluation of human experience.

2.3. Subjects

For this study we recruited 23 healthy volunteers. Most of the participants were undergraduate or graduate students who took courses at the Polytechnic University of Catalonia. We also recruited several older subjects. Every participant complied with the procedure of the experiment, and we did not experience any other problems during the study. Therefore, we could use all the collected data for the analysis. Out of 23 participants, 10 were women, and 13 were men. The average age for the women was 27.80 years (SD = 8.80) and for the men was 27.77 (SD = 6.13) years. The participants had diverse national backgrounds (four from Asia, 15 from Europe and four from South America). We required the subjects to have normal or corrected to normal vision and hearing. Prior to the experiment, each subject signed an informed consent form and was later rewarded with a small present for participation in the laboratory session that took approximately 1.5 hours.

2.4. Procedure

Every session of our experiment accommodated one participant. Thus, we had 23 sessions in total plus one pilot session that was conducted in order to test the technical aspects of the study. On arriving at the laboratory, participants were invited to sit upright on the couch. They were then given an informed consent form by the host and asked to read it thoroughly. If subjects had no questions with regard to the content of this form, they signed it. The next step was placement of the electrodes for monitoring of physiological signals on the bodies of the participants. The host, using illustrations, explained where the electrodes had to be attached and invited participants to do it themselves. Meanwhile, the host made sure that the electrodes were placed properly. Next, the electrodes were connected to the sensors, and the host confirmed the sensors were streaming signals of good quality. After placement of the electrodes and establishment of connection with the sensors, participants were asked to fill in a short questionnaire about their day-to-day experiences (Brown and Ryan 2003). While participants were filling in the questionnaire, the electrode gel soaked into their skin and, thereby, a more stable electrical connection was established (Figner and Murphy 2011). When the participants had finished the questionnaires, the host gave a detailed overview of the experiment and demonstrated a tutorial video clip. During the overview of the study, the participants were told that a number of film clips would be demonstrated and that retrospective reports about their feelings had to be provided after each video. For the tutorial, a neutral clip extracted from the movie *Coral Sea Dreaming: Awaken* (2010) was used. Then, participants were taught how to provide self-reports about their feelings after watching a film clip. For collection of the self-reports, we utilised the Assessment Manikin (SAM) (Bradley and Lang 1994) because it has a good track of applications in psychological studies. These reports were later used to determine if the subjects were consciously aware of their feeling when watching archetypal film clips. Although the host provided the subject with a description of the experiment, the actual goal of the experiment remained undisclosed, and, for this reason, the participants were not aware of any emotions or archetypes pictured in the video clips. Next, the light in the inner room was dimmed so that the viewing experience became similar to the one in a movie theater; the host left the subject alone and the presentation of the video clips began. The film clips were shown in a random order. Demonstration of every film clip was preceded by a special video that featured a breathing pattern (14 breaths per minute). This video lasted for 20 seconds, and its purpose was to dismiss psychological and physiological effects of the previous stimulus. During this video, the participant was required to follow the breathing pattern shown on the screen and thereby adjust the respiration rate to the common baseline. The physiological data recorded during the video with a breathing pattern were later used in the analysis as the physiological baseline. Upon completion of viewing a film clip, participants provided a retrospective self-report by rating their feelings along the dimensions of the SAM with paper and a pen. When a participant submitted the self-report for the last film clip, the light in the room was turned on, and the host helped detach the sensors and debrief the subject. Finally, participants were required to fill in the Myers-Briggs personality questionnaire (Myers *et al.* 1998) and were dismissed.

2.5. Physiological signals

According to the literature in the areas of psychophysiology and affective computing (Cacioppo and Tassinary 1990, Picard *et al.* 2001), psychological experiences of people lead to activations in the ANS that in turn result in specific patterns of physiological responses. In our study, we chose to measure two physiological signals: HR and skin conductance. This decision was motivated by several factors. First of all, previous studies in this field demonstrated that features extracted from these signals often contribute the most into the discrimination of psychological states (Kreibig 2010). Moreover, current technological advancements enable unobtrusive and reliable monitoring of HR and skin conductance in natural for people settings. Unlike measurements such as fMRI or EEG that require either placement of a subject in a magnetic scanner or, according to the international 10–20 system (Klem *et al.* 1999), attachment of up to 21 electrodes to the scalp, the physiological signals chosen for our study can be sensed without causing a subject to feel discomfort.

For measurement of the heart's electrical activity, we used electrocardiogram (ECG) because it provides the richest source of information. ECG measurements were taken with the Shimmer wireless sensor connected to a participant's body with four disposable pregelled Ag/AgCl spot electrodes. Two of the electrodes were placed below the left and right collarbones, and the other two were attached to the left and right sides of the belly. The electrode placed on the right side of the belly served as a reference. This configuration of ECG sensors provides sufficient information about cardiovascular activities of the heart and at the same time does not bother individuals with large number of electrodes. ECG was monitored at 256 Hz and then cleaned with low-pass, high-pass, and notch filters. ECG contains plenty of information about the cardiovascular activity, and in the psychophysiological domain, it is commonly used for the calculation of the HR and heart rate variability (HRV). The HR is a simple measurement that characterises the heart's activity in terms of the number of heart beats per minute (Neuman 2010). The app we developed automatically obtained HR from the ECG signal by identifying beats with an algorithm provided by Afonso *et al.* (1999) and computing the average HR over non-overlapping moving windows of five seconds. We expected to see a relation between the psychological states of the subjects and their HR because this measure had been widely applied in affective computing (IzsÓ and Láng 2000), and according to Kreibig (2010), the HR is the most often reported cardiovascular measure in psychophysiological studies of emotion. Next, several HRV parameters from time and frequency domains were calculated based on the heart beats data with the HRVAS software package (Ramshur 2010). Time domain parameters included the standard deviation of the beat to beat intervals (SDNN), the square root of the mean of the sum of the squares of differences between adjacent beat to beat intervals (RMSSD), and the standard deviation of differences between adjacent beat to beat intervals (SDSD) (Camm *et al.* 1996). A pool of frequency domain parameters consisted of a total power, a power in a very low-frequency range (0–0.04 Hz), a power in a low-frequency range (LF, 0.04–0.15 Hz), a power in a high-frequency range (HF, 0.15–0.4 Hz), and a ratio of the power in a low-frequency range to the power in a high-frequency range (LF/HF) (Camm *et al.* 1996).

Skin conductance of the participants was monitored with the Shimmer galvanic skin response sensor. The sensor was connected to two disposable pregelled Ag/AgCl spot electrodes that were attached to thenar and hypothenar eminences of the participant's palm on a non-dominant hand. Skin conductance describes variations in the electrodermal activity of skin and is associated with processes of eccrine sweating, which are controlled by the sympathetic branch of the ANS (Figner and Murphy 2011). According to Lang *et al.* (1993), skin conductance is closely related to psychological processes and particularly to the level of arousal. Skin conductance has tonic and phasic components. The tonic component reflects relatively slow changes in skin conductance over longer periods of time lasting from tens of seconds to tens of minutes. Thus, it is indicative of a general level of arousal and is known as the skin conductance level (SCL). A different perspective is given by the phasic component of skin conductance, which is called the skin conductance response (SCR) because it reflects high-frequency variations of the conductance and is directly associated with observable stimuli (Figner and Murphy 2011). The skin conductance signal was recorded at 64 Hz. Although such a high sampling rate is not imperative for measurement of the skin conductance signal, complex analysis approaches and smoothing procedures can benefit from higher resolution data (Figner and Murphy 2011). Our app automatically calculated the SCL from the raw skin conductance signal by applying a low-pass filter at 1 Hz. An additional high-pass filter was set at 0.5 Hz for the SCR.

2.6. *Data mining and extraction of features*

In order to make physiological data from different individuals comparable, the baseline values were subtracted from the data corresponding to stimuli presentations. The result of the subtraction was then normalised to a range from zero to one for each subject separately. Since the film clips were approximately one minute long, the data formed temporal sequences. In affective computing, the feature-based approach to time sequence classification dominates (Novak *et al.* 2012). We also found this method to be more suitable for a number of reasons. First, it provides a convenient way to include non-temporal attributes, such as some HRV features that are calculated over the full film clip interval or gender of the subjects, into the analysis, which, for instance, dynamic time warping (DTW) and Hidden Markov Model (HMM) methods do not (Kadous and Sammut 2005). Second, contrary to HMM, this method does not require a large amount of training data (Kadous and Sammut 2005). Third, the creation of a template stream in the DTW method for representation of a typical time series corresponding to a given psychological state is not trivial. Based on this decision, the physiological data collected during the study had to be transformed into a set of feature vectors that could be used for statistical analysis and classification.

The main goal pursued by the extraction of features is a compression of data sequences to smaller sets of static features. The sliding window, the discrete wavelet transform (DWT), and the discrete Fourier transform (DFT) (Agrawal *et al.* 1993, Geurts 2001, Chan 2003) are the three common methods for conversion of time series to static data. The sliding window method performs best with time series of low frequency and short length because an increase in the frequency and length leads to the generation of high-dimensional feature vector. For long and high-frequency data series, the DWT and DFT approaches have been introduced. The idea behind these methods is the transformation of a sequence from the time domain to the time–frequency plane (DWT) or to the frequency domain respectively (DFT). Taking into consideration the short length of the film clips utilised in our study, the sliding window method for extraction of feature vectors was an appropriate way to prepare the dataset for the classification because it is simple, can be applied online, and at the same time, as evidenced by previous studies in affective computing (Novak *et al.* 2012), provides satisfactory results. Another name of this approach is segmentation since it involves partition of a time axis into multiple segments with equal length and, then, averaging of temporal data along the segments (Geurts 2001).

We divided physiological data corresponding to each of the film clips into 12 non-overlapping segments. A segment, therefore, lasted for five seconds, and the temporal data were averaged over its duration. The number of the segments was empirically chosen. This procedure was performed for HR, SCL, and SCR signals. For the SCR, we additionally calculated absolute values of the signal (Figner and Murphy 2011). Then, we performed fusion of physiological data coming from different signals through concatenation. As an outcome of the transformation we had an integrated dataset consisting of 44 features that could be used for statistical analysis and classification. Twenty of these features were extracted from ECG including 12 features of the HR signal and eight features of the HRV measures. The remaining 24 features were taken from the SCL and SCR signals.

2.7. Statistical analysis

The first question that we formulated in the introduction section was whether there is a relationship between archetypal experiences of people and patterns of physiological activations of their bodies. It was also interesting to know if there are any variations due to gender of the participants and how responses elicited by explicit emotions are different from the ones caused by beholding the archetypal appearances. A number of statistical tests had to be conducted in order to answer these and other questions. Each subject watched all the film clips that formed our sets of stimuli for the explicit emotions and the archetypal experiences. Thus, the study had a repeated-measures design where physiological measurements were made on the same individual under changing experimental conditions. Moreover, the subjects provided reports via the SAM ratings after every experimental condition. An appropriate statistical test for this type of design would be multivariate analysis of variance (MANOVA) for repeated measures (O'Brien and Kaiser 1985). A software implementation of statistical procedures included in SPSS Version 19 (SPSS, Inc.) was used to run the tests. Physiological responses of the subjects and the SAM ratings were treated as dependent variables, the categories of archetypal experiences and explicit emotions represented independent variables. The main effect of MANOVA tested whether the patterns of the participants' physiological responses were different between various categories. All statistical tests used a 0.05 significance level.

2.8. Classification algorithms

If the statistical analysis demonstrated that there is a significant relationship between psychological experiences of people and physiological signals, it would be necessary to further investigate this relationship and see how accurately physiological data can predict archetypal experiences or explicit emotions. For this purpose, we selected several computational intelligence methods. With these algorithms, we would create prediction models for classification of psychological states. Five classification methods frequently used in affective computing (Novak *et al.* 2012) were evaluated. K-nearest neighbour (kNN) is a simple algorithm that performs instance-based learning classifying an object based on the classes of its neighbours. The second classifier was support vector machine (SVM) that constructs a set of hyperplanes for classification purposes. The third classification method relied on a probabilistic model built with the naïve Bayes algorithm. The fourth approach was linear discriminant analysis (LDA) that is well suited for small data samples and is easy in implementation (Novak *et al.* 2012). Finally, the fifth classification method was the C4.5 algorithm for the generation of decision trees. The decision trees were used in combination with Adaptive Boosting (AdaBoost) (Freund and Schapire 1997) in order to achieve higher accuracy. It was important to guarantee that the classification algorithms are not trained and tested on the same dataset because we wanted to obtain subject-independent results. Therefore, a leave-one-out cross-validation technique was employed for assessments of the classification performance.

Prior to performing classification, it was beneficial to reduce the dimensionality of the dataset with physiological data. Generally, reduction of the dimensionality is a recommended step in data mining procedures. There are various techniques for the reduction of the features space including principal component analysis (PCA) and LDA. These two approaches are particularly common for the reduction of dimensionality. For this study, LDA was chosen over PCA because PCA does not capitalise on between-class information, while LDA uses both within- and between-class information for better performance (Martinez and Kak 2001). Two aspects of LDA should be mentioned here. First, strictly speaking, LDA is not a feature selection but a feature extraction method that obtains the new attributes by a linear combination of the original dimensions. The reduction of dimensionality is achieved by keeping the components with highest variance. Second, LDA can be used for both identification of important features and classification (Novak *et al.* 2012).

While the aforementioned methodology was utilised for between-subject classification, later we also had to perform within-subject classification, and due to the small number of data samples, it required a special approach for the reduction of dimensionality. We borrowed this approach from the domain of image recognition where the high-dimensional datasets with small sample size are common. In these circumstances, the traditional LDA algorithm cannot be used because its within-class scatter matrix is always singular (Yang and Yang 2003). A popular technique to address this difficulty is called PCA plus LDA (Belhumeur *et al.* 1997, Yu and Yang 2001). In this approach, PCA is applied to reduce the dimensionality before using LDA. PCA plus LDA approach was verified both practically and theoretically (Yang and Yang 2003). In PCA reduction, we kept the minimum number of variables that were required to explain at least 90% of the variance in a dataset.

3. Results

Upon completion of the study, we proceeded with an exploratory data analysis. For this purpose, physiological data of the subjects was averaged and plotted on several line charts that are well suited for the display of a sequence of variables in time. The exploratory analysis of the HR signal revealed that presentation of each video clip generally led to a decelerating response in HR. This pattern of response had place even with the neutral stimuli and is illustrated in Figure 1. The deceleration of HR due to diversion of attention to an external task, such as perception of an audio-visual stimulus, is a known effect that is explained by Laceys' theory of intake and rejection (Lacey and Lacey 1970). Based on our previous study (Ivonin *et al.* 2013) and other literature in the related fields (Winton *et al.* 1984, Palomba *et al.* 1997), we anticipated this effect and made adjustments in the data analysis procedure in order to account for the decelerating response present across all categories of the stimuli. This adjustment enabled us to highlight the differences in responses to various stimuli and improve the classification accuracy.

Following the exploratory analysis, several statistical tests were conducted. We started with analysis of the self-report evaluations provided by the subjects after watching the film clips. MANOVA for repeated measurements

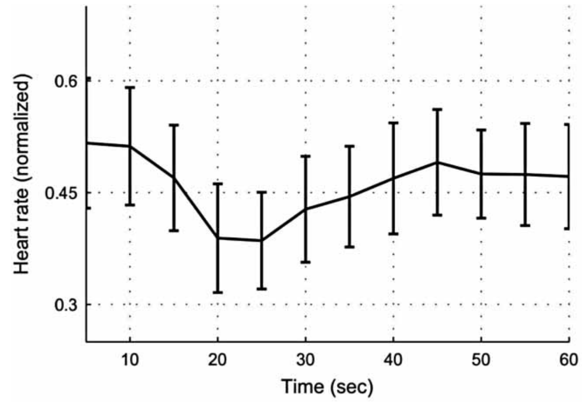

Figure 1. The pattern of the subjects' HR signals corresponding to the presentation of neutral film clips. The mean values and 95% confidence intervals of the HR are represented by the bold lines and the vertical bars.

Table 2. Mean values and standard errors (SE) of the SAM ratings.

Archetype or emotion	Valence		Arousal		Dominance	
	Mean	SE	Mean	SE	Mean	SE
Anima	5.879	0.298	4.515	0.418	5.803	0.360
Hero departure	4.015	0.233	4.485	0.372	4.515	0.400
Hero initiation	3.864	0.271	4.909	0.392	4.439	0.353
Hero rebirth	5.924	0.282	4.455	0.361	6.197	0.299
Hero return	6.318	0.298	4.818	0.381	6.742	0.330
Mentor	6.273	0.198	3.455	0.279	6.348	0.300
Shadow	4.591	0.229	4.576	0.426	5.212	0.330
Active-pleasant	7.232	0.360	3.522	0.333	6.768	0.282
Active-unpleasant	2.623	0.237	5.986	0.386	3.522	0.371
Neutral	7.406	0.293	1.580	0.130	6.812	0.366
Passive-pleasant	8.043	0.176	3.087	0.343	7.391	0.246
Passive-unpleasant	3.478	0.293	4.014	0.313	4.130	0.389

Note: The ratings were provided by the participants after viewing the film clips. The range for each rating was from one to nine. The left column indicates which archetype or explicit emotion was presented in the film clips.

was performed for the SAM ratings of valence, arousal, and dominance. It demonstrated a significant main effect of the archetypes presented in the film clips on the SAM ratings [$F(18, 351.210) = 10.060$, $p < .001$ (Wilks' lambda)]. Similarly, the explicit emotions exhibited in the film clips had a significant main effect on the SAM ratings provided by the participants [$F(12, 227.826) = 25.301$, $p < .001$ (Wilks' lambda)]. Estimated marginal means of the SAM ratings are given in Table 2. Then, we added gender of the participants as a between-subject factor to the MANOVA tests in order to see if women and men rated their psychological experiences in a different manner. The results of the tests indicated that the interaction effect between the subjects' gender and the archetypes was not significant [$F(18, 334.240) = 1.166$, $p = .288$ (Wilks' lambda)]. The interaction effect between the gender of the participants and the explicit emotions [$F(12, 217.243) = 1.476$, $p = 0.135$ (Wilks' lambda)] was not significant either.

When the statistical analysis of the SAM ratings was complete, we looked into the physiological data of the subjects. MANOVA conducted for the features extracted from the physiological signals indicated that there is a significant main effect of the archetypes pictured in the film clips on physiological responses of the subjects [$F(216, 583.757) = 1.396$, $p = .001$ (Wilks' lambda)]. Another MANOVA test was performed in order to see the relationship between the physiological data and the explicit emotions presented in the film clips. The outcome of this test was significant as well [$F(144, 213.766) = 1.985$, $p < .001$ (Wilks' lambda)].

Next, we examined if there was a connection between gender of the participants and their physiological responses to the film clips. The gender was added into the analysis as a between-subject variable. The results of the MANOVA tests demonstrated that there were no significant interaction effects between the archetypes and the gender [$F(216, 548.182) = 1.034$, $p = .379$ (Wilks' lambda)] or between the explicit emotions and the gender [$F(144, 197.835) = 0.872$, $p = .808$ (Wilks' lambda)].

Our statistical analysis uncovered several interesting findings. There were significant relationships between the archetypes and the SAM ratings, between the explicit emotions and the SAM ratings, between the archetypes and the physiological responses, and between the explicit emotions and the physiological responses. In order to further explore these findings, we needed to build and evaluate predictive models that would quantify these relationships. The evaluation was performed through comparison of classification accuracies achieved by the predictive models obtained with five different methods (kNN, SVM, naïve Bayes, LDA, and AdaBoost with decision trees).

We started with models for prediction of the archetypal experiences based on the SAM ratings. Due to the fact that in our study there were video clips for elicitation of seven different archetypal experiences, the classification task was considerably difficult. Moreover, four out of the seven archetypes were related to a hero. This circumstance added even more confusion into the subjects' self-reports. For this reason, we divided the set of films picturing the archetypes into four subsets. Every subset included the archetypes of anima, mentor, shadow, and one of the hero archetypes. The best classification accuracy (28%) for the complete set of archetypes was achieved with the kNN classifier. Similarly, the kNN method demonstrated the most accurate result (42%) for the subset that included the archetype of hero departure. For the subset with the archetype of hero initiation, the precision of classification was between 40.9% (with SVM classifier) and 43.1% (with AdaBoost classifier). It was also the most accurately predicted subset out of the four. The subset with the archetype of hero rebirth featured the lowest classification rate (38.4%) among all of the subsets. Finally, for the subset that included the archetype of hero return, the classification methods enabled us to achieve the accuracy of 40.6%. A more detailed overview of the classification results can be found in Table 3.

Our next step was to see how accurately the explicit emotions presented in the film clips could be differentiated based on the SAM ratings given by the subjects. For this purpose, we performed classification with the same classification algorithms as were used for the film clips with the archetypes. The analysis was conducted with two datasets: the complete dataset that included the self-reported data for all the film clips featuring the explicit emotions and the dataset that was obtained from the complete dataset by removing the data related to the active-pleasant emotional state. The motivation for introduction of the second dataset was justified by the fact that one of the film clips for active-pleasant emotion turned out to be controversial. Our observations of the participants' facial expressions during the study indicated that some of them found this clip to be unpleasant or confusing, while other subjects perceived it as funny. Therefore, we expected considerable variations in the subjects' self-reports. Moreover, classification results of the second dataset for the explicit emotions and any of the four reduced datasets for the archetypes could be easily compared because they had the same number of classes. The best classification accuracy (50.4%) for the complete dataset of the explicit emotions was achieved with the kNN method. According to our expectations, the classification of the subset that did not include the data corresponding to the active-pleasant emotion was noticeably more precise

Table 3. Classification results obtained for recognition of the archetypes and explicit emotions from the self-reports.

Categories of the film clips	N	kNN	SVM	Naïve Bayes	LDA	AdaBoost
Anima, hero departure, hero initiation, hero rebirth, hero return, mentor, shadow	7	**28.0**	24.2	24.6	24.7	25.5
Anima, hero departure, mentor, shadow	4	**42.0**	40.2	38.0	40.9	37
Anima, hero initiation, mentor, shadow	4	42.4	40.9	42.0	42.0	**43.1**
Anima, hero rebirth, mentor, shadow	4	**38.4**	37.7	36.2	38.0	34.4
Anima, hero return, mentor shadow	4	**40.6**	39.9	39.5	39.5	39.9
Active-pleasant, active-unpleasant, neutral, passive-pleasant, passive-unpleasant	5	**50.4**	49.0	49.0	48.4	47.3
Active-unpleasant, neutral, passive-pleasant, passive-unpleasant	4	63.4	63.8	63.0	**64.9**	63.0

Note: The first column reports the categories of the film clips that were included in the classification. The number of categories (N) included in the classification is specified in the second column. Other columns state the classification accuracy (per cent) achieved with various classification methods.

Table 4. Classification results obtained for recognition of the archetypes and explicit emotions from the cardiovascular responses of the participants.

Categories of the film clips	N	kNN	SVM	Naïve Bayes	LDA	AdaBoost
Anima, hero departure, hero initiation, hero rebirth, hero return, mentor, shadow	7	25.5	**29.3**	27.2	29.0	18.5
Anima, hero departure, mentor, shadow	4	38.4	41.3	**42.8**	42.4	31.9
Anima, hero initiation, mentor, shadow	4	39.3	40.0	37.8	**41.1**	35.6
Anima, hero rebirth, mentor, shadow	4	38.4	40.2	40.6	**44.6**	42.4
Anima, hero return, mentor shadow	4	42.8	43.8	40.6	**44.2**	35.5
Active-pleasant, active-unpleasant, neutral, passive-pleasant, passive-unpleasant	5	30.7	35.1	32.8	**35.9**	26.4
Active-unpleasant, neutral, passive-pleasant, passive-unpleasant	4	38.4	39.9	43.1	41.7	34.4

Note: The first column reports the categories of the film clips that were included in the classification. The number of categories (N) included in the classification is specified in the second column. Other columns state the classification accuracy (per cent) achieved with various classification methods.

(64.9%). Table 3 provides more details on the classification results for the explicit emotions.

Having conducted the analysis of the SAM ratings, our next goal was to evaluate the feasibility of recognising the archetypes and the explicit emotions from the physiological data of the participants. This evaluation was performed in three steps. On the first step, recognition of the archetypes and the explicit emotions was carried out using the feature variables extracted from cardiovascular responses of the subjects. For the second step, only the features of the skin conductance signal were used. Finally, on the third step, we utilised the complete set of the features extracted from the ECG and skin conductance signals. The breakdown of the analysis process into three steps enabled us to discover and compare the importance of different physiological signals with respect to the classification. Similar to the analysis of the SAM ratings, we used five classification methods for every step.

The cardiovascular data of the subjects enabled us to classify the film clips corresponding to the seven archetypes with an accuracy of up to 29.3%. This recognition rate was achieved with the SVM algorithm. The recognition performance reached 44.6% (LDA) if the number of archetypes in the classification was decreased by isolating four smaller subsets following the approach taken during the analysis of the self-reports. The accuracy of classification for each of the subsets was slightly above 40%, ranging from 41.1% (for the subset with the archetype of hero initiation) to 44.6% (for the subset with the archetype of hero rebirth). For three out of the four subsets, the best results were achieved with the LDA algorithm. The classification of the explicit emotions based on the cardiovascular data was possible with the accuracy of up to 35.9% (LDA) in case of five classes of the emotions and up to 43.1%(Naïve Bayes) if the data corresponding to the active-pleasant emotional state were excluded. A detailed overview of the recognition results for the ECG data is presented in Table 4.

Next, we performed analysis based on the skin conductance data of the participants. The analysis followed the same procedure as in the case of the cardiovascular data. The prediction model trained based on the responses in skin conductivity of the subjects to presentation of the archetypal film clips enabled us to classify seven archetypes with the accuracy of 28% (LDA). Then, the original dataset was split into four subsets in such a way that every subset included only one of the hero archetypes. The classification performance varied from 39.5% to 45.5% among the subsets. Similar to the ECG signal, the most accurate results were obtained with the LDA method. The explicit emotions were predicted with the precision of 40.6% (LDA) in case of five classes and 46.0% (SVM) in case of four classes. Additional information about the classification is provided in Table 5.

Finally, we integrated the features extracted from the ECG and the skin conductance signals into a unified dataset and built several prediction models in order to evaluate the feasibility of recognising the archetypes and the explicit emotions from the physiological data. In the case of classifying seven archetypes, the accuracy was in the range between 28.4% (AdaBoost) and 36.7% (LDA). When the data were rearranged into several subsets, in such a manner that each of them corresponded to only four archetypes, the classification performance achieved 57.1% (LDA). This result was accomplished on the subset with the archetype of hero initiation. The recognition of explicit emotions demonstrated similar outcomes. With four classes of emotions, 57.2% of the cases were accurately classified using the LDA method. When five explicit emotions were included in the analysis, the recognition rate decreased to 50.7% (LDA). In Table 6, we provide further details about the analysis of the complete dataset of the physiological signals.

As we completed the analysis of the participants' self-reports and their physiological responses to the film clips, it was necessary to put the results next to each other to facilitate a comparison and further discussion. This is done in Table 7, which reports the best classification accuracies achieved on the datasets that were built based on the self-reports and the physiological data. Additionally, this table illustrates the relationship between the recognition performance and the number of the film clips' categories in the datasets.

Table 5. Classification results obtained for recognition of the archetypes and explicit emotions from the skin conductance of the participants.

Categories of the film clips	N	kNN	SVM	Naïve Bayes	LDA	AdaBoost
Anima, hero departure, hero initiation, hero rebirth, hero return, mentor, shadow	7	21.0	23.0	23.7	**28.0**	18.0
Anima, hero departure, mentor, shadow	4	36.6	39.9	35.5	**40.9**	37.0
Anima, hero initiation, mentor, shadow	4	37.5	44	44.7	**45.5**	22.5
Anima, hero rebirth, mentor, shadow	4	29.7	**39.5**	37.3	**39.5**	22.8
Anima, hero return, mentor shadow	4	37.0	39.1	35.9	**39.5**	27.2
Active-pleasant, active-unpleasant, neutral, passive-pleasant, passive-unpleasant	5	38.2	**40.6**	40.0	**40.6**	30.4
Active-unpleasant, neutral, passive-pleasant, passive-unpleasant	4	40.9	**46.0**	41.7	44.6	24.3

The first column reports the categories of the film clips that were included in the classification. The number of categories (N) included in the classification is specified in the second column. Other columns state the classification accuracy (per cent) achieved with various classification methods.

Table 6. Classification results obtained for recognition of the archetypes and explicit emotions from the complete dataset of the physiological signals.

Categories of the film clips	N	kNN	SVM	Naïve Bayes	LDA	AdaBoost
Anima, hero departure, hero initiation, hero rebirth, hero return, mentor, shadow	7	33.4	34.6	33.4	**36.7**	28.4
Anima, hero departure, mentor, shadow	4	52.9	50.7	**53.3**	51.4	50.7
Anima, hero initiation, mentor, shadow	4	54.1	56.0	55.6	**57.1**	45.8
Anima, hero rebirth, mentor, shadow	4	49.2	51.4	50.0	**52.9**	38.0
Anima, hero return, mentor shadow	4	**56.1**	52.2	53.6	52.9	49.3
Active-pleasant, active-unpleasant, neutral, passive-pleasant, passive-unpleasant	5	47.5	49.0	50.1	**50.7**	44.1
Active-unpleasant, neutral, passive-pleasant, passive-unpleasant	4	54.7	55.1	**57.2**	56.2	41.6

Note: The first column reports the categories of the film clips that were included in the classification. The number of categories (N) included in the classification is specified in the second column. Other columns state the classification accuracy (per cent) achieved with various classification methods.

Table 7. Comparison of classification accuracy achieved using the self-report questionnaires and physiological data.

Categories of the film clips	N	Self-reports	Physiological data
Anima, hero departure, hero initiation, hero rebirth, hero return, mentor, shadow	7	28.0	**36.7**
Anima, hero departure, mentor, shadow	4	42.0	**53.3**
Anima, hero initiation, mentor, shadow	4	43.1	**57.1**
Anima, hero rebirth, mentor, shadow	4	38.4	**52.9**
Anima, hero return, mentor shadow	4	40.6	**56.1**
Active-pleasant, active-unpleasant, neutral, passive-pleasant, passive-unpleasant	5	50.4	**50.7**
Active-unpleasant, neutral, passive-pleasant, passive-unpleasant	4	**64.9**	57.2

Although up to this point we focused on conducting between-subject classification, there is an opinion that due to physiological differences between individuals the algorithms for recognition of affective states work better if they were personalised. For instance, judging from the review provided in Novak *et al.* (2012), the studies that performed within-subjects recognition of psychological states achieved better results than the experiments where between-subjects approach were utilised. Although the main focus of our study was on investigating the feasibility of developing algorithms for between-subjects recognition of the archetypal experiences, we could also analyse the data from the participants individually. After we split the original dataset into 23 subsets in such a way that every dataset contained physiological data for one individual, two types of analysis were conducted.

First, we trained prediction models using one of the classification algorithms introduced above to recognise the archetypal experiences of the subjects. Before the training took place, we had to considerably reduce the number of features in order to avoid the unbalanced classification problem that is characterised by a high-dimensional and small sample size dataset. The reduction was performed using the technique described in the Methods section. It should be noted that although the actions for prevention of the unbalanced design were implemented, our results for the within-subject classification are still likely to be overoptimistic and should be interpreted as preliminary. A dedicated study with an emphasis on the within-subject design is required for more reliable evaluations. Having completed the classification for each of the participants, we calculated

Table 8. The means and standard errors (SE) of the recognition accuracies (per cent) calculated based on the within-subject classification.

		kNN		SVM		Naïve Bayes		LDA		AdaBoost	
Categories of the film clips	Gender	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Seven archetypes	Mixed	53.6	3.1	**70.3**	3.7	45.8	2.7	63.5	3.5	58.9	2.7
	Female	46.5	4.9	**67.0**	5.5	42.1	5	62.7	4.6	57.4	3.1
	Male	59.0	3.9	**72.9**	5.5	48.7	4.6	64.0	5.7	60.1	4.5
Five explicit emotions	Mixed	75.1	2.7	86.4	2.9	63.5	3.0	**86.6**	2.2	67.0	1.9
	Female	73.3	5.3	**86.0**	4.8	60.7	4.8	84.7	4.2	66.7	3.3
	Male	76.4	3.0	86.7	3.9	65.6	4.2	**88.2**	2.6	67.2	2.6

The classification rates were aggregated over the entire population of the subjects and in breakdown by genders. The data was obtained with the following five classification techniques: k-nearest neighbourhood (kNN); support vector machine (SVM); naïve Bayes, linear discriminant analysis (LDA); and Adaptive Boosting in combination with decision trees (AdaBoost).

separately the means and standard errors of the recognition accuracies across the whole population and for two gender groups. The best classification rate (70.3%) between seven archetypes was achieved with the SVM technique for the entire population of the subjects. If the participants were divided into gender groups, the recognition accuracy for the men was 72.8% (SVM), while for the women only 67.0% (SVM).

Second, the steps taken for the classification of the archetypal experiences were repeated in order to obtain prediction models for the explicit emotions. In this analysis, the LDA and the SVM techniques demonstrated almost identical performance. The five explicit emotions were classified with an average accuracy of 86.6% (LDA) on the dataset that consisted of the physiological data from the participants of both genders. Similar to the recognition of the archetypes, we could more reliably predict the explicit emotions for men (88.2%) rather than for women (84.7%). A detailed overview of the classification results is presented in Table 8.

4. Discussion

According to Jung, people share certain impersonal traits, which do not develop individually but are inherited and universal. These traits, which were described as the collective unconscious, motivate, and influence human behaviour, albeit individuals are not aware of their presence. In this way, they are different from explicit emotional feelings that are directly accessible for conscious recollection. The explicit emotional and cognitive states have been extensively studied with regard to their impact on HCI, but the feasibility of developing an interface that can capture implicit human experience remains an open question. It is not clear whether manifestations of the archetypes can be unobtrusively and accurately sensed by a machine. This question was investigated in our study, as the archetypal experiences were elicited in the subjects with the film clips and their psychophysiological responses were monitored with small wearable sensors.

4.1. *Self-reports data*

Besides recording the physiological signals of the subjects, we asked them to provide self-reports about their feelings by means of the SAM rankings after viewing every video clip. The statistical analysis indicated there was a significant relationship between the archetypal experiences pictured in the film clips and the SAM evaluations provided by the participants. Therefore, it seems the subjects could to a certain extent consciously report their feelings about the archetypes. Unsurprisingly, the relationship between the explicit emotions and the SAM ratings also was statistically significant. This finding was expected based on the previous literature in this field. Interestingly, the gender of the participants did not have any significant effect on their SAM evaluations. This observation merited attention because later we would see that the gender had some influence on the results of the within-subject analysis of the physiological data. While the MANOVA tests demonstrated that both the archetypes and the explicit emotions had a significant impact on the SAM rankings provided by the subjects, a further investigation was required in order to clarify the strength of these relationships. Therefore, we trained several classifiers on the SAM data and then compared their performance. The comparison indicated that the explicit emotions could be recognised with a considerably higher accuracy than the archetypes. From our point of view, this finding could be explained with two reasons. First, the archetypal appearances in the film clips were not readily registered and interpreted by the conscious minds of the participants. On the other hand, the subjects could consciously recognise and rate the explicit emotions more easily. Second, the SAM tool might be better suited for describing the explicit emotions rather than the archetypes because it was made specifically for this purpose. From our point of view, the SAM tool still was the most appropriate instrument we could use for the evaluation of the subjects' conscious responses because, to the best of our knowledge, there is no assessment technique that measures conscious reactions of an individual to archetypes.

4.2. Physiological data

According to the analysis we conducted, there was a statistically significant relationship between the physiological reactions of the participants to the presentation of the film clips and the categories of the explicit emotions portrayed in the videos. Further investigation involved training prediction models for recognition of the explicit emotions and evaluation of their performance using the cross-validation technique. This evaluation indicated that five classes of the explicit emotions could be recognised with an accuracy of 50.7%, and by removing one of the classes, we achieved the accuracy of 57.2%. Based on the review provided in Novak *et al.* (2012), it is evident that the predictive power of our models is on par with other affect recognition studies in terms of classification accuracy. There are studies where higher accuracies have been reported, for instance in Picard *et al.* (2001), Healey and Picard (2005), Sakr *et al.* (2010), and Soleymani *et al.* (2011) researchers were able to achieve classification precision of up to 97.4%. While we acknowledge their accomplishments, it is necessary to take into account two types of limitations that seem to exist in these studies. First, in many cases, the classification is subject-dependent, meaning that recognition algorithms are trained and optimised to perform well with physiological data from a particular person and cannot be successfully used for the general population. Second, the number of psychological states, which are predicted, is generally smaller. In fact, the greatest accuracy was obtained with the classification of only three affective states. Obviously, the more classes that need to be predicted, the more difficult the classification problem becomes. For example, in the case of two classes, an accuracy of 50% is attained simply by chance, while in a situation with five classes, the chance level is 20%. We should also emphasise the fact that that while in our study only two physiological signals were recorded (ECG and skin conductance), other researchers commonly include additional sources of data, such as EEG or eye gaze. The additional sources of data clearly contribute to the improved classification accuracy, but we intentionally kept the number of measurements low in order to obtain evaluations applicable to realistic application scenarios. Based on the classification results for the explicit emotions, we could conclude that our experimental design and methods were valid. It was then safe to proceed with the interpretation of the experimental findings for the archetypal experiences.

Similar to the explicit emotion, the statistical analysis identified a significant main effect of categories of the archetypal film clips on physiological responses elicited in the subjects by these videos. The results of the classification demonstrated that prediction models constructed with established data mining techniques and trained on the physiological data of the subjects achieved the accuracy which was considerably higher than the chance level. The models for seven classes of the archetypes featured classification rates up to 36.7%. When the number of the classes was reduced from seven to four, the recognition accuracy achieved was 57.1%. It was difficult to compare these results with the state of the art because we were not aware of studies that examined archetypal experiences of people from a psychophysiological perspective. In order to have a relative benchmark, obtained results could be set against the findings related to the explicit emotions. From the comparison presented in Table 7, it follows that the archetypal experiences were predicted with approximately the same accuracy as the explicit emotions. In fact, the recognition rate for the group of archetypes, which included the archetype of hero initiation, differed from the classification accuracy for the set of four explicit emotions only on a fraction of per cent.

Prior to the study, one of our concerns was that, in both film clips and real life, other factors may strongly influence emotional arousal and valence. Moreover, these effects may be sufficient to complicate recognition of the archetypal experiences with competing signals, i.e. we expected there to be a significant potential for confusion of the recogniser when confronted with variable emotional states. It also bears emphasis that emotion-influencing stimuli are likely more prevalent in day-to-day experience than archetype-inducing stimuli.

The results suggest that our concern was not justified. As we hypothesised, each of the archetypes triggers a particular pattern of affective and cognitive reactions in a subject. These reactions led to activations in the ANS of the subjects that were measured with physiological sensors. Naturally, a superposition of the affective and cognitive responses forming an archetypal experience and another affective state could occur. Moreover, we are confident that such overlays took place when the subjects were watching the film clips during this experiment, and from our point of view, it is not possible to avoid them. This is likely one of the reasons why the classifier could not achieve accuracy higher than 57.1%. On the other hand, the film clips that depicted one of the pure explicit emotional feelings were not classified with a better accuracy than the archetypal film clips. Thus, it seems the archetypes lead to considerably powerful physiological reactions of the subjects, which could be identified even though the recogniser had to deal with competing signals.

We also analysed the potential for recognition of the subjects' psychological states from independent physiological signals. According to the results presented in Table 4, prediction models trained exclusively on the ECG data achieved recognition rates of up to 44.6% for the archetypes and 43.1% for the explicit emotions. On the other hand, as it can be seen from Table 5, the skin conductance data enabled us to train models that featured accuracies of up to 45.5% for the archetypes and 46.0% for the explicit emotions. It seems that a fusion of the independent physiological signals is required to achieve more reliable classification results.

Overall, the experimental findings indicate a positive relationship between the physiological signals of subjects and the induced archetypes. Moreover, we were able to train prediction models, which differentiated between four archetypes with an accuracy of up to 57.1%. Our results for the classification of the explicit emotions and the archetypes were almost identical. From our point of view, the fact that a similar recognition accuracy of archetypes compared to the classification of arousal and valence was achieved is a good accomplishment. Prior to the study, we expected a lower classification performance due to the complex nature of archetypes.

Although the obtained prediction models demonstrated performance that was considerably higher than the chance level, they still may not be good enough for practical applications. For this reason, we sought ways to improve the recognition performance. A common approach to address this problem in affective computing is to use within-subject rather than between-subject datasets for training of the classifiers. Our findings summarised in Table 8 suggest that a switch from the between-subject to within-subject classification indeed could lead to better performance. Although these results may be overoptimistic due to a relatively low number of data samples per individual, they can be considered as preliminary evidence in favour of the proposed approach. Another observation related to the within-subject classification is that the prediction models were generally more accurate for male participants. This finding was interesting because we expected that women may have a higher predisposition for being 'touched' by the film clips and, consequently, exhibit more pronounced patterns of the physiological activations.

4.3. Archetypal stimuli

The selection of the archetypal stimuli was primarily based on the feedback obtained from the experts. After the experiment, the collected data also enabled us to indirectly evaluate validity of the chosen film clips.

According to Rottenberg *et al.* (2007), validation of film clips on the basis of self-reported emotional ratings is a significantly limited approach because even the most robust self-reported norms provide no guarantee that a film will elicit the desired emotional experience. In case of the films with archetypal appearances, it was reasonable to expect even less benefit in the application of this approach.

For this reason, it was decided to approach the problem of selecting and validating the archetypal stimuli in a qualitative manner. We contacted one of the most competent research organisations that specialise in the archetypal symbolism: The ARAS associated with The C.G. Jung Institute of San Francisco. The film clips were then evaluated by a group of four experts from this organisation. They were asked to independently rate the film clips using a very simple scale. Each film clip was classified either as 'good enough' or 'not good enough'. A film clip had to be approved by all the four experts in order to be selected. Therefore, the inter-rater reliability for the chosen film clips measured with the intraclass correlation coefficient was 1.0. The inter-rater reliability on the judgment among all 21 clips (including the non-selected ones) given by the four reviewers was 0.4. A pool of the film clips obtained through this collaboration was used in our previous experiment (Chang *et al.* 2013b). This pool of stimuli served as an input for the present study.

After the study, we could apply the principle of triangulation (Moran-Ellis *et al.* 2006) in order to estimate whether the film clips elicited the expected archetypal experience. Healey (2011) illustrated that the triangulation of multiple sources of information leads to a better set of affective labels. We combined the qualitative recommendations obtained from ARAS with the quantitative physiological data. The qualitative information served as a primary source of validation. Additionally, the classification performance of the prediction models trained on the physiological data corresponding to the archetypal stimuli suggested that these stimuli led to uniform response patterns in the ANS of the participants.

Finally, we applied the approach known as 'direct and indirect measures' (Reingold and Merikle 1990) for the measurement of the participants' conscious awareness about the archetypal stimuli. According to this approach, the subjects are consciously unaware of the effects of the stimuli if the sensitivity of the indirect measure is greater than the sensitivity of the direct measure. In our study, the self-reports were assumed to fulfils the role of the direct measure and the physiological responses were considered as the indirect measure. As the analysis of the data collected in the experiment suggests, the indirect measure seemed to perform better than the direct measure in case of the archetypal stimuli.

Overall, the problem of selection and validation of the archetypal stimuli is challenging. This study represents one of the first steps in this direction. We hope to address this problem with a greater detail in the future research.

4.4. Limitations

The present study has some limitations. One limitation is the relatively small number of participants. If we talk about the within-subject classification then it is necessary to mention that more data samples per subject would be beneficial. Another limitation is that the participants did not move much during the presentation of the stimuli and, thus, movement artefacts in the physiological measurements were minimal. In many practical scenarios it is reasonable to expect movements of users. For this reason, additional filters for the elimination of the noise generated by movements have to be introduced. Also, strictly speaking, the results of the study just showed that the archetypes in the film clips could be distinguished by the physiological reactions of their viewers. The results do not imply that the archetypes were actually activated in individuals. Besides, it is necessary to mention that the SAM instrument could only capture the emotional aspects of the archetypal experiences. This instrument could not possibly cover other facets of the archetypal experience, such as thoughts or ideas. Finally, the generalisability of the experimental findings is limited. We did our utmost to ensure the obtained models provided valid predictions by applying an appropriate statistical technique but the reported results should be repeated in several other studies for the final confirmation of their generalisability.

5. Conclusion

Besides explicit emotional feelings that are easily available for conscious recollection, people have unconscious experiences that nevertheless drive their decisions, motivations, and behaviours. Unlike explicit emotions, unconscious or implicit experiences have received little attention in the field of HCI. In this study, we investigated whether the archetypal experiences of users, which in part constitute the unconscious, produce distinct patterns of physiological responses and estimated the feasibility of the automated recognition of such experiences with wearable sensors for measurement of cardiovascular and electrodermal activities. Seven archetypes and five explicit emotions were included in the study and presented to subjects by means of the film clips. Following the presentation of every video, the participants were asked to provide a conscious report about their feelings. The statistical analysis demonstrated that the film clips with both the archetypes and the explicit emotions led to significantly different psychophysiological responses. Then, the data mining techniques were applied to the subjects' self-reports and their physiological data in order to construct several prediction models. In case of the archetypal film clips, the models trained on the physiological data demonstrated better performance (57.1%) than the models built based on the self-reports (43.1%). We encountered an opposite finding during the evaluation of the models for the explicit emotions. The models that were built based on the SAM reports featured higher classification accuracy (64.9%) than the models trained on the physiological data (57.2%). Thus, it seems that by using the physiological signals the archetypes could be distinguished as accurately as the explicit emotions. Moreover, our research findings suggest the subjects had more conscious awareness about the explicit emotions rather than the archetypal experiences. Although the classification performance for the archetypes was considerably higher than the chance level, it may not be robust enough for practical applications. Therefore, we carried out a preliminary evaluation to see whether a switch from the between-subject to within-subject modelling could benefit the recognition accuracy. Our analysis was performed on small data samples and may be overoptimistic, but it indicated that the classification rate for seven classes of the archetypes could be improved up to 70.3% by using within-subject models. Overall, our findings suggest the archetypes could be identified in human experience through physiological measurements even though they may not always be consciously recognised by the individuals.

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Note

1. https://play.google.com/store/apps/details?id=org.hxresearch.archesense.

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