Heartefacts: Augmenting Mobile Video Sharing Using Wrist-Worn Heart Rate Sensors

Anonymized for blind review.

ABSTRACT

An increasing share of our daily interactions with others is mediated through mobile communication technologies. People communicate not only via text, but also emoticons, emojis and rich media such as audio and video. In this paper, we present a survey examining video sharing behaviour, and an exploratory study examining the benefits and feasibility of automatically detecting highlights in media content by monitoring people's heart rates with wrist-worn sensors. Our results show that people do indeed have measurable responses with respect to their heartbeat patterns to six different emotions elicited by video clips. We compare these to video highlights verbally identified by our participants and an expert in video art and present a prototype of a *Heartefact,* a video composed of highlights determined by heart rate changes.

Author Keywords

HR; Smartwatch Interaction; Empathic Computing; Mobile Computing.

ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION

Communication services such as email, text messaging, and instant messaging, have heralded an increase in the share of our daily interactions with others taking place online instead of in person. Fast mobile communication networks, smartphones and social media have enabled anytime, anywhere, and anyplace sharing of rich media such as pictures and videos.

At the same time, recent advances in mobile sensing have enabled devices and corresponding services to recognize our physical activity [7,19], movement patterns [17], level of attentiveness [24] and even boredom [23]. Wearables such as smartwatches give further potential to collect personal data with physiological sensors that are intended to be constantly in contact with the wearer's body, such as optical heart rate (HR) monitors.

In this paper, we investigate the potential of using wearables with embedded HR monitors to enrich mobile interactions. These devices are becoming more common and are usually linked to our smartphones via Bluetooth, providing the possibility for a constant stream of physiological data that can be tapped into by mobile applications. However, we have yet to see many applications that employ HR data for other purposes than fitness tracking.

Recently, the Apple Watch [36], embedded with a HR monitor, enabled wearers to share a representation of their HR with people in their contact lists. However, it has been shown that people can have reservations towards directly sharing their HR with others. Slovák et al. [30] report that participants expressed a need for knowing the context in which a HR was shared. We found that people thought that directly sharing their HR together with videos or social media was an invasion of privacy or considered to be "weird", which we will discuss later in the paper. Similarly, Werner et al. [35] found that some people may feel like they are under surveillance when continuously and directly sharing their HR with a partner.

Instead, in this paper, we explore the potential of HR monitoring to indirectly augment mobile video sharing. In particular, we investigated the possibility of using a person's HR to create a video artefact, or *Heartefact,* composed of highlights that the person responded to physiologically. The popularity of short video cuts, which can be seen on video services such as Vine and Instagram suggest that quick video edits can still produce videos that are widely shared. The results of our exploratory studies suggest that it is feasible to automatically detect highlights in videos using continuous HR sensing on wrist-worn wearables.

We make the following contributions:

- We present insights from an online survey with 48 participants on current video sharing behaviours, with a particular focus on emotional aspects of video sharing.
- We conducted an exploratory study with 14 participants to investigate whether people indeed show changes in HR that are measureable by wrist-worn

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HR sensors in response to a set of emotion-provoking videos.

- We use these changes in HR to determine possible highlights in each video and created a video artefact (*Heartefact*) based on these highlights. We compare this video artefact with highlights of the videos as determined by an expert.

RELATED WORK

There has been some interest in the community in enabling people who may be physically separated to share HR data in order to maintain a feeling of closeness. Slovák et al. [30] examined using technology to enable sharing HRs with people in other locations, and indeed, participants expressed that they felt physically closer to each other when they could get another person's HR feedback. Thus, sharing one's HR can become a way of creating presence in absence. Werner et al. [35] developed a prototype for a set of rings to be worn by couples that measure the wearer's HR and send it to their partner's ring. The rings were found to help create and reinforce feelings of intimacy. Participants reported that feeling their partner's HR created a sense of artificial corporeality.

Changes in Heart Rate During Emotional Responses

The HR in beats per minute (bpm) can vary according to different factors, such as a person's age, body weight, heart conditions, or their physical condition. The normal resting HR for an adult human being usually averages 60 to 80 bpm, but can occasionally exceed 100 bpm in unconditioned sedentary individuals, and can be as low as 30 bpm in professional endurance athletes [8]. Physiological responses such as the HR (HR) or galvanic skin response (GSR) are widely thought to have a relation to changes in emotion [16]. Additionally, people's physical state or behaviour such as speech, facial expressions [5], or body postures [31] have been used in emotion recognition technology.

Physiologically, a person's HR is regulated by the sympathetic and parasympathetic nervous system [25]. The sympathetic nervous system stimulates the body's fight-or-flight response. For example, when people are confronting potential dangers, the HR will increase. The other autonomic nervous system is the parasympathetic branch, which stimulates the body to "rest and digest" or "feed and breed". The parasympathetic branch acts faster and with greater precision in terms of influencing a person's HR [32].

Heart Rate Sharing

Slovák et al. [30] distinguish two types of HR data that is commonly shared: HR as information, and HR as connection. Participants expressed a need for contextual information to guide interpreting the HR and they thought HR could be interesting and useful only in situations that were emotionally relevant to others. Many people consider HR as an uncontrollable reflection of their internal emotions. In some contexts people may not be willing to disclose their HR as a result of privacy concerns [30]. However, for annotating shared media, the context of sharing information is quite clear (i.e., people sharing media with friends), which can minimize concerns that people have towards HR sharing.

As opposed to sharing direct biometric HR information [9], previous studies have also investigated creating more abstract HR representations [14,15]. Our idea of creating video artefacts (or Heartefacts) based on HR data is inspired by these examples.

Heart Rate Changes While Watching Pictures or Videos

Vrana and Lang [33] found that when participants in their study were confronted by a real threatening stimulus and their memories were actively processing fear information, they showed HR *acceleration* in response to fear and distress. By contrast, a person's HR *decreases* when shown representations of fearful or aversive stimuli. When participants viewed unpleasant films or pictures without being directly in the aversive context themselves, they showed HR deceleration rather than acceleration. Additionally, Vrana and Lang's results showed an average increase of 2.1 bmp during 6 seconds of the participant being shown fearful images [33]. They also report that the HR response for startling from being shown images is not as robust as for the startle probe.

The follow-up study conducted by Bradley et al. [4] provided more details about how HR can fluctuate in the context of picture views. Specifically, HR deceleration was largest when viewing unpleasant pictures compared to neutral pictures. Palomba et al. [22] found similar results showing HR deceleration when participants viewed slides representing pleasant, neutral as well as unpleasant stimuli for 6 seconds each. Unpleasant stimuli triggered the largest deceleration, followed by neutral and pleasant stimuli. Anttonen and Surakka [2] reported that participants' HRs recovered more rapidly from positive emotions than from negative emotions. When exposed to positive stimuli, the average HR of the subjects decreased for the first two seconds and then started to revert back while the HR continued to drop during negative emotional simulation.

Mobile Applications Using Physiological Data

Sas et al. developed AffectCam [28], a combination of SenseCam and BodyMedia SenseWear that measured galvanic skin response to distinguish pictures that were taken during higher and lower arousal. EmoSnaps [20] is a mobile application for emotion recall through facial expressions. It unobtrusively captures pictures of people's facial expressions through their smartphones to improve the reliability of experience sampling.

Shirokura et al. [29] developed AffectiView, a mobile video camera application that captures people's affective response using their skin conductance level (SCL) while they are capturing videos. The video can then be shared, along with affective data. Their user study showed a positive effect and that it is possible to share affective experience by sharing physiological signals. This idea is similar to our concept, but we use HR rather than SCL to measure emotional changes as a result of the development of wearable technology.

ONLINE SURVEY ON VIDEO SHARING BEHAVIOUR

We conducted an online survey to get a better understanding of people's online video sharing and viewing preferences and behaviours. The survey ran for approximately 3 weeks (27 days) and was announced on social media and on university mailing lists. It consisted of 24 questions collecting information about demographics, video sharing behaviour, mobile and wearable device usage and attitudes towards sharing, monitoring and utilising HR information. Participants took on average approximately 10 minutes to fill in the survey.

Participants and Demographics

We collected 48 complete responses to the survey. Participants (22 female, 26 male) had a mean age of 33.31 (SD = 9.57, min = 23, max = 66). Most participants were between 20 and 40 years old (89.6%), with the largest group being between 25 and 35 years old (64.6%). In terms of their occupation, most participants described themselves as being either a professional (43.8%) or a student (39.6%).

Device Usage

Wearable Devices and Heart Rate Monitoring Capabilities

Survey respondents were asked which wearable devices they used: an activity tracking bracelet, a smartwatch, both, or neither. The majority of participants (77.1%) indicated they did not use either of these devices, while only 7 (12.5%) used an activity tracking bracelet and 4 (8.3%) used a smartwatch. One participant reported using both.

Of the people using wearable devices, 7 out of 11 indicated that their devices monitor their HR, which suggests that HR monitoring is becoming a common feature in both wearable activity trackers and smartwatches.

Device Usage for Sharing, Receiving and Viewing Videos

We also inquired about the devices people mostly use for viewing videos and for sharing videos with others, and on which device they usually receive videos from others. The possible options for these three multiple choice questions were: a wearable device (e.g., a smartwatch), a smartphone, tablet, laptop, desktop, or large screen (e.g., a TV or projector).

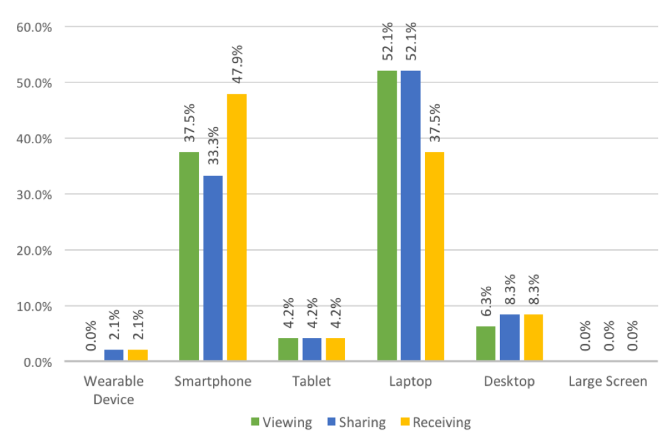

Figure 1. Number of participants using different devices for viewing, sharing and receiving videos.

As shown in Figure 1, participants mostly used their smartphones and laptops for all three activities. Smartphones were used most for receiving videos (47.9%), while laptops were mostly used for viewing videos and sharing them with others (52.1%). Only one participant received and shared videos on their wearable device, but did not view them on the device.

We can see from this data that videos are viewed on a smartphone almost as often as on a laptop. We hypothesize that people use both mobile devices and devices with larger screens such as laptops, but that they use them for different purposes. O'Hara et al. [21] observed that people watched certain content together with their partners or families, and that viewing this content on mobile devices would remove this opportunity for a shared experience. Nevertheless, they found that mobile devices were used to shift video viewing to other environments (e.g., to pass time on a commute) or to watch content that their partner or family members do not like, and thus may not be watched together [21].

Participants reported that they did not often view online videos on larger screens. Again, O'Hara et al. [21] reported similar findings due to the specific affordances of mobile devices. For example, mobile devices allow people to watch videos in a shared space while still maintaining a degree of separateness, and watching videos on the main TV in the household is dominated by who controls that device.

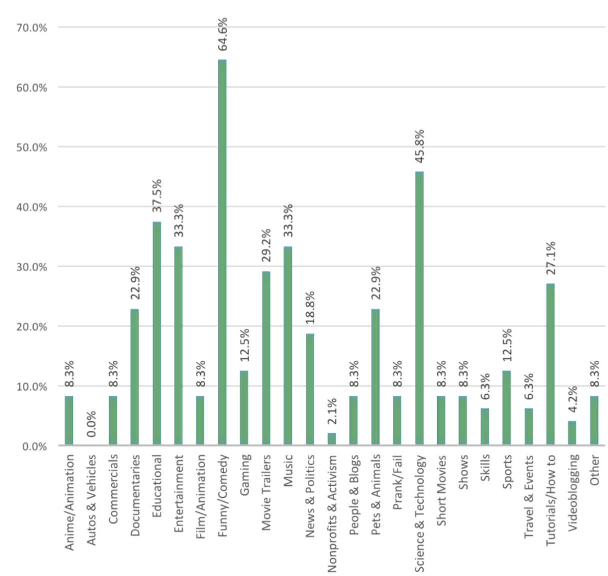

Figure 2. Types of shared online videos (percentage of participants that selected each answer).

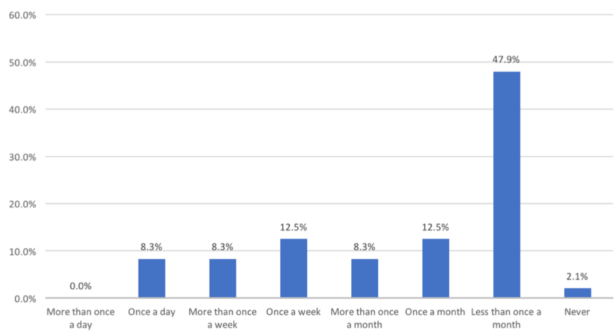

Figure 3. Frequency of sharing online videos.

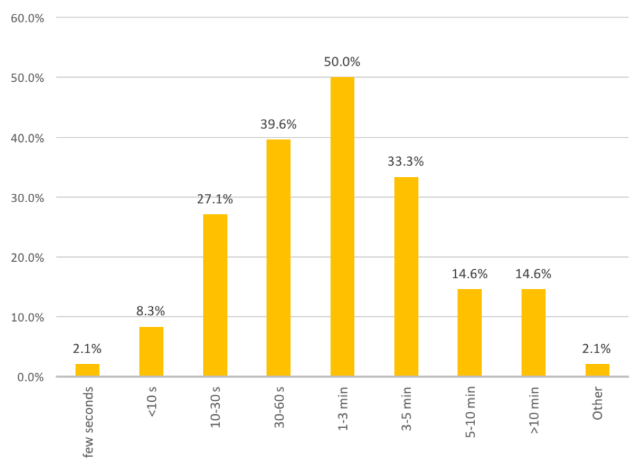

Figure 4. Duration of shared online videos (percentage of participants that selected each answer).

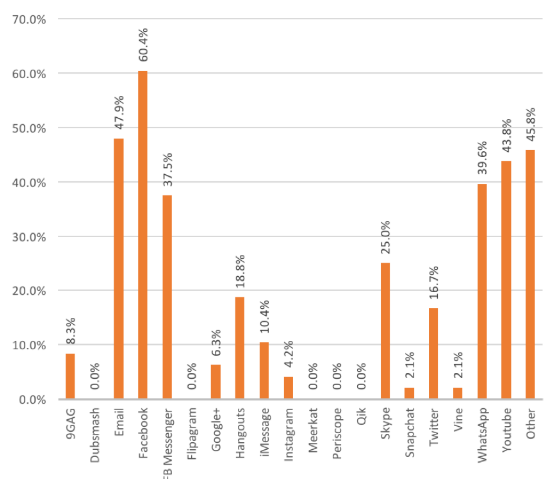

Figure 5. Video sharing services used by respondents (percentage of participants that selected each answer).

Video Content and Means of Sharing

Video Sharing Services

We asked respondents which services they use to share videos. We provided 19 predefined answers, based on a set of popular messaging and online video platforms (e.g., YouTube, Facebook, Whatsapp) and also allowed respondents to enter other services that were not listed.

Figure 5 shows the different services respondents indicated they used for video sharing. People use a variety of different services. Facebook is used most (60.4%), followed by email (47.9%) and YouTube (43.8%). Instant messaging apps and services such as WhatsApp (39.6%), Facebook Messenger (37.5%), Skype (25%) and Hangouts (18.8%) are also popular. In terms of other services, several respondents mentioned they also used cloud services (e.g., Dropbox, Google Drive) for video sharing. The prevalence of mobile services and social networks paves the way for coupling HR monitoring and mobile video consumption and sharing.

Duration of Videos

Respondents were asked about the duration of the videos they shared, with a range of possible durations (multiple choice). As shown in Figure 4, participants mostly shared short videos. Most participants indicated they share videos that are shorter than 3 minutes, with a minority of respondents reporting they shared videos longer than 5 minutes.

Previous studies have found that more than 20% of videos on YouTube were shorter than 1 minute in 2007, and still made up more than 16% of videos in 2013 [6]. A new trend in video services such as Vine and Instagram demonstrates the desire to create and share very short clips. This also motivates creating short video artefacts based on physiological signals that can be shared later.

Frequency of Video Sharing

Figure 3 shows the frequency with which participants tended to share videos. About half of the respondents reported sharing videos at least once a month (50%), with less than a third of participants (29.1%) reporting that they share videos at least weekly.

Type of Videos Shared

We asked participants about the type of videos they shared, and the source of the shared videos (who created them). We provided a list of video types based on YouTube's list of video categories.

As shown in Figure 2, people mostly share funny videos. Most people shared videos they either found online (77%) or created themselves (19%).

Target Audience for Video Sharing

Participants reported mostly sharing videos with their friends (91%) and family (62.5%). In addition to this, 23% of participants reported sharing videos publicly.

Communicating Responses to Shared Videos

We asked respondents how they communicate their feelings about videos that were shared with them. Most respondents (83.3%) indicated they relied on text (e.g., instant messages, comments on social media). Additionally, they used emoticons (45.8%) and/or acronyms (27.1%) such as LOL, OMG, or WTF. Interestingly, none of them indicated that they would share a video, picture or selfie of their reaction to the video.

Attitudes towards HR Sharing

To get a better understanding of people's attitudes towards sharing their HR data in response to video, we asked respondents whether they thought this was a useful feature, and how they wanted their HR data represented along with the video.

Sharing Physiological Signals on Social Media

When asked how interested respondents were in sharing their HR on a 5-point Likert scale ranging from 1 (not interested at all) to 5 (very interested), they reported not being very interested in this feature (mean = 2.31, SD=1.15). This confirms earlier findings with respect to people's reservations towards directly sharing their HR with others [30,35]. Several respondents commented that this was "weird", "too personal", a "scary concept", and "an invasion of privacy". However, we did also receive a few other comments suggesting that this was "an interesting idea".

These findings suggest that people regard this data as being sensitive and private and have reservations about HR data sharing on social media. Despite this, we hypothesized that creating a representation of HR data rather than directly sharing a HR could be a more attractive prospect.

Representation of Heart Rate

Finally, respondents were asked for their preference on representations of HR changes. Despite reservations about having their HR represented alongside a video, many indicated a preference for a visual graph of the HR (43% of participants) or a beating heart symbol (37.5%). Vibrations were the least popular option (12%). Some people in Werner et al.'s study [35] also reported being irritated by vibrations representing a HR. This tells us that an aggregated representation of changes in HR is preferable over a continuous representation.

Seven participants wanted no representation at all. One participant indicated in the comments they wanted to have this representation before watching the video and not during, so that it would not distract them. This made us think about creating a representation of the HR using the video itself.

EXPLORATORY STUDY

To investigate the feasibility of detecting highlights in videos using wrist-worn HR sensors, we measured participants' HRs while watching 7 videos on a smartphone. Given the popularity of funny videos in the survey, we used video clips that elicit emotional responses. We based our study on previous experiments by Gross and Levenson [11] and Rottenberg et al. [27], who provide a set of example video clips that have been verified to work well for eliciting certain emotional responses. We selected seven videos out of this set: six videos that elicit amusement, sadness, anger, fear, disgust, and surprise respectively, in addition to an emotionally neutral video.

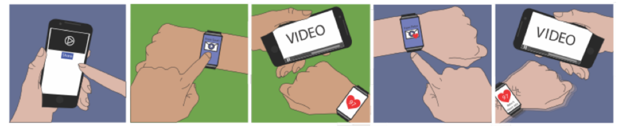

Figure 6. Tom (blue background) shares a video with Lisa (green background) using ShareABeat [8]. After Lisa has watched the video, Tom receives Lisa' highlights and heart beat.

While watching the videos, the participant's HR was recorded via two different wrist-worn sensors. We then analysed participants' HRs in the different videos. Additionally, participants were asked to indicate their subjective highlights of the video that best represented the strongest emotion they encountered (e.g., the funniest or scariest parts of the video).

Participants

Fourteen participants (3 female, 9 male) between 20 and 28 years old, with a mean age of 24.3 (SD = 5.3) took part in the study. Participants were recruited via institutional mailing lists and personal contacts. All participants were university students. None of them had used a smartwatch before nor had previous experience with having their HR recorded while watching a video.

Apparatus

To conduct the study, we extended an exploratory application, ShareABeat [10], with logging support and the ability to play local videos. In ShareABeat, a person's HR is sent from their smartwatch to an Android smartphone application playing the video, where it is then aligned to the video. People's reactions to videos are created from generating a shortened version of the video by selecting a 10-second window around the moment in the video with the highest recorded HR. The person's heartbeats are represented by vibrations on the other person's smartwatch.

The original application was implemented on a Samsung Android smartphone connected via Bluetooth to a Samsung Galaxy Gear Live smartwatch (running Android Wear) and allowed people to share highlights of YouTube videos based on their HR data.

For the study described in this paper, we showed locally stored videos in a custom Android window on a Motorola Moto G (2nd generation) smartphone with a 5” display. HR measures were recorded using optical HR sensors on two devices: a Moto 360 Android Wear smartwatch worn on the left wrist and a Mio Link wristband worn on the right wrist of the participants. The phone ran an Android application that was connected to the Moto 360 smartwatch and Mio Link via Bluetooth LE. The user interface of the application consisted of a full screen video player interface. Recorded HR data from both wrist-worn sensors was captured, logged and synchronized with the video timings when the video started playing. The smartphone and smartwatch ran on Android 5.0.2 and 5.1.1 respectively.

Although we set out to measure HRs using two devices, we could not get reliable measurements with the Moto 360 for several participants. In contrast, the Mio Link gave us consistently reliable and smooth results. Because of this, we decided to only analyse the Mio Link data in the study. Even though dedicated sports HR monitors such as the Mio Link tend to be more reliable at the moment, we expect smartwatch technology to catch up in coming years.

Tasks and Procedure

The study was conducted in a quiet meeting room to reduce any distractions. Participants were asked to agree to a consent form before starting the study and were provided with a short explanation of the study procedure. Participants were informed they could quit the experiment at any moment if they felt uncomfortable.

Before starting the main experiment, participants filled in a short pre-study questionnaire. We collected demographic data and inquired about previous experiences with smartwatches and HR sensors.

Each participant was then asked to watch seven different videos, which were counterbalanced across participants. When participants were watching videos on the phone, the lights were turned off to allow participants to better concentrate on the videos and avoid glare effects on the mobile phone from overhead lighting.

We used the recommended videos from Rottenberg et al.’s instructions for emotion elicitation using films [27]. They recommended twelve videos that represent seven different emotions: amusement, anger, disgust, fear, neutral, sadness and surprise. We chose seven of these videos that represent six different emotions in addition to a neutral video. We created the different video clips based on the detailed editing instructions provided by Rottenberg et al. [27].

As mentioned earlier, these videos have been proven to elicit an emotional response from viewers and therefore we were confident that they would produce HR changes that could be picked up by our application. We hypothesized that funny or amusing videos may elicit a larger change in HR and therefore more clearly identify highlights to be used in creating a heartefact. However, we wanted to see if

Figure 7. The different video clips used in the study: (a) amusement, (b) anger, (c) disgust, (d) fear, (e) neutral, (f) sadness, and (g) surprise. Clips were selected and edited based on earlier experiments by Rottenberg et al. [3].

videos shown to elicit other types of emotions were equally affective on participants’ HRs.

The following films were used (representative still frames of the films are shown in Figure 7): When Harry Met Sally – Amusement (Figure 7a); My Bodyguard – Anger (Figure 7b); Pink Flamingos – Disgusting (Figure 7c); The Shining – Fear (Figure 7d); Alaska’s Wild Denali – Neutral (Figure 7e); The Lion King – Sadness (Figure 7f); and Capricorn One – Surprise (Figure 7g).

Participants were assisted with putting on both wearable devices on the left and right wrist respectively. As mentioned earlier, we eventually only analysed data from the Mio Link. After making sure that at least one HR monitor was was correctly working, participants started to watch the videos in the order that was given to them by the researcher.

After participants finished watching each video, they were asked to fill out a short post-film questionnaire about it. Participants were asked to rate the strength of each of the six emotions as experienced while watching the video. The strength of the emotions was rated on a 9-point Likert scale ranging from “not at all” (0) to “extremely” (8), which was inspired by the existing experiments by Rottenberg et al [27]. We used this data to confirm that the selected video clips effectively evoked an emotional response.

Finally, participants were asked to indicate the most representative emotional parts of the video clip. The researcher reviewed the video with the participant after watching it to record the timestamps for these highlights. Filling in post-film questionnaires usually took about five to six minutes. Participants expressed that this short break was long enough for them to calm down in between video clips.

Finally, we conducted a semi-structured interview to get qualitative feedback on the application after participants finished watching all the videos. The average experiment completion time for each participant was one hour.

RESULTS

We now report on the results of our exploratory study using video to evoke emotional responses from participants wearing wrist-worn HR monitors.

Emotional Effectiveness of the Video Clips

As mentioned earlier, participants were asked to rate the videos in terms of six emotions on a 9-point Likert scale. This allowed us to confirm whether the videos evoked emotional responses, and whether these emotions corresponded to those reported by Rottenberg et al. [27]. The overall results of self-reported emotions are presented in Table 1.

These results are generally in line with Rottenberg et al.'s [27] experiments. Taking "When Harry Met Sally" as an example, an ANOVA demonstrates a significant effect (F(5, 43.15), Pr>F=2e-16, p<~0)) with a post-hoc Tukey analysis showing Amusement and Surprise being significantly different (p<0.05) to all the other emotions for this video (but not to each other). We report this in the table by the number in square brackets identifying how many other emotions it statistically dominates, if there is any significant effect at all. Thus, a video that has one dominant emotion will have a value of 5 in between square brackets. As shown in Table 1, all videos except for "Alaska's Wild Denali" (the neutral video) evoke a clear emotional response, with the strongest emotion being the one identified by Rottenberg et al.. For the neutral video, no particular emotion is strong, though Amusement is still significantly greater than other emotions. Note that the video clip we used for amusement ("When Harry Met Sally") additionally evoked surprise, an effect that was not present in the original study [27]. This might be due to the fact that 13 out of 14 participants had not seen this video clip before (being mostly of a younger generation).

HR Measurements

As mentioned earlier, we recorded the HR of participants while they watched each of the seven video clips. To compensate for people having different resting HRs, we first aligned all HRs to start from zero when the video started playing. From that point on, we calculated the HR change over time (in bpm) compared to their starting HR. From this data, we then plotted the mean HR change over all participants for each video.

Due to technical issues with our application, we lost HR data for 6 out of 98 (14x7) video logs. In particular, we lost the HR data of two participants for "My Bodyguard", and data of one participant for "The Lion King", "Pink Flamingos", and "Capricorn One". Additionally, we excluded data from participants whose HR fluctuated more than twice the standard deviation during each video. For example, P9's HR fluctuated between 75 and 175 bpm when watching one of the videos. Since this only happened during some of the videos, we assume this was due to a technical issue with our apparatus as opposed to an underlying medical condition.

	Amusement	Anger	Fear	Disgust	Sadness	Surprise
When Harry Met Sally	**6.07** (1.38) [4]	0.43 (0.76)	0.93 (1.86)	1.29 (1.33)	0.29 (0.61)	5.86 (2.06) [4]
My Bodyguard	0.79 (1.42)	**4.79** (2.08) [4]	2.29 (2.09)	1.93 (2.20)	3.64 (2.20)	2.35 (1.90)
The Shining	0.5 (0.76)	0.5 (0.76)	**4.14** (1.56) [4]	0.71 (1.20)	1.00 (1.70)	2.36 (2.13)
Pink Flamingos	2.29 (2.43)	1.29 (1.77)	1.14 (1.35)	**5.64** (2.30) [4]	0.71 (1.44)	3.93 (2.50)
The Lion King	1.14 (1.66)	2.64 (2.13)	1.64 (1.82)	0.79 (1.12)	**5.79** (2.26) [5]	2.43 (2.31)
Capricorn One	0.79 (1.12)	0.79 (1.12)	2.71 (1.90) [4]	0.64 (1.39)	0.86 (1.40)	**5.93** (1.14) [5]
Alaska's Wild Denali	2.93 (2.43) [4]	0.43 (0.93)	0.71 (2.12)	0.35 (0.63)	0.50 (1.16)	1.57 (1.95)

Table 1. Mean (SD) for self-reported emotions from the seven videos. The number of other emotions pairwise-dominated by the identified one if there is a significant effect, in [].

For the personal highlights of the video clips, we calculated the mean start and end point of the highlights over all recorded timestamps as indicated by our participants. When there were multiple highlights in a video, we manually checked whether they corresponded to the same highlight or whether it was a different one. In what follows, we analyze participants' HRs for each video.

Amusement

To elicit amusement, we used a video clip from the movie "When Harry Met Sally" [26]. The video depicts Harry and Sally sitting together in a crowded restaurant.

Figure 8a shows the average HR of participants in response to the video. Note that there is a continuous, slight deceleration during the first minute of the video, followed by a steep drop at around 80 seconds. At that moment in the video, Sally starts to loudly fake an orgasm. The remainder of the video depicts the funny consequences of this situation. Even though people report the last part of the video to be the highlight of the video, the data suggests that something interesting is happening in the video around 80–100 seconds. At around 100 seconds, the HR seems to recover from that drop and rises again towards the end of the video with a couple of smaller peaks.

Previous studies report different effects of amusement on people's HR, including deceleration, acceleration as well no change in HR [16]. Since surprise was another emotion reported for this video, some effects in the HR graph may be caused by a response to this emotion instead.

Sadness

We used a video clip from the movie "The Lion King" [1] to evoke sadness. The clip depicts the death of Mufasa, the father of the main character, a lion cub called Simba. Simba finds his father's dead body and cries.

Analyzing the HR graph in Figure 8b, we see that participants indicated two emotional highlights. The first one corresponds to the scene where Mufasa is pushed of the cliff by Scar (14s – 23s). The second one (93s – 131s) corresponds to the part in the video where Simba discovers that his father is dead. In the first part, we see a very apparent deceleration in the HR data (approximately 5 bpm). The HR rises again later in the video with no equally remarkable changes in HR, even though there is another slight drop during the second highlight. Some previous studies have indeed reported HR deceleration in response to films that evoked sadness [16].

Disgust

To evoke disgust, we used a video clip from "Pink Flamingos" [34]. This clip shows a drag queen eating fresh dog feces.

The graph in Figure 8c shows two noticeable drops in HR: one at around 10 seconds, and another one at 35 seconds. The first deceleration corresponds to the close-ups of the actor's face, while the second one corresponds to the part where the actor picks up and eats the dog's feces. Participants also reported this second part to be the highlight of the video. In total, the average HR drops strongly compared to the starting HR (approximately 7 bpm). Previous studies have indeed found that "negative" emotions such as disgust show stronger HR deceleration [2,33]. On the other hand, several studies show that contamination-based disgust such as in this video was associated with HR acceleration [16].

Anger

We selected a video clip from the movie "My Bodyguard" [3] to elicit anger. The video depicts the main character being bullied, and ends with the bully pushing the main character's motorcycle into a lake. Figure 9b shows the HR graph for this video clip.

The video starts with a confrontation between the main character and their bully. At around 20 seconds, the bully pushes the main character down onto a table. There is a steep drop in the averaged HRs (a change of approximately 5–6 bpm) around 20 seconds, as shown in Figure 8d. For the remainder of the video, the HR fluctuates with a number of smaller peaks and valleys. Note that the reported level of anger was fairly low for this video clip and the emotional responses also included sadness (see Table 1), which may influence results. Nevertheless, there is a clear deceleration at around 20 seconds. The highlight indicated by participants generally refers to the resolution of the confrontation: when the bully pushes the motorcycle into the lake. However, there does not seem to be a discernible response in HR to this part of the video.

Fear

To evoke fear, we use a video clip from Kubrick's "The Shining" [18]. The scene shows Danny, a little boy, playing with toy cars on a carpet. Suddenly, a tennis ball rolls into him. He looks up, and sees a long corridor with no one there. Danny then walks into the corridor, and sees an open door.

In the HR graph (Figure 8e), we see a clear deceleration (approximately 4 bpm) starting around 15 seconds. This is the moment in the video where the ball bumps into Danny. Participants also indicated this part of the video as their highlight. HR deceleration has been found before in response to film clips evoking fear [16], in contrast to claims made by Vrana and Lang [33].

Surprise

For the surprising video, we used a clip from the movie "Capricorn One" [13]. The movie shows a man sitting on his bed, followed by a crash as the door gets smashed in.

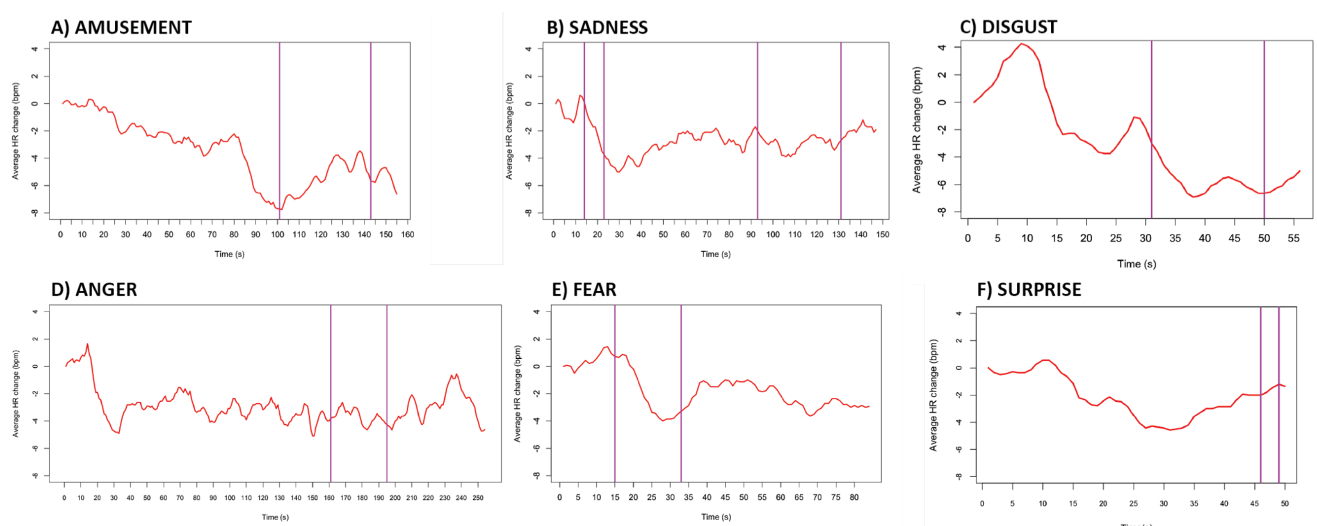

Figure 8. Average HR responses to the six different emotions. Highlight(s) indicated by participants lie between the vertical lines.

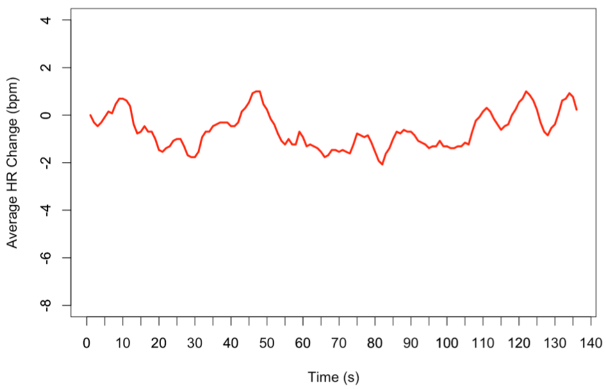

Figure 10. Average HR data for the neutral video. Participants did not indicate that there was a highlight in this video.

The HR graph in Figure 8f shows a continual deceleration towards about 30 seconds, after which the HR slowly rises again. This deceleration can be explained by participants being drawn into the movie as it is not clear what is going to happen. Suspense has indeed been found to induce HR deceleration [16] in the context of film clips.

Participants reported the highlight of the video to be around 46 seconds, which is the part in the video clip where the door is smashed in. Looking at the HR graph in Figure 8f, we can see that there is a slight acceleration at this point, which is consistent with previous studies [16]. Although not shown in the graph as these were the last few seconds of the video, we noticed that participants' HRs also quickly decelerated again after the video.

Neutral

For the neutral video clip, "Alaska's Wild Denali" [12] was selected. The video portrays nature, wildlife and rafting scenes in Alaska's Denali National Park.

Figure 10 shows the HR data for this video. While participants showed a small amount of amusement, the overall emotions can be categorized as being neutral. In general, the HR fluctuates around 3 bpm, but there are no striking peaks or valleys in the HR data.

Summary

Our results showed an overall tendency of HR deceleration in response to highlights in videos, apart from the surprising and neutral video. HR deceleration is obvious in response to disgusting, amusing, sad and fearful These effects are consistent with previous findings (e.g., [2]) and suggest that it is feasible to detect such strong decelerations using wrist-worn sensors.

EXPERT VIDEO HIGHLIGHTS

A professional video artist provided an expert opinion on the highlights of the used clips. We asked this expert to review the video clips that were shown to our participants and identify dramatically significant highlights in each. The expert found considerably more highlights than were ver-

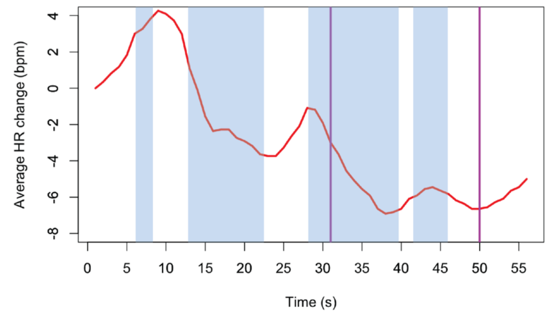

Figure 9. Average HR data for the disgust video. Expert highlights are overlaid in blue.

bally identified by our study participants. Interestingly, these our expert's highlights appeared to coincide with the changes in HR, as seen in Figure 9 for the disgust video.

DISCUSSION & CONCLUSION

Changes in physiological signals such as HR as a reflection of emotional state is a known and widely accepted phenomenon. It is not uncommon to exclaim "my heart is racing!" after having been surprised or scared.

We believe there is significant potential for using HR data in mobile applications for other purposes than fitness tracking. The rising popularity of wrist-worn HR monitors through smartwatches and activity bracelets enables us to start to explore this in mobile applications. Informed by a survey on online video behaviour, we propose to create and share video artefacts (heartefacts) from HR data while watching videos. We suggest that it is feasible to automatically detect highlights in videos using continuous HR sensing on wrist-worn wearables. We created an example heartefact (see video figure for this paper) based on HR decelerations in the sadness video (The Lion King). We also compared identified highlights based on the HR with highlights identified by a professional video artist.

Future work will explore creating heartefacts both from individual data and from averaged HR changes from multiple people. Data from multiple people's HRs might be used by video sharing services to create group heartefacts or video compilations.

Our experiment was conducted in a lab setting with sedentary participants. It is still an open issue how reliably we can detect highlights in a real life setting, as our HRs are influenced by many stimuli.

We realize from discussions with our expert that video editing is an art form that relies on aesthetic sensibilities of the editor, director, or artist, which has advantages over automatically generated edits based on HR data alone. That being said, we think that our heartefact example is a good step towards creating a short, but still meaningful, video clip that encapsulates the emotional highlights for sharing.

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