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

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ABSTRACT

An increasing share of our daily interactions with others is mediated through mobile communication technologies. People communicate via text, emoticons, emojis and rich media such as video. We explore the design of *Heartefacts,* short video clips composed of highlights determined by heart rate changes while watching videos. Our survey investigated video sharing behaviour, and our feasibility study examined the possibility of detecting highlights in videos by monitoring people's heart rates measured with off-the-shelf 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 video highlights verbally identified by our participants to physiological highlights as indicated by their heart rate data and also discuss and compare the automatically generated Heartefacts with video highlights created by an expert in video art. We close with design considerations for Heartefacts in mobile technology.

Author Keywords

HR; Smartwatch Interaction; Affective Computing; Mobile Computing; Video Artefacts.

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 sharing of rich media such as pictures and videos.

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Figure 1. We explore the design of *Heartefacts*, short videos composed of highlights determined by HR changes using wrist-worn HR sensors (as found in smartwatches and activity trackers) while watching videos on mobile devices.

At the same time, recent advances in mobile sensing have enabled devices and services to recognize our physical activity [8,24], movement patterns [22], level of attentiveness [31] and even boredom [30]. Wearables such as smartwatches give further potential to collect personal data with physiological sensors that are worn 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. Moreover, unlike other physiological sensors such as those measuring galvanic skin response (GSR), these HR sensors are non-obtrusive: they are built into devices that people may already be wearing, such as smartwatches or fitness trackers. Despite the proliferation of HR sensors in commercially available wearables, we have yet to see many applications that use HR data for purposes other than fitness tracking.

Our contribution is an exploration of the potential of HR monitoring to *indirectly* augment mobile video sharing. This stands in contrast with directly using and sharing an HR representation (as with the Apple Watch [44]), which people tend to have reservations about [38]. In particular, we investigate the possibility of using a person's HR to create a video artefact, or *Heartefact* (heart-artefact)*,* composed of highlights of a video that the person responded to physiologically

(Figure 1). The popularity of short video cuts, which can be seen on video services such as Vine and Instagram indicate that quick video edits can still produce videos that are widely shared. Our study results suggest the feasibility of identifying highlights in videos using continuous HR sensing on commercially available wrist-worn wearables and generate meaningful video artefacts from this data.

This paper focuses on the design and feasibility of Heartefacts. 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 and mobile and wearable computing.
- We confirm the feasibility of using a person's HR to create a meaningful video artefact (*Heartefact*). We conducted an exploratory study with 14 participants to investigate whether people indeed show changes in HR that are measureable by wrist-worn HR sensors in response to a set of emotion-provoking videos. Based on these changes in HR, we propose creating Heartefacts from personal highlights in each video.
- We show that Heartefacts can be meaningful summaries of the video clips by comparing them to professional edits created by an expert.
- We conclude with a discussion of design considerations for Heartefacts and possible applications.

Our end goal is not to encourage people to share their HR data, but to provide people with a physiological method of creating video clips that will let them share their own emotional video highlights with their friends. Essentially, this will let people create something new by imprinting their own personal data upon a video that they were emotionally affected by, show what it is that they found sad or funny, as the case may be, without them personally needing to be as skilled as a professional video artist or editor.

There is contradicting evidence for whether emotional arousal while watching videos results in acceleration or deceleration in HR [21], therefore rather than provide a specific implementation, we provide insight into what an algorithm could look for. We explore whether HR changes while watching videos on mobile devices are detectable with wrist worn sensors, and if these HR changes (peaks and valleys) over the course of viewing the videos mapped to expert-identified highlights. Further, we wanted to know whether manually creating an edit of the videos based on these peaks and valleys (what an algorithm would do), would produce a video artefact that still made sense.

RELATED WORK

Earlier work can be categorized into five areas: studies of HR changes due to emotional responses, HR changes while looking at pictures or watching videos, HR sharing, the use of physiological data in mobile applications, and the creation of artefacts based on HR and other physiological data.

Changes in HR and Relation with Emotions

A person's 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 exceed 100 bpm in unconditioned sedentary individuals, and can be as low as 30 bpm in professional endurance athletes [9]. Physiological responses such as the HR or GSR are widely thought to be related to changes in emotion [21]. Additionally, people's physical state or behaviour such as speech, facial expressions [6], or body postures [39] have been used in emotion recognition technology.

Physiologically, a person's HR is regulated by the sympathetic and parasympathetic nervous system [32]. The sympathetic nervous system stimulates the body's fight-or-flight response. For example, confronting potential dangers increases a person's HR. The other autonomic nervous system is the parasympathetic branch, which stimulates the body to "rest and digest" or "feed and breed". In terms of influencing a person's HR, the parasympathetic branch acts much faster than the sympathetic nervous system [40].

HR Changes During Picture or Video Viewing

Vrana and Lang [41] 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. In 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 vagal (the vagus nerve interfaces with the parasympathetic system) HR deceleration rather than acceleration.

A follow-up study conducted by Bradley et al. [4] provided more details about how a person's 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. [29] found similar results showing HR deceleration when participants viewed slides representing pleasant, neutral as well as unpleasant visual, auditory or audiovisual 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 participants decreased for the first two seconds and then started to revert back while the HR continued to drop during negative emotional simulation.

In a literature review of physiological responses to emotions, Kreibig [21] discusses several studies that examined HR fluctuations in response to emotional film clips. Some studies found contradictory results, with both increasing and decreasing HR for certain emotions. People's HRs tend to decrease for emotions that include an element of passivity, for example, in mutilation-related disgust, imminent-threat fear, and suspense. Surprise was generally linked to an increase in

HR. However, our focus in this paper is not to find a definitive answer to what emotion causes which HR response, but to explore the design of video artefacts generated from HR changes. That is, can we pick the right parts of the video, given changes in HR.

HR Sharing

The Apple Watch [44], embedded with a HR monitor, enables 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. [38] report that participants expressed a need for knowing the context in which a HR was shared. In our survey (see later), 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". Similarly, Werner et al. [43] found that some people may feel like they are under surveillance when continuously and directly sharing their HR with a partner.

Slovák et al. [38] distinguish between two types of HR data sharing effects: HR as information and HR as connection. Participants expressed a need for contextual information to guide interpreting their HRs and they thought it could be interesting and useful only in situations that were emotionally relevant to others. Many people consider their HRs to be an uncontrollable reflection of their internal emotions. In some contexts, people may not be willing to disclose their HR because of privacy concerns [38]. With Heartefacts, our focus is not on sharing HR information, but rather on creating a tool that will let people harness their own HR to create and edit video clips that are emotionally meaningful for them.

Mobile Applications Using Physiological Data

Sas et al. developed AffectCam [36], a combination of SenseCam and BodyMedia SenseWear that measured GSR to distinguish pictures that were taken during higher and lower arousal. EmoSnaps [27] 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. Listen To Your Heart [26] helps people wearing chest-strap-mounted HR sensors identify information relevant to them on a public display by blinking a highlight around that information in synchronization with their HR.

Shirokura et al. developed AffectiView [37], 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 experiences by sharing physiological signals. This idea stands in contrast to our concept, as we use HR rather than SCL in combination with watching videos rather than shooting them.

Artefacts Based on HR and Other Physiological Data

As opposed to sharing direct biometric HR information [10], several projects have explored creating more abstract HR representations through fabricating material objects [17], drinks [18], or chocolate messages [19]. These projects focus mostly on physical representations of physical activity and our idea of creating Heartefacts based on HR data is inspired by these examples.

A particularly relevant project is Rowland et al.'s [35] generation of photo stories as souvenirs of theme park visits. Rowland et al. [35] captured participants' facial expressions and physiological data while they were riding a rollercoaster. After the visit, they were asked to select a number of emotional pictures to create a photo story souvenir. Rowland et al. indicate interest in automating photo story generation by combining facial expressions and physiological data, which is similar to our goal with Heartefacts.

LAFCam [25] is an affective camcorder that can produce an automatically edited video based on arousal measured through a glove worn by the videographer that measures GSR. With Heartefacts, we instead explore whether this is possible using off-the-shelf wrist-worn HR sensors, and we focus on the viewing experience, i.e. we aim to produce edits based on HR responses while *watching* a video (not while shooting it). Future research could explore creating Heartefacts based on HR changes while shooting videos, extending earlier work on measuring emotional affect using GSR or facial expressions during a shoot [25, 36, 37].

APPROACHING THE DESIGN OF HEARTEFACTS

Evidence from related work indicates that despite the fact that HR data is increasingly available through simple wearable technology, people are apprehensive about sharing this intensely personal data. However, the availability of technology may now open an opportunity – not to encourage people to share their HR, but to empower people to use their own HR data. This can be an opportunity to build tools that will let people make use of their own HR data to assist them in creating edited videos based on their emotional responses. To explore the potential of this design opportunity, we first conducted an online survey and then studied the technological feasibility of this idea. In our second study, we investigated whether changes in people's HR were detectable, whether this could be aligned to video features and whether these video features make sense from a professional video editing perspective.

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, and their use of mobile and wearable devices for this. 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 approximately 10 minutes on average to complete the survey.

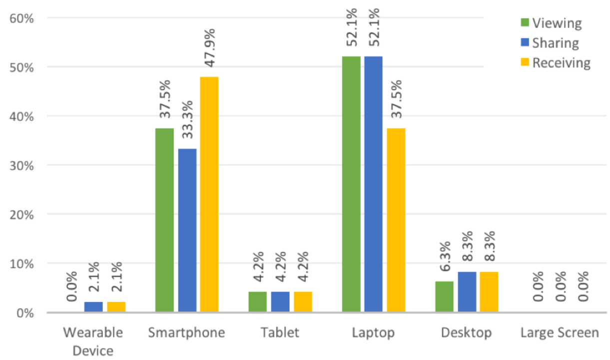

Figure 2. Number of participants using different devices for viewing, sharing and receiving videos.

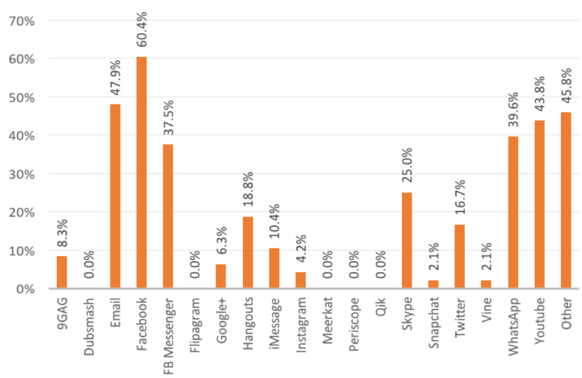

Figure 3. Video sharing services used by respondents (percentage of participants that selected each answer).

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%).

Key Findings and Implications

We start with an overview of the key findings in our online survey in order to relate these to the detailed results later. The four key findings of our survey are:

- F1. HR monitoring is becoming a popular feature in both wearable activity trackers and smartwatches.
- F2. People mostly receive shared videos on their smartphones, and view videos on their mobile devices almost as often as on laptops and desktops.
- F3. The majority of videos that are shared are short (less than 5 min), found online, and funny.
- F4. People do not favour directly sharing their HR.

Findings F1 and F2 motivate the viability of our approach in the current technology landscape, and pave the way for coupling HR sensing and mobile video consumption and sharing. Additionally, the tendency to share short, funny videos (F3) and the hesitance to directly share HR signals (F4) motivates assisting people to create a shortened (edited) version of the video based on their HR. In what follows, we discuss the detailed results of the survey.

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. 6 participants (12.5%) used an activity tracking bracelet, 4 (8.3%) used a smartwatch, and 1 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 popular feature in both wearable activity trackers and smartwatches (finding F1).

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. As shown in Figure 2, participants mostly used their smartphones and laptops for these three activities. Smartphones were used most (47.9%) for receiving videos (finding F2), while laptops were mostly used for viewing videos and sharing them with others (52.1%). Only 1 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 (F2). 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. [28] 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. They additionally found that, due to the specific affordances of mobile devices, people do not tend to view online videos on larger screens, which is consistent with our findings (Figure 2).

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 3 shows the variety of different services that people use.

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%),

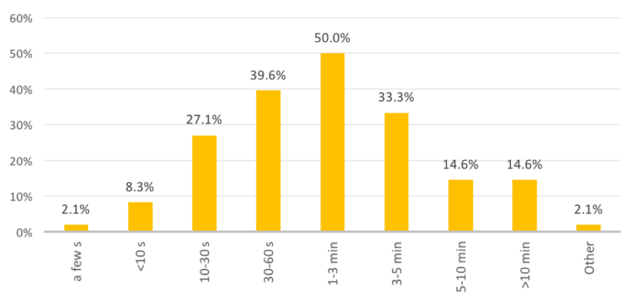

Figure 4. Duration of shared online videos (percentage of participants that selected each answer).

Skype (25%) and Hangouts (18.8%) are also popular. In terms of other services, several respondents mentioned they also use cloud services (e.g., Dropbox, Google Drive). The popularity of mobile services and social networks provides an opportunity to tap into existing mobile video consumption and sharing behaviour for creating and sharing Heartefacts.

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 (finding F3), with a minority of respondents reporting that they shared videos 5 minutes or longer in length.

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 [7]. A new trend in video services such as Vine and Instagram demonstrates the desire to create and share very short clips (F3).

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, and provided the option for participants to add their own category if desired.

As shown in Figure 5, people most often share funny videos (F3). Most people shared videos they either found online (77%) or created themselves (19%). Some participants added the categories "family" or "personal".

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. No one 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

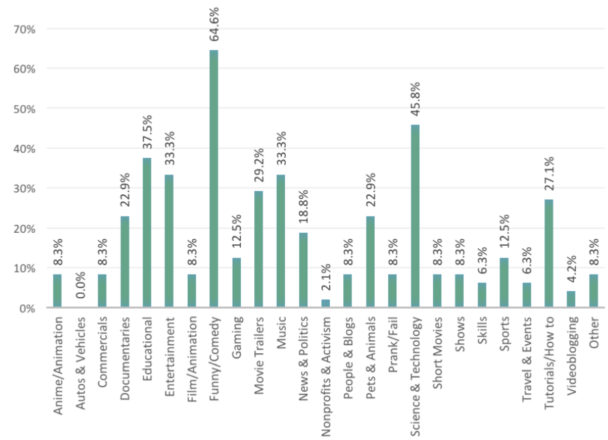

Figure 5. Types of shared online videos (percentage of participants that selected each answer).

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 [38,43]. Several respondents commented that this was not appropriate, commenting that they found it "weird", "too personal", a "scary concept", or "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 (finding F4). We propose enabling people to use their own HR data to create and edit video clips that are emotionally meaningful for them rather than directly sharing their HR.

FEASIBILITY STUDY

To investigate the feasibility of detecting highlights in videos using wrist-worn HR sensors, we measured participants' HRs while watching seven videos on a smartphone. Given the popularity of funny videos in the survey (F3), we used video clips that elicit different types of emotional responses. We based our study on previous experiments by Gross and Levenson [13] and Rottenberg et al. [34], 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.

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 (5 female, 9 male) between 20 and 28 years old, with a mean age of 24.5 (SD = 2.5) 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 earlier application, ShareABeat [12], 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. ShareABeat used a simple algorithm to identify highlights in videos by selecting a 10-second window around the moment in the video with the highest recorded HR change.

For the study described in this paper, we showed locally stored videos in a custom Android window on a Motorola Moto G (2^{nd} 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 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 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. Nevertheless, the circumstances in which participants viewed videos (e.g., wearing a wrist-worn HR sensor, sitting, viewing videos on a mobile device) are not altogether different from real-world settings in which people may view and share videos (e.g., in a living room, waiting for the bus with headphones). Participants were asked to sign 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.

Film Title	Associated Emotion	Seen Before?
When Harry Met Sally	Amusement	1
The Lion King	Sadness	13
Pink Flamingos	Disgust	1
My Bodyguard	Anger	0
The Shining	Fear	1
Capricorn One	Surprise	0
Alaska's Wild Denali	Neutral	0

Table 1. List of film sources for videos used in the feasibility study, their associated emotions, and how many participants indicated having seen each film before the study.

We used the recommended videos from Rottenberg et al.'s instructions for emotion elicitation using films [34]. 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. [34].

Table 1 lists the videos that were used. As shown in Table 1, with the exception of the Lion King, most participants had not seen these videos before.

As mentioned earlier, these videos have been shown to elicit an emotional response from viewers and therefore we hypothesized that they would produce HR changes that could be picked up by wrist-worn HR sensors. We envisioned that funny or amusing videos could cause a larger change in HR and could therefore more clearly identify highlights to be used in creating a Heartefact. However, we wanted to see if videos shown to elicit other types of emotions also affected participants' HRs.

Participants wore both wearable devices, one on each wrist (Mio Link left, smartwatch right). We only analysed data from the Mio Link. Participants then watched the videos in the predefined order specified by the researcher.

After participants finished watching each video, they were asked to fill out a short questionnaire about it. They were asked to rate the strength of each of the six emotions as experienced while watching the video on a 9-point Likert scale ranging from "not at all" (0) to "extremely" (8). This was inspired by the existing experiments by Rottenberg et al. [34]. Participants were not told which emotion they were expected to feel. We used this data to confirm that the selected video clips effectively evoked an emotional response.

Participants were then 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 5–6 minutes. Participants expressed that this short break was long enough for them to calm down in between video clips. On average, each participant's experiment completion time was one hour.

RESULTS

We now report on the results of our feasibility study using videos to evoke changes in HR and assess the feasibility of identifying these as measured by 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. [34]. The overall results of self-reported emotions are presented in Table 2.

Taking "When Harry Met Sally" as an example, an ANOVA demonstrates a significant effect ($F_{1,5} = 43.15$, $p < 0.2e^{-16}$) 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 2, 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. [34]. 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 additionally evoked surprise, an effect that was not present in the original study [34]. This might be due to the fact that 13 out of 14 participants had not seen this video clip before (see Table 1). These results are thus generally in line with Rottenberg et al.'s experiments.

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, we lost HR data for 6 out of 98 (14x7) video logs. Additionally, we excluded data from participants whose HR fluctuated more than twice the standard deviation during each video. For example, P9's HR varied 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.

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

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

Table 2. 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 [].

there were multiple highlights in a video, we manually checked whether they corresponded to the same highlight. Next, we analyzed participants' HRs for each video.

Amusement. To elicit amusement, we used a video clip from the movie "When Harry Met Sally" [33]. The video depicts Harry and Sally sitting together in a crowded restaurant. Figure 6a 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 (i.e., the fake orgasm). 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 [21]. 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 6b, 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

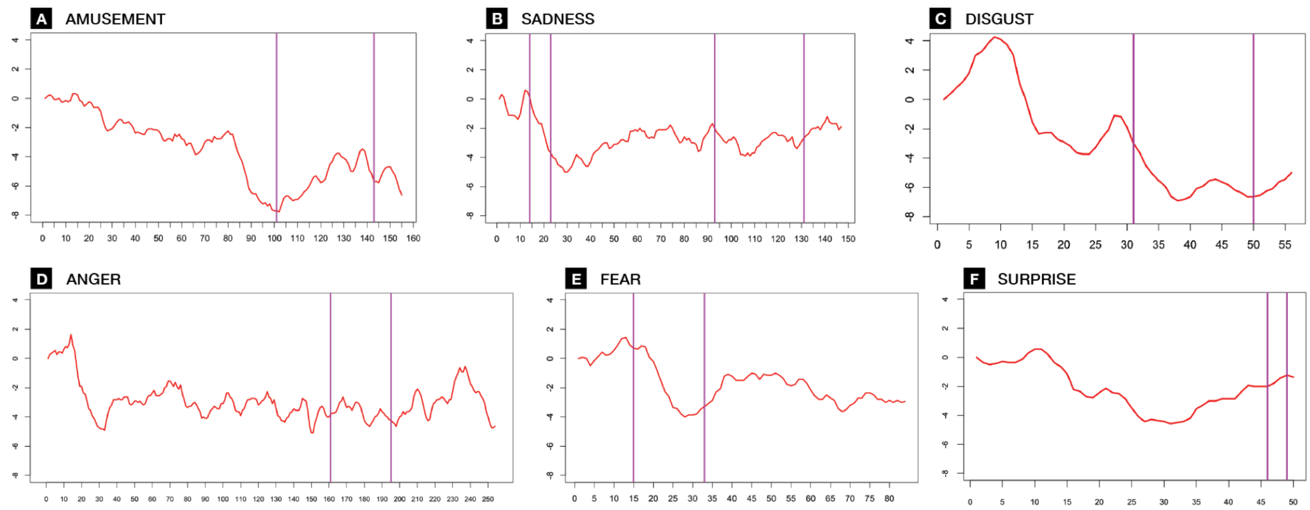

Figure 6. Average HR responses to the six different emotions. Highlight(s) indicated by participants lie between the vertical lines. Time elapsed in seconds is on the X axis of each graph, change in HR in beats per minute is on the Y axis.

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. Previous studies have indeed reported HR deceleration in response to films that evoked sadness [21].

Disgust. To evoke disgust, we used a video clip from "Pink Flamingos" [42]. This clip shows a drag queen eating dog feces. The graph in Figure 6c 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 [2,41]. On the other hand, some studies show that contamination-based disgust such as in this video was associated with HR acceleration [21].

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 6d shows the HR graph for this video clip. 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.

The biggest change in HR is at the beginning of the video, at around 20 seconds, coinciding with a physical confrontation between the main character and their bully. Here, there is a steep drop in the averaged HRs (a change of approximately 5–6 bpm), as shown in Figure 6d. Interestingly, participants did not report this as being a highlight of the video although there is a strong deceleration in their HRs. 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 2), which may influence results.

Fear. To evoke fear, we use a video clip from Kubrick's "The Shining" [23]. The scene shows Danny, a little boy, playing with toy cars on a carpet. Suddenly, a ball rolls up to him. He looks up, and sees an empty corridor–no one is there. Danny then walks down the corridor and sees an open door. In Figure 6e, we see a deceleration (approximately 4 bpm) starting around 15 seconds. This is the moment when the ball bumps Danny. Participants also indicated this part of the video as a highlight. HR deceleration was found before in response to clips evoking fear [21].

Surprise. For surprise, we used a clip from the movie "Capricorn One" [16]. The clip shows a man in his apartment. At the end of the video, his front door gets smashed in. The HR graph in Figure 6f shows a continual deceleration towards about 30 seconds, after which the HR slowly rises again. This deceleration could 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 in the context of film clips [21]. Participants did not indicate any highlights in this part of the video.

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 6f, we can see that there is a slight acceleration at this point, which is consistent with previous studies [21].

Neutral. For the neutral video clip, "Alaska's Wild Denali" [15] was selected. The video portrays nature, wildlife and rafting scenes in Alaska's Denali National Park. Figure 7 shows the HR data for this video. While participants showed a small amount of amusement, the overall emotions can be

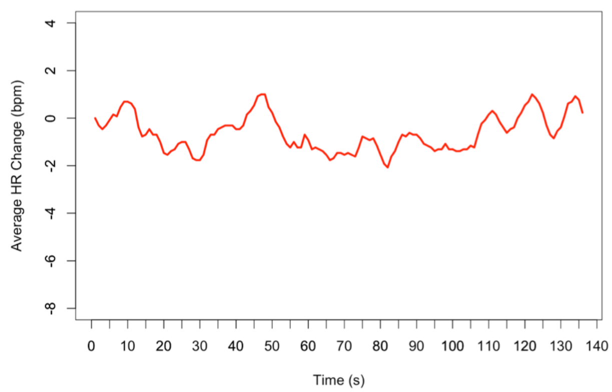

Figure 7. Average HR data for the neutral video. Participants did not indicate a highlight in this video.

categorized as being neutral. The HR fluctuates around 3 bpm, but there are no striking peaks or valleys in the HR data and participants did not indicate any highlights.

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 scary videos. This consistency with previous findings (e.g., [2]) suggests that it is feasible to detect such strong decelerations using wrist-worn sensors.

DESIGN DISCUSSION

With Heartefacts, our goal was to explore empowering people to use their own HR data to create edited versions of videos. Our results show that this is possible and lay the groundwork for building tools to support semi-automatic creation of personal video (He)artefacts. In this section, we discuss whether the Heartefacts generated from HR data in our feasibility study make sense from a professional video artist's perspective. We also present possible uses and applicability, meaning-making, and limitations to be considered when developing a tool to create Heartefacts.

Prototype Heartefacts & Expert Video Highlights

We created prototype Heartefacts for all videos except "Alaska's Wild Denali" based on the HR changes in Figure 6. To do this, we isolated the most prominent peaks and valleys in the HR data, isolated the corresponding sections of video, and used these to make new clips. The sections of the disgust video isolated are shown in the top graph in Figure 8.

To consider how a Heartefact relates to video highlights created by experts, we asked a professional video artist to provide an expert opinion on the highlights of our studied clips. We asked this expert to review the video clips that were shown to our participants and to identify dramatically significant highlights in each. The expert found considerably more highlights than were verbally identified by our study participants. Interestingly, the expert's highlights appeared to coincide with both the changes in participants' HRs and the Heartefact, as seen in Figure 8 for "Pink Flamingos".

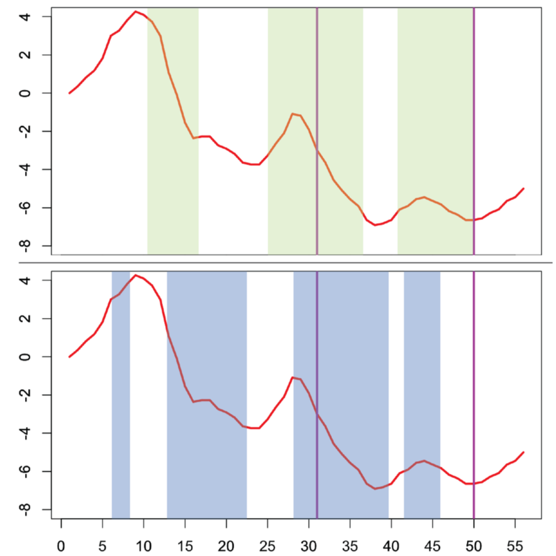

Figure 8. Average HR data for "Pink Flamingos" (disgust). Possible edits for a Heartefact are indicated with green highlights (top); expert highlights are overlaid in blue (bottom); personal highlights are indicated by the thin vertical lines. Time elapsed in seconds is on the X axis of each graph, change in HR in beats per minute is on the Y axis.

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, and this can have advantages over automatically generated edits. That being said, we think that our exploration shows the potential for using Heartefacts to create personalized video clips that encapsulate one's emotional highlights for sharing.

Uses and Applicability

There are many compilation videos on YouTube made up of highlights of popular videos, and television channels often put together teaser previews made up of short clips from future episode broadcasts in order to entice viewers. Heartefacts can be used by individuals to create *personal* teasers or highlight reels of videos that they wish to share with others from *personal* data, and these can subsequently be compared with Heartefacts from others to see if similar highlights were identified by their HRs. Instead of assisting people to tell stories using videos they shoot themselves (e.g., [20]), Heartefacts compile a few highlights based on a person's HR response to a pre-existing video.

We intend the creation of a Heartefact to be a playful experience. Enabling people to appropriate media and imprint data on it can enable new engaging and creative experiences, as shown in [14] in the context of photography. We anticipate that people may try to change their HRs to affect the resulting Heartefacts, by jumping up and down or running to cause an increase, similar to what Khot et al. found with TastyBeats [18]. Additionally, people may try to slow their HR down by meditating, and this can open up possibilities for therapeutic uses of Heartefacts.

Giving Meaning to Heartefacts

Rather than verifying a particular emotion caused by a video, we are interested in whether a person's HR is affected by watching the video and can be harnessed to create a personal edit. Giving people the opportunity to apply their own HR data to a pre-existing video can add personal meaning to the resulting edit and can create enjoyable and surprising results. This also creates a new and rich representation (video) of a deeply visceral body process that previously was inaccessible through off-the-shelf technology.

Limitations and Future Work

There are many factors that can affect changes in HR. Laughing or weeping can cause changes to HR [5] and this may need to be considered when detecting highlights for the resulting Heartefact. Additionally, we conducted our feasibility study in a controlled lab environment with reduced external stimuli. If a person who wants to create a Heartefact is situated in a busy public space or is otherwise distracted from watching the whole video, the created Heartefact would be a less accurate representation of the person's HR response to the video they were watching. People may, however, try to manage their HR and "pose" for a Heartefact in the same way that they pose for a selfie. This can provide opportunities for playful experiences.

We have not provided an implementation of Heartefacts, but we have shown that peaks and valleys in the HR data and particularly large decelerations (e.g., changes around 4–5 bpm), are promising targets for a highlight detection algorithm. Video edits based on these HR changes tend to coincide with highlights identified by our video editing expert, and can result in interesting Heartefacts.

Certain kinds of videos may be difficult or unsuitable for creating Heartefacts. Videos such as "Alaska's Wild Denali" [15] that evoke an emotionally flat response in most people may not change a person's HR enough to generate a Heartefact in the first place. We could address this by adding some sensitivity controls, but it is an open question whether this could still successfully produce a meaningful Heartefact. Further, creating a Heartefact out of an extremely short video (i.e. a Vine) could be difficult as there will not be enough physiological highlights during the course of the video. This could be addressed by allowing for looping playback while gathering HR data.

Future research could investigate how familiarity with a video can influence HR response. Our results showed a strong HR response to the Lion King, despite the fact that most participants reported having seen it before (see Table 1). This is also supported by the phenomenon of people creating memes and watching funny videos over and over again on YouTube. Given this, and depending on the video, we suspect that repeated viewing might still generate sufficient arousal for Heartefacts to work.

It would be possible to simulate a Heartefact by tapping a smartwatch to indicate which scenes to highlight. However, we are more interested in the possibility of creating Heartefacts from individual data as well as 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 (similar to [11]). Further investigation is needed into HR change in response to a larger set of video clips, settings and people, to explore how people experience creating their own Heartefacts.

CONCLUSION

Experiencing changes in physiological signals, such as HR, in response to emotions is a known and widely accepted phenomenon. It is not uncommon to exclaim "my heart is racing!" after having been surprised or scared. There is significant potential for using HR data in mobile applications for other purposes than fitness tracking. The popularity of wrist-worn HR monitors in smartwatches and activity bracelets enables us to start exploring 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. Heartefacts are representations of deeply personal data, and let people reflect on and share what they responded to most in a video clip without requiring professional video editing skills. Details about raw HR data are obscured in a Heartefact, which can address concerns about sharing this data with others.

We showed that it is feasible to identify highlights in videos using continuous HR sensing on wrist-worn wearables, and created Heartefacts based on HR data gathered in our study. Unfortunately, due to copyright constraints, we cannot attach a Heartefact made from the videos used in our study as a video figure, however, one made from "Pink Flamingos" can be approximated using the editing instructions from Rottenberg et al. [34] and information from Figure 8. The edits of the videos in our study based on highlights generated from participants' HR changes mostly correspond with highlights identified by an expert. This suggests that physiological response to videos can be used to create a personal edit that is similar to one that would be created by a professional editor. Learning to be a video editor can take years of training. With Heartefacts, we hope to provide steps towards empowering people to use their own personal data to create shareable, meaningful video clips without acquiring the skills of a professional editor or video artist.

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