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EMOTION-REACTING FASHION DESIGN INTELLIGENT GARMENT AND ACCESSORY RECOGNIZING FACIAL EXPRESSIONS

Junko ISHIUCHI[a], Misako ANDO[a], Sakiho KAI[b], Chiaki UJIHIRA[a], Hiroki MURASE[a], and Takao FURUKAWA[a1]

[a] *Kyoritsu Women's University, Japan*

[b] *Kobe Design University, Japan*

ABSTRACT

Although mental disorders have emerged as serious social challenges, social stigma, including prejudice and misunderstanding, hinder suitable treatment for the patients. It is crucial to monitor our internal psychological and emotional states to avoid the unconscious progression of mental disorders. This research aims to achieve emotion-reacting garments and accessories, based on a passive and continuous emotion recognition system in real time. First, this study proposes a systematic design for emotion-reacting garments and accessories, which employs emotion estimation based on facial expressions. Next, emotion-reacting fashion design is discussed for intelligent garments and accessories that interact with our bodies and mind. To achieve this system, a functionally extended collar made of transparent polycarbonate material is designed for integration with the digital camera modules. In addition, this study discusses how to create a physical stimulus on emotion-reacting garments and accessories. The intelligent garments and accessories using RGB-LEDs create visual effects that reflect emotions. In terms of audio effects, emotion-related keywords are employed to select the music played in intelligent garments. Finally, prototypes reacting to emotions are shown.

Keywords: *Emotion-reacting garment, Facial expression, Wearable computing, Fashion design*

[1]Corresponding author: Takao FURUKAWA, Department of Textile and Clothing, Kyoritsu Women's University, 2-2-1 Hitotsubashi, Chiyoda-ku, Tokyo, 101-8437, Japan. tfurukawa@kyoritsu-wu.ac.jp

1. INTRODUCTION

In the context of the widespread usage of information and communication technologies, including smartphones and mobile devices, positive computing has been proposed to preserve an individual's physical and mental health and obtain well-being (Carvo & Peters, 2014). The present designs and forms of smartphones and mobile devices will be altered in the future. For example, flexible devices based on printed electronics can be combined into clothing and the human body as a second skin (Oh & Bao, 2019). In the field of social robotics for a few decades, humanoid or pet robots have achieved communication with artificial intelligence and remote interpersonal communication (Leite, Martinho & Paiva, 2013). In addition, wearable, soft robots supporting human body movements have also been designed (Zhou et al., 2021). In some way, these robots can be regarded as active and functional clothing. Thus, active and functional clothing should be considered in the next-generation clothing, which pushes the boundaries of the existing clothing framework. Based on these technological innovations, clothing defined as "the second skin" needs to be redefined.

Instant messaging applications have been employed to send and receive text messages between computers in near real time since the 1990s. Since the introduction of smartphones in 2007, the globally accessible WhatsApp and Facebook Messenger applications have become fundamental for daily communication. In emotion-enhancing garments (Tsetserukou et al., 2009), AffectIM was employed to estimate nine emotions and their intensity by examining text data of instant messenger. Users wearing emotion-enhancing garments input text messages to ensure the system recognizes their emotions. However, this is a restriction of the system, which must be enhanced to passively recognize emotions. This research intends to create an emotion-reacting garment employing a passive and continuous system to estimate emotions in real time. This research describes how to develop and implement a wearable system that reacts to emotions based on a prototype (Kai et al., 2022).

2. EMOTION RECOGNITION

This research considers (i) high-level psychological states, including self-actualization and self-esteem in terms of emotion, affect, and mood, and (ii) low-level emotional states including joy, anger, and sadness, as demonstrated in Figure 1. The high-level psychological states are categorized in the upper levels of Maslow's hierarchy of requirements. The low-level emotional states, which are present in both human beings and primates, are closely related to instincts. Verbal information obtained from the linguistic analysis of text data is adequate to identify high-level psychological states. In Student Life (Wang et al., 2014), smartphone-based online questionnaires and the ecological momentary assessment were employed to estimate psychological states. Furthermore, a smartphone's accelerometer and GPS were employed to record body movements and mobility. In addition, conversations obtained from phone calls and sleep states estimated by an illuminance sensor were employed. In MIND (Zaman, Silenzio & Kautz, 2020), the browsing history of YouTube, SNS, etc. were employed to estimate high-level psychological states, based on the assumption that a person with low self-esteem does not search for specific information.\

Many studies on identifying lower-level emotions employing biometric information, including electroencephalography (EEG), electrocardiogram (ECG), pulse wave, skin conductance resistance, skin temperature, and respiration, have been reported (Dzedzickis, Kaklauskas & Bucinskas, 2020). These approaches map biological signals to the valence and arousal components of Russel's circumplex model of affect (Russell, 1980). Recently, machine learning techniques have been employed in multimodal biological signals to enhance the accuracy of emotion estimation. There is a close relationship between the arousal level and biological signals, including the heart and respiration rates. However, the relationship between the valence component that shows positive and negative emotions and biological signals is unclear. Although brain wave (EEG) analysis can estimate the valence component, further research would be needed at this time.

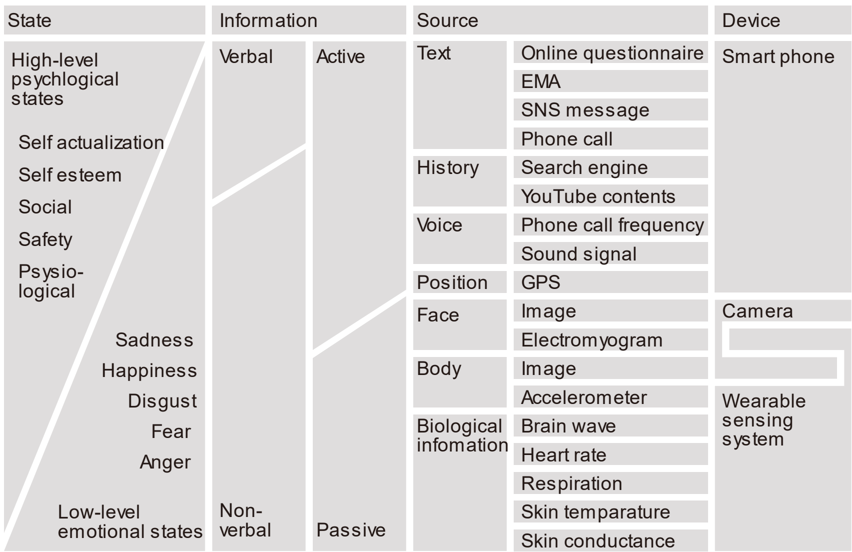


Figure 1. Information and source data for emotion recognition

Since the 1970s, Ekman has investigated basic emotions, including joy, anger, and sadness, which appear in facial expressions (Ekman & Friesen, 1971). A facial action coding system designed to describe facial expressions was employed to identify facial expressions in computer vision. Nowadays, cloud services, including Microsoft Azure Cognitive Services, which are capable of estimating emotions from facial images, have already been commercialized. Gaze movements are also employed to estimate emotions based on a detailed analysis of facial expressions. Compared to other animals, primates' visual perception and their ability to control muscles of facial expression have evolved to a high level. These perception and expression abilities make them communicate their emotions through facial expressions without employing language. Facial expression monitoring is a reasonable choice to estimate emotional states compared to the biological signal analysis. Thus, facial expressions were chosen as the source for estimating emotional states in this research.

3. SYSTEM DESIGN

3.1. Emotion estimation based on facial expression

Figure 2 demonstrates a schematic of emotion-reacting clothing that creates audiovisual effects. Emotional states were estimated by employing facial expression images captured using a digital camera. A wide-angle digital camera module (Simlu OV5647 Camera Module) is linked to a single-board computer (Raspberry Pi 4) through MIPI CSI-2 to capture facial images. To miniaturize the hardware system, a wide-angle camera was chosen to reduce the distance between the camera and the face. The computer sends facial images to Microsoft Azure Cognitive Services through the Face API and receives an 8D facial expression vector. In emotion estimation, landmarks reflecting facial expressions are examined by digital image processing as demonstrated in Figure 3.

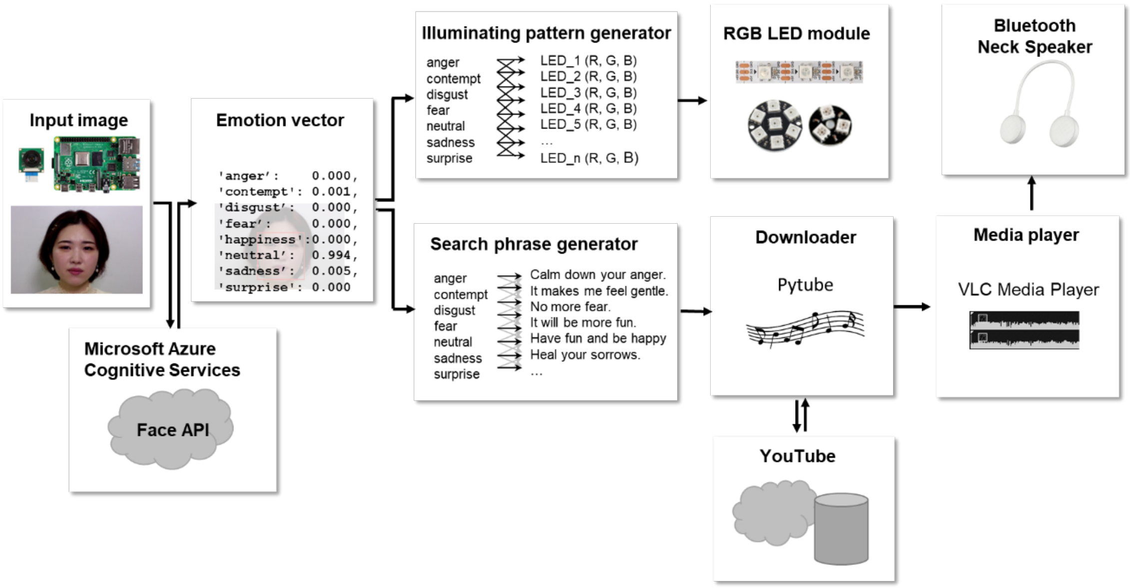
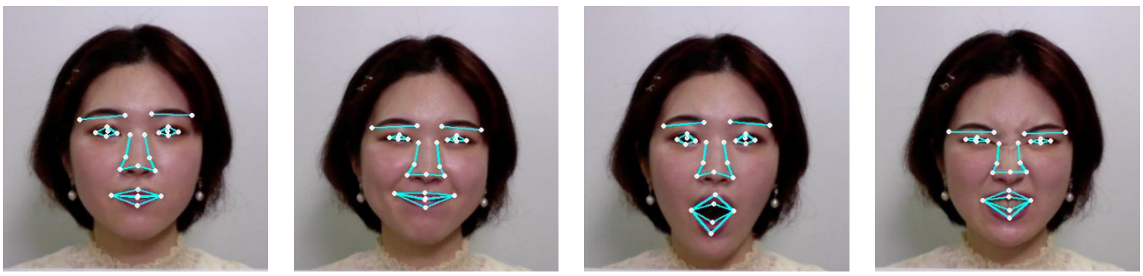


Figure 2. Schematic of the wearable system creating visual and audio effects



(a) Neutral (b) Happiness (c) Surprise (d) Disgust

Figure 3. Extracted feature points reflect facial expressions

Figure 3 demonstrates the landmarks of the eyebrows, eyes, nose, and mouth for several facial expressions. These landmarks are as follows:

- Eyebrows: inner and outer points
- Eyes: inner and outer points, top and bottom points, and centers
- Nose: root points, top and outer points of the nose alar, and tip points

- Mouth: Corners of the mouth, top and bottom of the upper lip, and top and bottom of the lower lip

For instance, when we feel happy, the zygomaticus major and minor muscles contract and raise the corners of the mouth. Based on the digital image analysis, the Face API returns an 8D facial expression vector made of anger, contempt, disgust, fear, happiness, neutral, sadness, and surprise. the 8D facial expression vector's elements range from 0 to 1, showing the confidence rates.

3.2. Visual effects reacting emotion

The wearable system creates visual impacts using illuminating RGB-LED modules linked to the computer through a general-purpose input/output interface. We designed an illuminating pattern generator that creates RGB values of the LED modules in response to the 8D facial expression vector. In social robot research expressing emotions by illumination (Terada, Yamauchi & Ito, 2012), mapped colors to Plutchik's wheel of emotion (Plutchik, 2001) were employed. The mapped colors are roughly consistent with the commonly known psychological impacts of color. Thus, our wearable system also uses the mapped colors in Plutchik's wheel of emotion in the initial trial. A close relationship between emotions and hue is known, but a single color is frequently mapped to various emotions. Thus, we also considered dynamic color patterns based on affective color in visualization (Bertram, Patra & Stone, 2017).

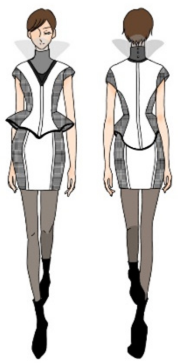
3.3. Visual effects reacting emotion

Based on the 8D facial expression vector, a rule-based search phrase generator produces a phrase for audio effects, which correlates with the music to be played on the system. For instance, if the emotional intensity of "anger" is high, the phrase generator produces the phrase "calm down your anger," which suppresses the negative emotion. The downloader searches for the content stored on YouTube (based on the produced phrase) and downloads the matching files employing the polytube module. Many phrases can be integrated to search the content; for instance, the search phrases composed "calm down your anger," "chill out," and "music" recommend the content—"Irritated mood, accumulated stress, and fatigue will disappear | Music for healing the autonomic nervous system." The media player plays the downloaded mp3 or mp4 files, and the audio signal is digitally transmitted to a Bluetooth neck speaker.

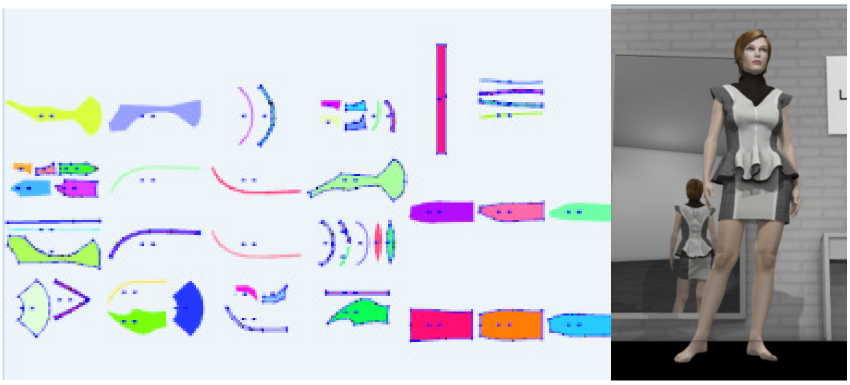
4. FASHION DESIGN

When combining the emotion recognition system into clothing, the attachment of a small digital camera module to capture facial images poses a design challenge. Various design ideas for combining the digital camera module into hats, ornaments, and accessories were discussed. Finally, it was decided to use an extended collar. Figure 4(a) demonstrates the fashion design of emotion-reacting garments. The fashion design concept was "retro-futurism," which imagines a bright and optimistic future imagined by the people of the past. A black ribbon-like decoration placed at the upper garment's hem highlights the peplum's 3D shape. A semi-tight skirt was integrated with the upper garment to create an outfit. The transparent collar, which was combined with the digital camera module, was expanded from the neckline. A 20-mm-wide flat cable linking the digital camera module to the control computer was a fashion design limitation. However, white ribbon-like areas on the front and back center lines joined the flat cable into a unified design. In addition, the integration of a transparent collar with a black high neck unified the whole design in a monotonic design but highlighted the contrast between black and white.

According to the illustrations demonstrated in Figure 4(a), 2D patterns were produced, and 3D virtual prototyping was conducted employing Lectra Modars 3D V8R3, as demonstrated in Figure 4(b). The color scheme and texture's detailed design are estimated in this prototyping process. The glen-check fabric (called the Prince of Wales checks) employed on the left and right sides is a symbol of British tradition and highlights the contrast with the futuristic silhouette. Figure 4(c) demonstrates a sequence of computer animation produced by CLO Virtual Fashion CLO3D employing the patterns in Figure 4(b).



(a) Illustration



(b) Pattern making and 3D virtual prototyping

(c) Computer animation

Figure 4. Fashion design and 3D virtual prototyping.

5. IMPLEMENTATION

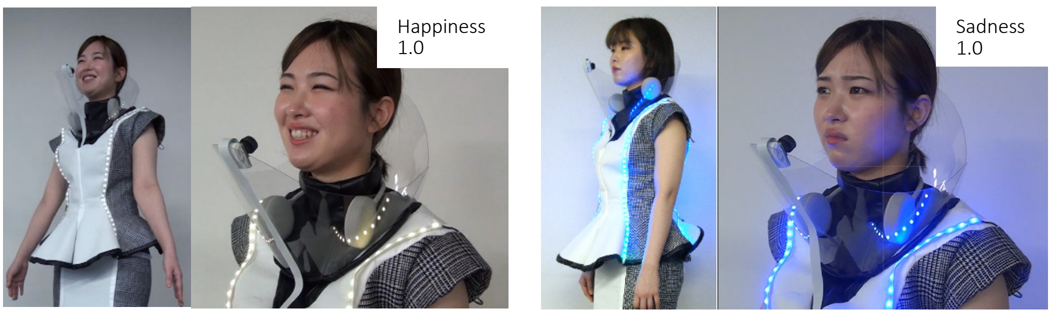
Figure 5(a) demonstrates the designed emotion-reacting garment. A woolen glen-check fabric was employed for the side parts of the upper garment and the skirt. White high milon, a raised fabric with a matte texture, was employed in the upper garment and the skirt's front and back center parts. White synthetic leather, which is unified with the digital camera module's flat cable, was stitched on the front and rear center lines. Black synthetic leather was stitched at the peplum's hems to highlight the spatial curves. RGB-LED strips for visual impacts were placed at the woolen glen-check fabric's boundaries and the white high milon fabric, producing a design accent that even the LEDs could not emit light. Gray Bluetooth speakers to produce audio effects were attached to the neck.

The extended collar, which was combined with the digital camera module, was composed of a transparent polycarbonate material. A ribbon-shaped fabric with concave-convex snap buttons was stitched at the back of the camera module. Since the transparent polycarbonate collar's tip has a hole, the snap buttons can fix the digital camera module's position and detach it. The control computer, the rechargeable mobile battery, and the 3.5-in. LCD panel were challenging to mount on the garment's surface. Therefore, they were combined into a waist pouch composed of black synthetic leather, as demonstrated in Figure 5(b). The flat cable linked to the camera module goes through the V-shaped neckline's tip, from the outside to the inside, and is linked to the control computer in the waist pouch.

Figure 6 shows the emotions estimated from facial expressions. In Figure 6(a), the "happiness" emotion visible on the facial expression emites the RGB-LED yellow color. Simultaneously, music content related to "more fun" was searched and downloaded from YouTube. The control computer plays the downloaded music content and transmits it to the Bluetooth speakers. In Figure 6(b), the "sadness" emotion visible on the facial expression emites the RGB-LED blue color. Simultaneously, music content related to "Heal your sorrows" is searched for and downloaded from YouTube. The control computer plays the downloaded music content and transmits it to the Bluetooth speakers. We visualized a negative emotion including sadness for the illustration, although it may be reasonable not to visualize negative emotions in this intelligent garment.

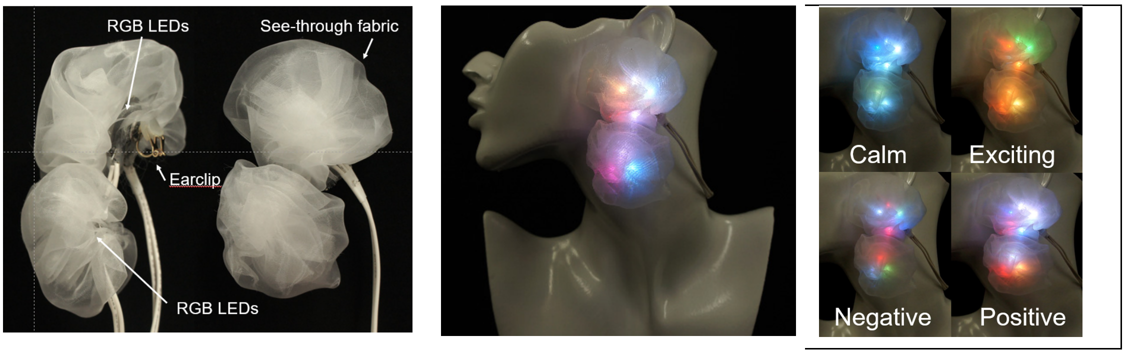
(a) Emotion-reacting garment and extended collar (b) Waist pouch storing hardware

Figure 5. Implemented emotion-reacting garment.



(a) Happiness (b) Sadness

Figure 6. Reactions to "happiness" and "sadness."



(a) Prototype (a) Operating states

Figure 7. Intelligent earrings.

Figure 7 (a) shows a prototype of intelligent earring that consists of RGB LEDs on round boards, a microcontroller, batteries as well as earclips and see-through fabrics for diffusing emitted light. We propose a spatiotemporal conversion to reflect impressions based on color bubble charts (Bertram, Patra & Stone, 2017) for this intelligent earring. In the color bubble chart, various colored and sized circles are randomly arranged in a plane. The spatiotemporal conversion maps the area of circles to the duration of RGB LEDs' colors to create similar impressions of the color bubble chart in the limited number of color elements. Figure 7(b) shows the operating states of the intelligent earring in which the RGB LED colors are controlled. According to the color bubble chart expressing calm, exciting, negative and positive emotions, the colors of RGB LEDs are dynamically controlled.

6. FACIAL EXPRESSION RECOGNITION

In this study, the accuracy of a facial expression's recognition is confirmed by employing Microsoft Azure Cognitive Services. First, facial image data were captured by shooting eight types of facial expressions. These data reflect emotions including anger, contempt, disgust, fear, happiness, sadness, surprise, and neutral. The estimated emotions from facial images were then compared, and the correlating emotion appeared in the facial expression in the image data. In the experiment, the participants were 10 females with a mean age μ = 22.9 and a standard deviation σ = 1.58. In this experiment, 10 facial images were captured for each facial expression reflecting emotion, and 800 facial images were captured and processed.

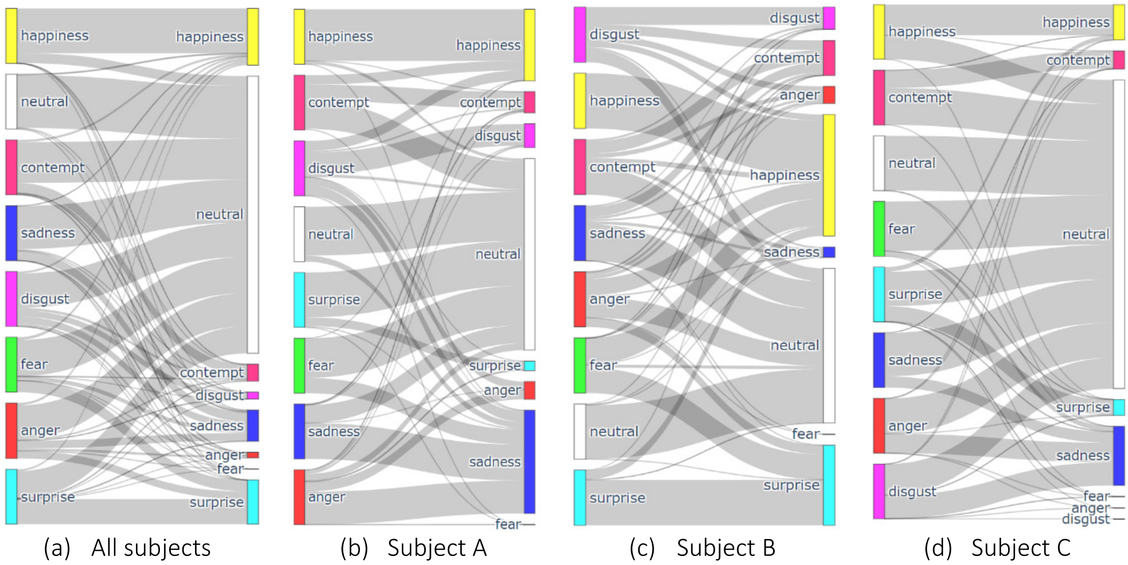


Figure 8. Estimated emotions using facial expression image analysis.

Figure 8(a) demonstrates the Sankey diagram, which shows the relationship between the estimated 8D emotion vector and the emotions that appeared in facial expressions. Although many facial expression images (except the neutral) were misidentified as neutral, happiness was identified almost correctly. For the surprise emotion, roughly 50% of the estimations were correct and the rest were incorrect. Table 2 demonstrates the correct estimation percentages for eight emotions. Figures 8(b)–(d) illustrates the findings obtained using three participants (A, B, and C); Figure 7(b), which shows the findings obtained using participant A, part of the anger and fear were misidentified as sadness, in addition to the correct estimation of sadness; Figure 8(c), which shows the findings obtained using participant B, part of the anger and fear were misrecognized as happiness, in addition to the correct estimation of happiness; and Figure 7(d), which shows the findings obtained using participant C, disgust and anger were misidentified as sadness, in addition to the correct estimation of sadness. Overall, many facial expression images were misidentified as neutral.

This experiment verified that happiness could be correctly identified, but the other emotions' recognition accuracy was not high. This finding proposes that the system should focus on happiness in the emotion estimation. For instance, the occurrence of happiness in a facial expression could be used for an emotion-reacting garment if we consider the misidentification of emotions based on facial expressions.

Table 2. Percentages of correct estimations

Emotion	Anger	Contempt	Disgust	Fear	Happiness	Sadness	Surprise	Neutral
Percentage	4.1	18.5	12.7	0.8	81.1	17.3	45.7	96.4

7. CONCLUSION

Users wearing emotion-enhancing garments must input text messages to help the system identify their emotions. Although verbal information is suitable for identifying high-level psychological states, it is incompatible with passive and continuous monitoring. In this study, an emotion-reacting garment employing a passive and continuous emotion recognition system operating in real time was proposed. Particularly, a fundamental design of a wearable system, whose core function is to estimate emotions by examining facial expressions obtained from facial images, was proposed. Next, 3D prototyping was employed to determine detailed fashion design components based on the "retro-futurism" concept. The design and implementation of hardware and software modules that offer audiovisual stimuli based on emotions were described, and a prototype was designed. Advanced algorithms for audiovisual stimuli based on an illuminating pattern generator and a search keyword generator that efficiently controls emotional states were also discussed. Accuracy of facial expression recognition depends of individual faces, so that personalization is required to operate the system. Moreover, the negative effects of emotional reaction must be avoided. Intelligent earrings to express emotions based on color bubble charts were also discussed. However, the performance examination remains a challenge to be addressed in the future.

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