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Intelligent Textiles: Designing a Gesture-Controlled Illuminated Textile Based on Computer Vision

Abstract

Artificial intelligence (AI) offers the potential for the development of e-textiles that give wearers a smart and intuitive experience. An emerging challenge in intelligent materials design is hand gesture recognition textiles. Most current research focuses on number gesture recognition via smart gloves, there is a gap in research that studies contact-less number gesture recognition textiles via computer vision. Meanwhile, there is lack of exploration on the integration of illuminating function and number gesture recognition textiles to improve interactivity by real-time visualizing detection results. In this research, a novel interactive illuminating textile with touch-less number gesture recognition function has been designed and fabricated by using an open-source AI model. It is used in sync with a Polymeric Optical Fibre (POF) textile with illuminative features. The textile is color-changing controlled by the system's mid-air interactive number gesture recognition capability and has a woven stripe pattern and a double-layer weave structure with open pockets to facilitate integration of the system's components. Also described here is a novel design process which permits textile design and intelligent technology to integrate seamlessly and in synchronization, so that design in effect mediates continuously between the physical textile and the intangible technology. Moreover, this design method serves as a reference for the integration of open-sourced intelligent hardware and software into e-textiles for enhancement of intuitive function and value via economy of labor.

Keywords: Intelligent textile design, hand gesture recognition, Polymeric Optical Fibre (POF), illumination.

Introduction

In the 21st century, textiles have evolved from passive fabrics into materials which can be integrated with electronic devices to enable seamless human-computer interaction (HCI) in daily life [1, 2]. Hayward [3] calculated in an IDTechEx research report that the market for electronic textiles (e-textiles) will be worth over US$1.4 billion by 2030. The increasing demand for comfort and convenience in a variety of product ranges may well lead to exponential growth in the value of the gesture recognition market. In 2020, the gesture recognition market is USD 9.8 billion and is projected to reach USD 32.3 billion in 2025, at a compound annual growth rate (CAGR) of 27.0%. Moreover, the touchless sensing market is projected to grow from USD 6.8 billion in 2020 to USD 15.3 billion in 2025 at a CAGR of 17.4%, according to Marketsandmarkets[4]. This shows that as their commercial value increases, e-textiles integrated with gesture detection function will play a significant role in the industry. Emerging technological improvements provide clear opportunities for the further exploration of gesture recognition intelligent textiles, especially touch-less detection under pandemic. Fast evolving factors such as the advancement and accessibility of technology[5, 6] as well miniaturisation and low-power of components[7, 8] with consumers' demands for intuitive products and services have provided opportunities in the exploration of gesture recognition intelligent textiles for HCI.

Gesture recognition requires input from the signals created by human movements. These gestures are then classified by the computer system[9, 10]. Hand gestures refer to finger, hand and arm motions, which are natural features of human non-verbal communication and a means of conveying messages to the external environment [11]. While number gesture is one of the most natural, ancient and common hand gestures in communication. Hand gesture recognition involves interaction between human hand gestures and computer vision technology. Besides, hand gestures have been integrated in the field of HCI since the first smartphone was introduced to the world. Gestures play an important role in HCI by controlling the computer and machine system via specific hand movements [11]. In recent years, gesture recognition systems have been used in a range of virtual reality (VR) and augmented reality (AR) applications, including gaming [12, 13], rehabilitation [14-16], health care monitoring [17-19], education [20, 21] and personal identification [22, 23].

With the increasing interest in interdisciplinary studies in the development of e-textiles, researchers and practitioners have developed methods, techniques and materials that enable electronic systems to be embedded in soft materials. Meanwhile, number gesture detection textiles as human-computer interfaces are needed in smart spatial applications as a natural and simple interactive approach. Most studies in this area have focused on conventional contact-based gesture recognition interactive textiles, especially contact via wearing mechanical gloves with high detection accuracy[24-31]. However, there is a lack of research on contact-free textile design with number gesture recognition for HCI. Moreover, it is found that user-visual feedback interfaces are vital for letting users know real-time detection status and the absence of such an interface may cause poor interactivity and participation. Therefore, a novel approach for number gesture recognition textile design was developed based on computer vision mechanism and an open-sourced deep-learning model. The research described here investigates an e-textile with the function of mid-air number gesture recognition that does not require the user to wear extra sensors, clothing, or equipment. In so doing, it creates the potential for wide and seamless application in wearables and interiors.

The integration of illuminative function is for increasing interactivity of the e-textile via illuminating and color-changing effect. Polymeric optical fibres (POF) have been applied to achieve illumination by different textile fabrication technology because of its flexibility, light weight and light emitting ability. The authors have research experience in developing interactive POF textiles via woven and knitted structures for fashion, interior and sensory environment applications[2, 32-37]. While, e-textile studies based on the integration of POF with illuminative features and hand gesture recognition by the use of artificial intelligence are currently under explored. Illuminative textiles could serve as novel materials combined with number gesture recognition function for increasing user-friendliness and interaction by giving visual response of detection results. In this paper, we present a new design model for the development of illuminated textile controlled by computer vision-based number gesture recognition. Open-sourced hardware system (Raspberry Pi) and deep-learning model were introduced as new design materials to realize rapid development. The authors have used an open-sourced artificial intelligence technology to create a controllable interactive e-textile, and in so doing expand the potential application of artificial intelligence in HCI.

Review of Gesture Recognition Textiles and Illuminative Textiles

Development of Hand Gesture Recognition

The most instinctive and widely used hand movement for recognition in HCI is the slide or swipe movement. Although this motion was designed to control digital page-turning or scrolling computer screens on digital reading devices and smartphones, it derives from the action of reading books or magazines[38] . However, here we are reminded of the words of Kurtenbach and Hulteen[39] 'A gesture is a motion of the body that contains information.' It is interesting to note that semiotic gesture recognition has been developed for both 'hard' and 'soft' interfaces, including two groups of language-like gestures and emblements[40] . Sign language and number gestures are detected by gloves made of gesture recognition textile and by devices of depth cameras or radar. Therefore, gestures of numbers can be grouped into those that involve contact and those (mid-air) that do not. Mid-air gestures are further classified into proximity and middle-range types.

The first gesture recognition textiles were touch-sensitive and were based on resistive or capacitive sensing principles. They were fabricated by integrating conductive materials into textiles as electrodes. The Firefly Dress[41] and the Musical Jacket[42] are the pioneer examples of touch-sensitive garments based on resistive and capacitive sensation respectively. With the development of textile electrodes arrayment, gestures of swipe[43] and fold[44] can be developed. In a parallel development, nano-materials in the form of fibres or film with piezoresistive and triboelectric characteristics have been increasingly utilized to create various gesture textiles, for example, Parzer, Sharma[45] introduced the SmartSleeve, which is embedded with a deformable textile sensor capable of various touch gestures, such as twirl, twist, fold, push and stretch. The GestureSleeve developed by Schneegass and Voit[46] is a smart sleeve enabled by an input system loaned from smart watch technology that uses the touch gestures of taps and strokes. Besides, Olwal, Moeller[47] of Google's Interaction Lab introduced the 'I/O Braid', an interactive textile cord made of conductive-core yarns and optical fibres with touch, twist and hover capabilities for the control of music playing systems. Braided optical fibres supply visual feedback of gesture recognition results by illuminating in different colours.

Number gesture recognition textiles as natural and universal interfaces for HCI are mainly reviewed to elucidate the development status and research gap. Gloves with detection function are mainstream for number gesture recognition in textile field. It performs relatively high accuracy of detection and broad applicability in complex environment, however, huge electronic controlling system coupled with gloves brings comfortable and aesthetic issues. Therefore, computer vision as an innovative mechanism in gesture recognition textiles serving as solutions for non-invasive and contact-less detection are reviewed.

Gloves with detection function and applications

Glove-based gesture recognition textiles provide immersive interaction for users in HCI, mainly developed number and sign language gestures. Accuracy of detection affects the recognition of hand gestures, as was shown in [31] study, which involved the researchers fabricating a data glove by sewing reduced graphene oxide (RGO)-coated fiber sensors on finger joints of glove. It was to use in real-time detection of number gestures from one to nine and Chinese Sign Language. The detection of the motions of ten finger joints was found to achieve a high accuracy percentage of approximately 98%. Wu, Guo[48] presented a pair of smart gloves which used a noncontact sensing mechanism of electrostatic induction and triboelectric effects to recognize gestures without contact between the fingertips and the palm using strain or pressure sensors on the skin. Number gestures (one, two, three, four, six, seven) have been successfully developed with reduced number of embedded-electrodes. While, Wen, Sun[49] developed a glove that could track finger motions in virtual environments. Recognition was facilitated by textile sensors and machine learning techniques. The high accuracy of detection and recognition capability of this glove are demonstrated by 3D VR/AR control in games of shooting, baseball pitching and flower arranging.

A number of researchers have developed smart gloves that use different applications to detect gesture recognition and interaction. Most number gesture recognition textiles are developed for HCI as universal and eye-free human-computer or human-machine interfaces to control mobile devices and VR by data-harvesting gloves. Shukor, Miskon [27] have developed a novel data glove system with 10 tilt sensors to capture finger bending. Malaysian Sign Language including number gestures of one, two, three has been programmed into the glove to assist people with hearing and speech impairment to communicate normally. Lu, Yu[28] designed a 'YoBu' glove that can detect number gestures from one to ten based on an innovation approach of extreme learning machine. While, Luzhnica, Simon developed a custom-built data glove by integrating 13 bend sensors, 7 motion sensors, 5 pressure sensors and a magnetometer to recognize natural hand gestures, involving number gestures from one to five. Similarly, number gestures have been detected by designing and fabricating data gloves as one mainstream approach by many researchers more recently[29, 31, 48].

Glove-based number gesture recognition textiles usually have relatively high accuracy without limitation of distance and posture for users by using IoT. These textiles use embedded multi-sensor devices to capture hand and finger movements in real time. However, as Kılıboz, Güdükbay[30] point out a data glove is cumbersome to wear with its connection cables and hardware. Users may not move their fingers naturally or interact with the environment or computer in an intuitive way[50, 51]. The sensing devices, computing units and power sources in those data gloves may impact long-time comfort due to additional weight, unbreathable quality and obtrusive contact of components with the hands. Therefore, the e-textile system described here is designed to overcome these limitations through the application of a contact-less textile system via computer vision to achieve vision-based hand gesture recognition.

Vision-based number gesture recognition

There are two main approaches to achieve real-time number gesture recognition from users, one is wearing data gloves, the other method is based on computer vision mechanism and optoelectronic devices. It is found that few research focused on vision-based recognition textiles for number gestures. Although, the vision-based method has been widely used in application of non-textile gesture recognition. Zhou, Xing[52] raised a device-free number gesture detecting method called DeNum based on deep-learning technology. Number gestures from one to ten have been developed by using a Support Vector Machine (SVM) algorithm with average accuracy of 94%. Dinh, Lee[53] presented a novel number gesture recognition approach using recognized hand parts in depth image. Number gestures from zero to nine were developed in recognition rate of 97.8% from five users. While, Islam, Siddiqua[54] developed a real-time gesture recognition system including American number gestures from zero to nine by using Artificial Neural Network (ANN) with feed forward, back propagation algorithm. Those vision-based number gesture recognition approaches together deep-learning algorithms provide new method and principle for developing number gesture recognition textiles.

Illuminative textiles & wearables

The polymethyl methacrylate (PMMA) polymeric optical fibre (POF) textiles serve as a visual display or feedback by the control of hardware components for certain smart functions. The integration of POF in textiles (usually via knitting and weaving) gives an illuminative effect to fabric by coupling to a light source. Designers and artists have used POF textiles to create appealing and colour changing effect for the purpose of achieving unique and personal aesthetic of products where the application is not limited to interior, architecture, and wearables[55]. Combined with open-sourced microprocessor programming and control system with a smart phone device to create a chameleonic garment that has the colour changing effect of POF fabric[56]. The garment could serve as a camouflage or safety warning based on user needs. Apart from the application on garments, researchers have integrated POF by computer embroidery and weaving with testing of the illuminance effect on both flat and bent states placed on the upper limbs. It is found out that POFs can be integrated into textile by using conventional and industrial textile manufacturing process[57].

Previous works has integrated POFs with textile based materials to create fabrics for fashion applications[37] . The photonic fabrics had been developed by jacquard weaving techniques for the application of soft furnishings in interiors[33]. Besides, knitting of POF is feasible and a new textile structure for illumination was created with a raglan form-fitting jumper[35]. In addition to the POF weaving and knitting techniques exploration in previous research, with the integration of electronic components, the design and fabrication of a touch sensitive POF woven fabric system by the application of conductive yarns was conducted. The system was made by capacitive sensor to achieve multi-touch sensing function on fabrics for colour changing effect[2] . Furthermore, an illuminated POF garment, the LUMI jacket, is developed to show the evidence on seamless integration of POF and touch-sensitive function into fashion wearables[32] . It is demonstrated that there is limited of exploration on POF textile integrated with number gesture recognition function for interactive applications both in wearables and interior[58]. Therefore, with the vision-based hand gesture recognition integrated into textile, no actual touching onto the surface or wearable is required to achieve the control of illumination effect on textile via HCI.

Design of a gesture recognition illuminated textile

Design Processes for Smart Materials

Tan [37] introduced a design method framework for the development of photonic soft furnishing which starts with two parallel processes in technology and design that are closely integrated to create product that has both aesthetic appeal and innovative technological functionality. It involves a cycle of continuous and evolving experiments in which certain requirements must be met before a design process is complete. In each step of the process, technology and design are considered concurrently to ensure a well-rounded product that possesses both aesthetic appeal and functionality [34, 59]. Kim, Kim [60] developed the iterative collaborative design process for visible lighting communication based smart fashion design, which consists of six main stages: planning, brainstorming, scenario development, concept development (technology and design), designing, and prototype development. In the concept development, it involves the stage of identifying hardware components, software and design elements of the prototype. The investigation of the fusion of engineering and design to achieve the needs from user. McCann [61] described the issues to be considered in the overall design process. The design brief, and 2D design development then follow, with 3D design development and final prototype development. Within the context of design development, it consists of few elements in this stage: the integration of wearable technology, smart textile technology, interconnections and communications, power, and design of technology interface.

The above design frameworks may serve as references, but in the study described here it was necessary to develop a novel design process for the AI integrated textile controlled by computer vision-based gesture recognition. The necessity is due to the application of open-sourced technology and intangible materials are not considered in the above-mentioned examples.

The design framework adopted in the proposed intelligent textile consists of a series of steps which emphasise synchronization of textile and technology in the exploration of material and interaction. Design is conceived to function as a mediator between the physical textile and the intangible technology (see Figure 1 below). The process begins with consideration of the textile parameters in sync with the well-trained AI and open-sourced hardware system in two stages. In the aspect of textile development, it involves the parameter of computer-aided design (CAD) and fabric construction requirement of integrating hardware component. In terms of technology, the well-trained gesture AI model and open-sourced hardware system achieves the interactive function. The design of the textile and the technology are viewed as mutually supportive and are integrated at each stage. The design process involves multiple iterations and redesigns until requirements are fulfilled for prototyping. The process is a continuous cycle of improvements, which culminates in the creation of an e-textile for gesture recognition.

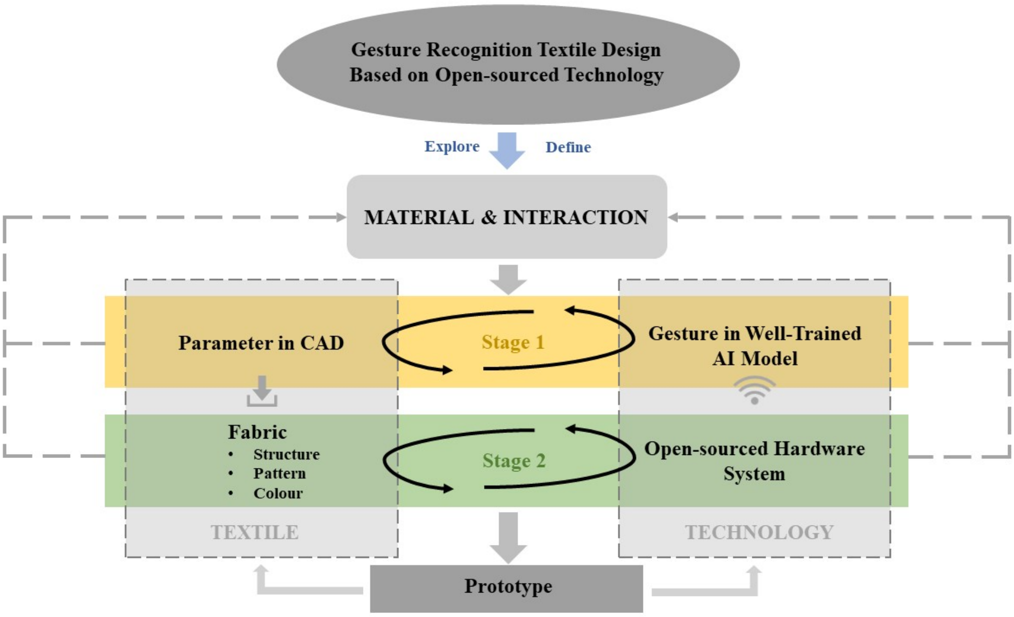


Figure 1 Design process of gesture controlled illuminated textile

Design of System

- *Computer Vision*

To integrate computer vision into the design of textiles, the authors adopted an interdisciplinary approach, deriving and integrating expertise from the disciplines of design, materials technology and engineering to develop an intelligent textile system which consists of the physical textile, software and hardware. Gesture recognition based on computer vision is the key mechanism and refers to a system of electronics integrated into the textile for real-time detection and recognition of hand movements from digital images or video inputs to realize the interaction between humans and computers [62]. Images or videos are collected by sensors, using normally a single camera to detect, track and recognize [51]. High-dimensional data from real world situations can be extracted and produced in the form of numerical and symbolic information for subsequent processes of decision making or reasoning. This is an interdisciplinary approach that encompasses machine learning, electronic engineering, optics and physiology in its investigation of computer vision.

Deep learning is a branch of machine learning and in this study, gestures are learned from static and dynamic hand images via existing algorithm architectures, such as recurrent neural networks (RNN), long short-term memory (LSTM), and convolutional neural networks (CNN) [63]. Multiple layers of networks are adopted in deep learning to increase the universality and accuracy of the gesture recognition mode. A micro colour camera and a compatible single-board computer were embedded into the illuminative textile by inserting the camera into the hollow structures of the double layer material. The components provide corresponding visual feedback for the gesture recognition HCI. A bottom-up software program was designed and developed, including a hardware abstraction layer, embedded operating system, middleware, and an application layer. An open-source AI model based on a deep learning algorithm was adopted to input gesture images.

- *Raspberry Pi*

Raspberry Pi 4 Module B (Raspberry Pi 4B) was chosen as the computing and controlling centre as it is equipped with the high-performance processor BCM2711 and 2GB LPDDR4-3200 SDRAM. It is cost-effective and possesses a high degree of electrical stability [64]. The Raspberry Pi 4B has great potential to be developed with embedded AI to achieve gesture recognition and does not have the limitations of the internet, such as poor connection in remote or confined situations. The processor has a range of ports that provide powerful hardware scalability for functionality. Wi-Fi enables the system to call the AI model in a cloud server [65, 66]. This means the functionality of gesture recognition or other AI applications can be extended by using this single-board computer to avoid high-cost hardware optimization. More importantly for the e-textile system, the Raspberry Pi 4B is about the size of a credit card, and so is portable and concealable. These are important considerations in addressing the need for comfort and aesthetic appeal in both wearable and non-wearable applications. The operating system ‘Raspberry Pi OS’ is based on Linux and is available for free download and installation.

- *Gesture recognition AI Model*

Software system development utilizes a well-trained and encapsulated gesture recognition model from Baidu Cloud. The application of an existing well-developed AI model provides economical digital material, and so makes the technical threshold less daunting for designers. The rationale is that deep-learning model training requires datasets that consist of large quantities of high-quality data. Achieving this requires expertise in both embedded software design and application software design. Open-source AI models facilitate innovation by eliminating much of the time, labour and financial costs involved in model development.

Early AI model training was based on CNN and performed poorly in terms of recognition when changes occurred in the environment, distance or users. While the unoptimized embedded AI model in Raspberry Pi 4B has a relatively large memory capacity and a relatively large data calculation capability, these properties can cause critical overheating of circuits. Therefore, an open-source AI model with 90% plus accuracy from Baidu Cloud was adopted. Its large calculation capability operates online, and so reduces energy consumption and minimises the heat effect on circuits.

The advantages of using this open-source AI model rather than training a deep learning model include:
1) a greatly shortened development cycle;
2) a wide range of gestures (Baidu offers 24 gestures, including those related to number, symbol and culture) providing rich intangible design materials and design flexibility [67];
3) support for multi-person detection with a range of 30 to 300cm (best range 30cm-100cm) [67];
4) the Baidu deep-learning model is optimized for real-time use and synchronization;
5) a software development kit (SDK) and an application programming interface (API) are provided free for calling online interfaces and embedding the offline terminal [68]; and
6) use of a professional open-source AI model has the potential to contribute to industrial concentration and thereby save time and labour costs.

- *The AI system*

The system described facilitates visualization of gesture recognition via the changing colours of illuminative POF fabrics. The embedded gesture recognition textile system, includes three main sections, ‘sensing-processing-actuating’. As Figure 2 below shows, in the sensing stage, a micro single-camera takes discontinuous photos of hand gestures around every $450ms$. In the processing stage, the Raspberry Pi 4B computing unit controls the micro camera in sending and uploading the gesture images to the Baidu server to process the results of recognition via the internet. In the actuating stage, the colour of the POF fabric changes, via the coupled LED light source, according to the results returning back to the Raspberry Pi 4B from the Baidu server. The corresponding relationship between the POF fabric colours and different gestures is pre-programmed in a repeated linear logical program. With a normal Wi-Fi connection or in a hot spot with a mobile device, the average frequency of the 'sensing-processing-actuating' process is approximately$2Hz$.

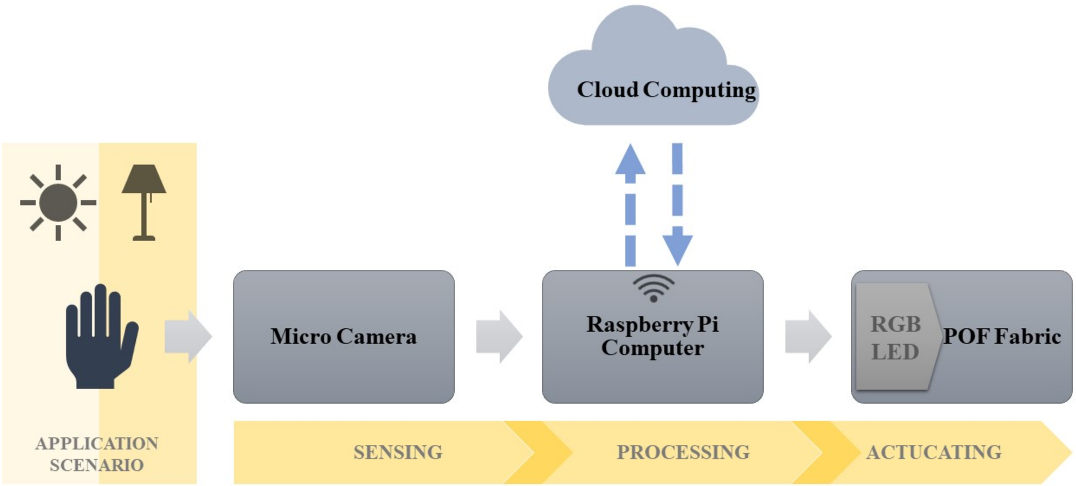


Figure 2 Operation of the 'Sensing-Processing-Actuating' framework

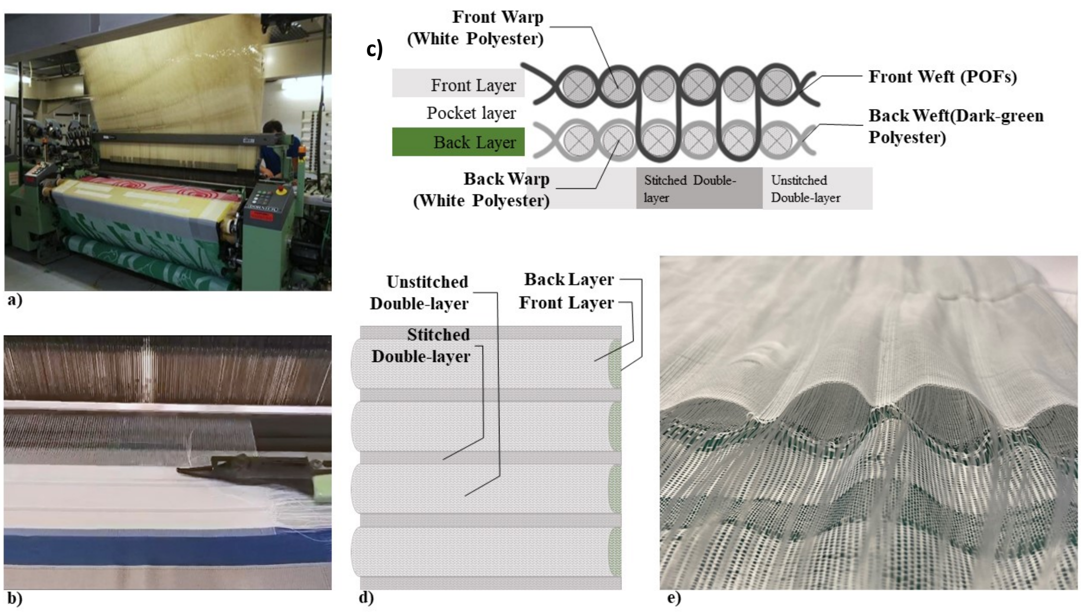
Design of POF textile

- *Materials*

A polymethyl methacrylate (PMMA) polymeric optical fibre (POF) was chosen for this study. PMMA POF is flexible and provides good handling when woven with textile-based yarns. The textile is of double-layer structure with stripes and is woven on a STAUBLI Jacquard Head JC6, Dornier Weaving Loom PTV 8/J with 8192 hooks. The fabric width is 167 cm (Figure 3a). The yarn and weaving specifications used in this study are listed in Table 1 below. The warp yarns made use of 100 denier off white polyester and the wefts consisted of two sets of yarns: 0.25 mm transparent POFs and 100 denier dark green polyester. The colour of the polyester was chosen to accord with the colours of the components (mostly dark-green and dark-grey). These colours enable the components to be integrated into the fabric without being visually obtrusive when it is not illuminated. The warp density was 47ends/cm, and the weft density was 18 picks/cm. The ratio of POFs and Polyester was 1: 1 to create an interconnecting stripe pattern. Two sets of weft yarns provided two independent layers of POFs and polyester in the textile. The POFs were woven on the front layer to allow textile surface illumination, while polyester yarns were woven on the back layer (Figure 3c).

Table 1 Yarn and weaving specification of the POF-polyester double-layer illuminated textile

	Material	Count	Yarn Colour	Density	Ratio
Warp	Polyester	100D	Off white	47 ends/cm	
Weft	POFs	0.25 mm	Transparent	18 picks/cm	1:1
	Polyester	100D	Dark green		



Figures 3 a) and b) show how the double-layer illuminated textile is woven on a STAUBLI Jacquard Head JC6, Dornier Weaving Loom PTV 8/J with 8192 hooks. Figure c) is a diagram of the woven structure of two sets of two independent layers of POFs and polyester in the textile. Figure d) shows the unstitched and stitched area of the double layer textile with separated front and back layers, and Figure e) illustrates the open pocket design of the illuminated textile.

- *Weave structure*

The design of the weave structure was created by the software ArahWeave®. The double-layer structure consists of two main areas which are unstitched and stitched to create alternate pocket slots along the stripe patterns (Figures 3d and e). The 3 cm open pocket design accommodates the electronic materials (size and shape of camera Module V2 (24 x 25 x 9 mm), and flexible printed circuit (FPC) ribbon interconnector (24 mm).

Each area is an independent layer of yarns within the textile. Figure 4 is the structure diagram of the POF-polyester double-layer illuminated textile. The alternate slots are composed of 3 cm open pockets (unstitched) (Figure 4a) with 1 cm interconnecting (stitched) areas in repeat (Figure 4b).

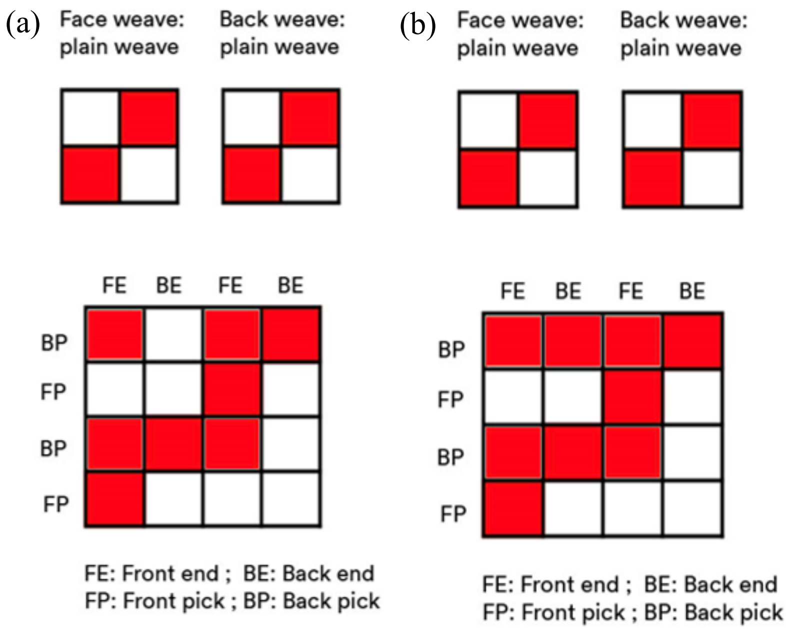


Figure 4 Structure diagram of POF-polyester double-layer illuminated textile: (a) Unstitched areas (open pockets) and (b) stitched areas (interconnection)

Gesture Recognition Textile

Hand gestures representing numbers from one to nine in the Baidu AI model, as well as colour mixing of light based on the 'Additive Primary Colours' RGB colour model (the RGB colour model) were the main intangible and digital elements for this interactive textile design. Number hand gestures and visual feedback were selected as key design elements for e-textile interaction since they share in common the characteristics of intuitiveness, comprehensibility and social acceptance, which make for a user-friendly experience. The interactive design was inspired by the basic mathematical relationships between numbers and colour-mixing, as shown in Figure 5. The number gestures were pre-programmed to correspond with the colour of the POF fabric when illuminating. The POF fabric changes colour by emitting different colours of light when users pose number gestures in front of it within a distance range of 30cm-100cm. Gestures number one, three and five refer to the primary colours red, green and blue (Figures 5a and b). Number gestures four, six, eight and nine represent yellow (red light and green light mixing), magenta (red light and blue light mixing), cyan (green light and blue light mixing), and white (red, green and blue light mixing) respectively (Figure 5c).

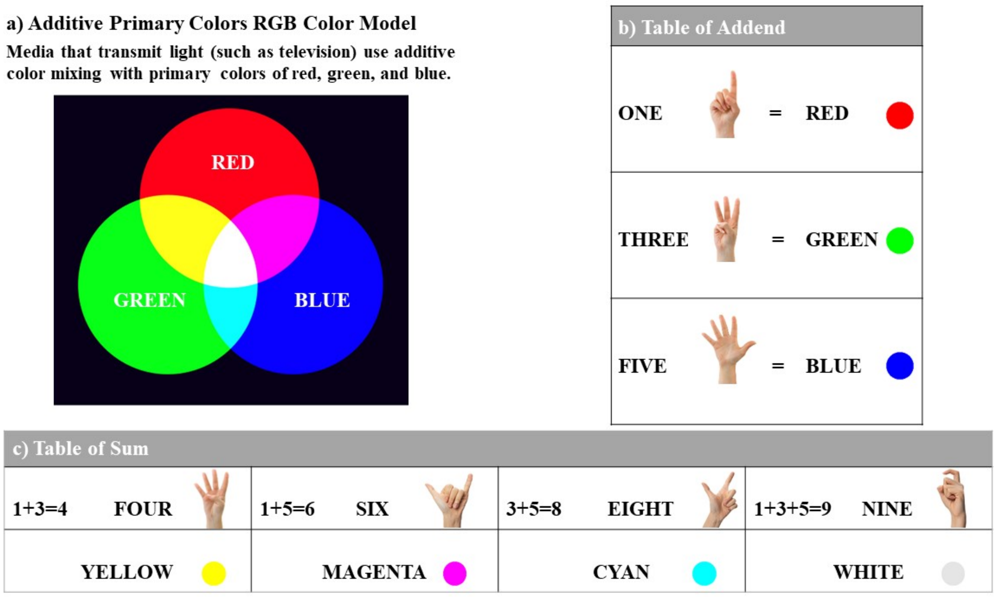


Figure 5 a) 'Addictive Primary Colours' RGB colour model for visible light mixing; b) corresponding number of addends and primary colours; c) the number-within-ten sums and corresponding colours of mixed-light

Figure 6 shows that the gesture recognition illuminative e-textile developed in this study comprises six components:

1) the striped POF fabric embedded with a micro single-camera;
2) RGB LED (external dimension: (D) 13.5 mm x (L) 38 mm, internal dimension: (D) 6 mm x (L) 38 mm) coupled with POF bundles;
3) Raspberry Pi 4B ((L) 85 mm × (W) 56 mm × (H) 16 mm) with heat dissipation case ((L) 95 mm × (W) 65mm × (H) 2 mm) (Raspberry Pi, 2019c);
4) the power supply: output 5V, 3A;
5) FPC Interconnector (W) 16 mm × (L) 10cm/20cm/50cm/100cm/200cm; and
6) the drive circuit for LED (L) 25 mm × (W) 20 mm × (H) 13 mm.

The colour micro single-camera serves as the sensing component of the system and is compatible with Raspberry Pi 4B Camera Module V2, which has a Sony IMX219 8-megapixel sensor (Sony, 2015). The dimensions of the whole module are (L) 25 mm × (W) 24 mm × (H) 8 mm (Raspberry Pi, 2019a, 2019b). Within the module, the exposed lens diameter is 7mm and is visible on the POF fabric. The actuator of the system refers to the POF fabric with embedded Camera Module V2 and FPC interconnector. It is noted that the sensor and the actuator are integrated in this system in the early stages of the design process.

The FPC interconnector is connected to the 2-lane MIPI CSI camera port on Raspberry Pi 4B as data input. At the edge of the warp, the POF textile is coupled to an RGB LED by connecting POF bundles with a metal interconnector screwed on the case of the LED. The pins of the general-purpose input/output (GPI/O) on the Raspberry Pi 4B serve as an output link to the RGB LED by interconnecting with a MOS-based drive circuit board. A portable power bank with a fast charge function (USB-C output port with 5V, 45W max) is adopted as the system power supply (Input 5V, 3A).

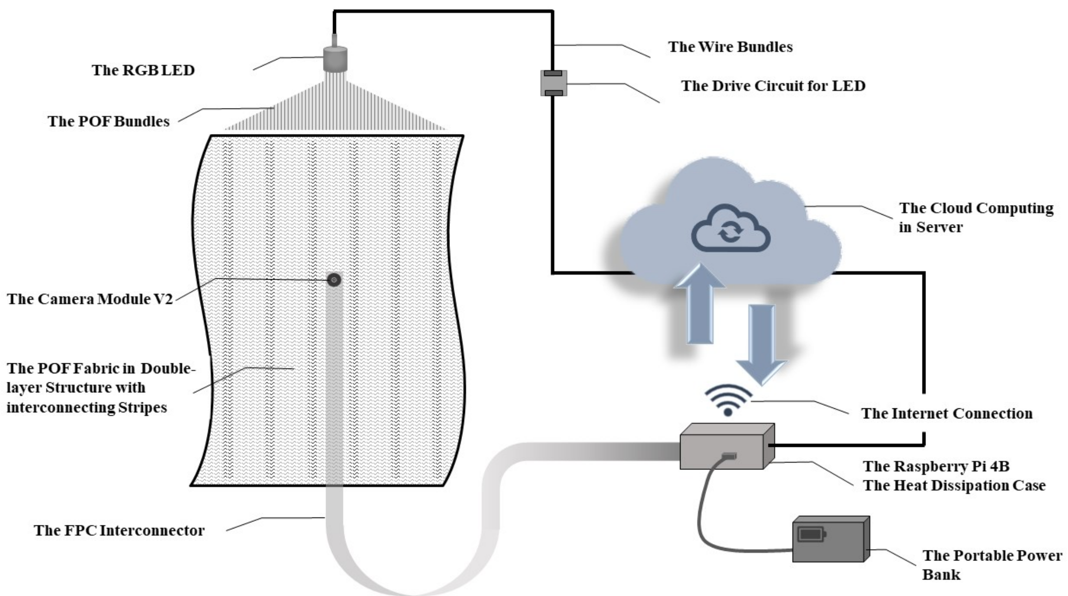


Figure 6 Structure diagram of gesture recognition POF textile with illuminative colour-changing function

The interaction was performed by a user posing number gestures sequentially at a 30cm distance in an indoor environment. In result, the colour of illumination changed based on the interaction with textile by number gesture in an indoor environment. The textile changed colour to red when the system detected gesture number one. The textile changed colour to green, blue, yellow, magenta, cyan and white when recognizing gestures for numbers three, five, four, six, eight, and nine respectively, as shown in Figure 7. It was found that there was normally a three to four second gap between gesture detection and textile colour change for each single number gesture. Operation time largely depended on the data transmission rate via the internet.

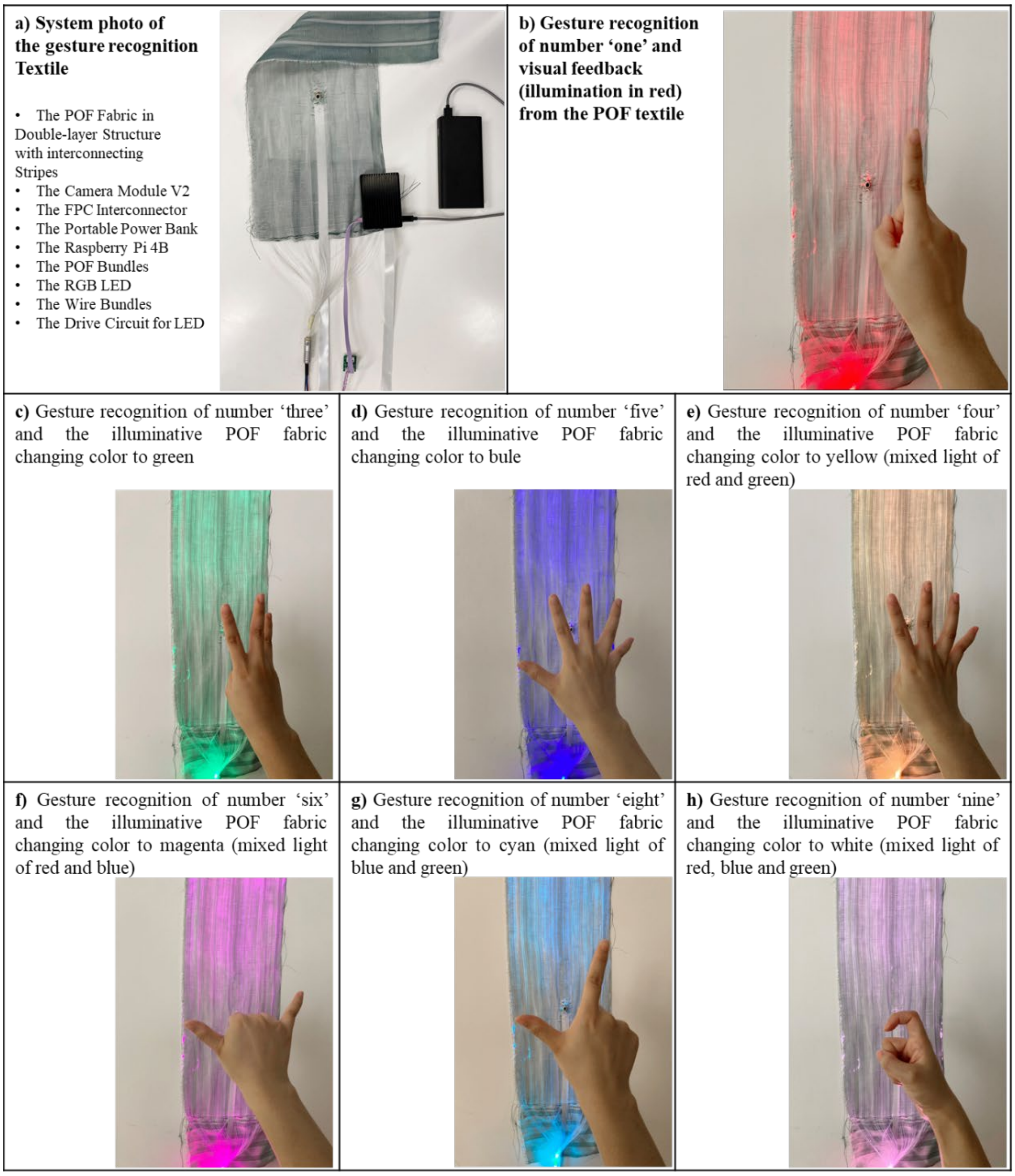


Figure 7a) shows the system of the gesture recognition textile with all components in situ; b) illustrates gesture recognition of number 'one' with visual feedback (illumination in red) from the POF textile; photographs c)-h) relate to gesture recognition of numbers 'three, five, four, six, eight, nine', with the illuminative POF fabric correspondingly changing colour to green, blue, yellow, magenta, cyan and white.

The visual appearance of the illumination on e-textiles emitted by the control of number gesture recognition function is provided in Figure 8. It is shown that the number gesture recognition woven e-textile design with POFs has great potential to be applied in fashion design and interior design.

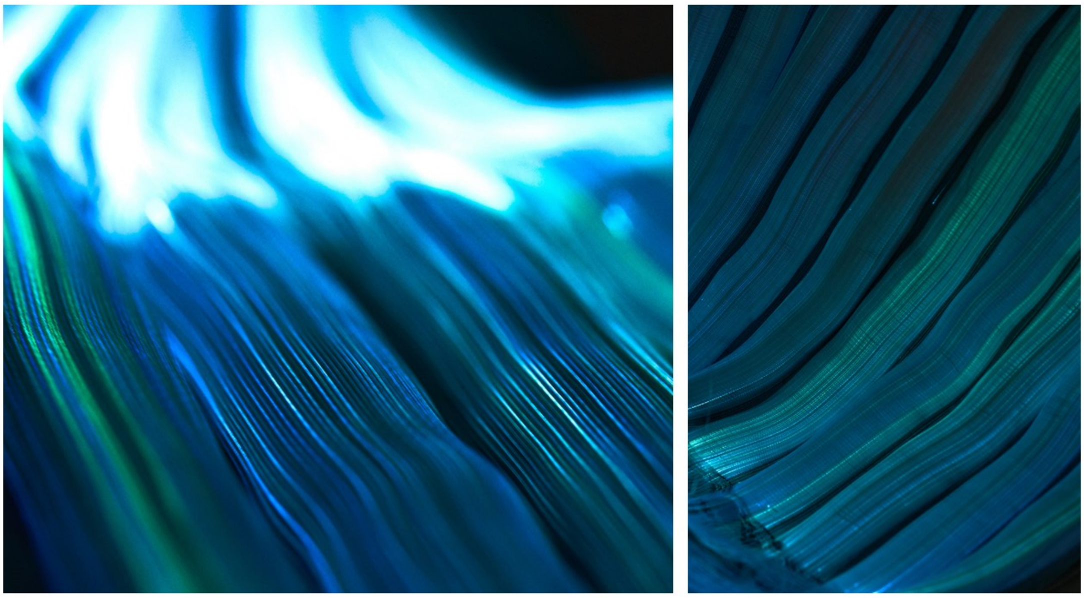


Figure 8 Illuminating POF e-textile

Conclusion

This paper introduced an interactive illuminative POF e-textile controlled by number gesture recognition system via open-sourced AI model. The POF e-textile was woven with an alternative stripe pattern with hollow structures to facilitate the integration of a vision-based hand gesture computing device. A novel design process for the AI integrated textile controlled by computer vision-based gesture recognition was presented which emphasizes the synchronization of open sourced technology in the early stages of the process, so that design interacts continuously between the physical textile and the intangible technology to minimise the labour and financial costs of development. A number gesture recognition textile prototype with illuminating function was fabricated and presented in this research work. This research has addressed the gap for touch-free number gesture recognition in the area of e-textiles design by developing a novel gesture-controlled illuminated textile based on computer vision via an open-sourced AI model. This preliminary prototype possess potential for further development for applications within the sectors of multi-sensory environments and smart wearables.

This contact-less interactive nature of the system has the potential to enhance the way in which users interact and communicate in everyday spaces and fashion, without compromising on the hygiene considerations of the 'new normal'.

The study described here is a work in progress, the limitations of this study are:

1) The bulkiness of system components increases the challenges of integrating them into the textile, although the components are small, but they still possess bulk that requires further streamlining to be integrated seamlessly into textiles;
2) The directionality of the camera should be of standard specifications in prototype development;
3) Successful interaction with the e-textile described here demands successful connection to the internet network with certain signal strength, to avoid failed detection and time delay; and
4) Functional hand disabilities may exclude some potential users, from experiencing the benefits of the textile.

Recommendations for future research include:
1) To conduct investigations into textile-based hardware for hand gesture recognition using computer vision and AI to reduce the cumbersome hardware in the textile. The development of a different woven structure is also important since this could offer the opportunity for better integration of components. The system can potentially work well both outdoors and indoors, but the visibility of the illumination in conditions of strong ambient light is problematic and needs further investigation.
2) In terms of prototype development, it is possible to create an interactive wearable or environmental product by expanding the types of e-textile used, thereby and widening the range of people that could benefit from the product; and
3) User tests will need to be conducted to gather feedback on levels of user satisfaction and to remedy any problems identified.

References

1. Fernández-Caramés TM and Fraga-Lamas PJE. Towards the Internet of smart clothing: A review on IoT wearables and garments for creating intelligent connected e-textiles. 2018; 7: 405.
2. Tan J, Bai Z, Ge L, et al. Design and fabrication of touch-sensitive polymeric optical fibre (POF) fabric. 2019; 110: 1529-1537.
3. Hayward J. E-textiles and Smart Clothing 2020-2030: Technologies, Markets and Players. USA: IDTechEx Research, 2020.
4. MarketsandMarkets. Gesture Recognition and Touchless Sensing Market by Technology (Touch-Based and Touchless), Product (Sanitary Equipment, Touchless Biometric), Type (Online, Offline) Industry and Geography - Global Forecast to 2025. MarketsandMarkets Research Private Ltd., 2019.
5. Bhat G, Deb R and Ogras UY. OpenHealth: Open Source Platform for Wearable

Health Monitoring. 2019.
6. Tsai T-H, Huang C-C and Zhang K-L. Design of hand gesture recognition system for human-computer interaction. *Multimedia tools and applications* 2020; 79: 5989-6007. DOI: 10.1007/s11042-019-08274-w.
7. Mohamed A, Wahab M, Suhaily S, et al. Smart Mirror Design Powered by Raspberry PI. *ACM International Conference Proceeding Series*. ACM, 2018, p. 166-173.
8. Amir A, Taba B, Berg D, et al. A Low Power, Fully Event-Based Gesture Recognition System. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR 2017), 2017.
9. Rautaray SS and Agrawal AJIJoU. Real time hand gesture recognition system for dynamic applications. 2012; 3: 21.
10. Gupta S, Bagga S and Sharma DK. Hand Gesture Recognition for Human Computer Interaction and Its Applications in Virtual Reality. *Advanced Computational Intelligence Techniques for Virtual Reality in Healthcare*. Springer, 2020, pp.85-105.
11. Xu Y and Dai YJCES. Review of hand gesture recognition study and application. 2017; 10: 375-384.
12. Rautaray SS and Agrawal A. Interaction with virtual game through hand gesture recognition. In: *2011 International Conference on Multimedia, Signal Processing and Communication Technologies* 2011, pp.244-247. IEEE.
13. Zhu Y and Yuan B. Real-time hand gesture recognition with Kinect for playing racing video games. In: *2014 International Joint Conference on Neural Networks (IJCNN)* 2014, pp.3240-3246. IEEE.
14. Cohen MW, Voldman I, Regazzoni D, et al. Hand rehabilitation via gesture recognition using leap motion controller. In: *2018 11th International Conference on Human System Interaction (HSI)* 2018, pp.404-410. IEEE.
15. Han S-H, Ahn E-J, Ryu M-H, et al. Natural hand gesture recognition with an electronic textile goniometer. 2019; 31: 1387-1395.
16. Li W-J, Hsieh C-Y, Lin L-F, et al. Hand gesture recognition for post-stroke rehabilitation using leap motion. In: *2017 International Conference on Applied System Innovation (ICASI)* 2017, pp.386-388. IEEE.
17. Mahmoud NM, Fouad H, Soliman AMJC, et al. Smart healthcare solutions using the internet of medical things for hand gesture recognition system. 2020: 1-12.
18. Moschetti A, Fiorini L, Esposito D, et al. Toward an unsupervised approach for daily gesture recognition in assisted living applications. 2017; 17: 8395-8403.
19. Veeralingam S, Sahatiya P, Kadu A, et al. Direct, one-step growth of NiSe2 on cellulose paper: a low-cost, flexible, and wearable with smartphone enabled multifunctional sensing platform for customized noninvasive personal healthcare

monitoring. 2019; 1: 558-568.
20. Yang D, Lim J-K and Choi Y. Early childhood education by hand gesture recognition using a smartphone based robot. In: *The 23rd IEEE International Symposium on Robot and Human Interactive Communication* 2014, pp.987-992. IEEE.
21. He S, Han M, Patel N, et al. Converting Handwritten Text to Editable Format via Gesture Recognition for Education. In: *Proceedings of the 51st ACM Technical Symposium on Computer Science Education* 2020, pp.1369-1369.
22. Guerra-Casanova J, Sánchez-Ávila C, Bailador G, et al. Authentication in mobile devices through hand gesture recognition. 2012; 11: 65-83.
23. Lee U and Tanaka J. Finger identification and hand gesture recognition techniques for natural user interface. In: *Proceedings of the 11th Asia Pacific Conference on Computer Human Interaction* 2013, pp.274-279.
24. Huang Xa, Wang Q, Zang S, et al. Tracing the motion of finger joints for gesture recognition via sewing RGO-coated fibers onto a textile glove. *IEEE Sensors Journal* 2019; 19: 9504-9511.
25. Wu H, Guo H, Su Z, et al. Fabric-based self-powered noncontact smart gloves for gesture recognition. *Journal of Materials Chemistry A* 2018; 6: 20277-20288.
26. Wen F, Sun Z, He T, et al. Machine Learning Glove Using Self-Powered Conductive Superhydrophobic Triboelectric Textile for Gesture Recognition in VR/AR Applications. *Advanced Science* 2020: 2000261.
27. Shukor AZ, Miskon MF, Jamaluddin MH, et al. A new data glove approach for Malaysian sign language detection. *Procedia Computer Science* 2015; 76: 60-67.
28. Lu D, Yu Y and Liu H. Gesture recognition using data glove: An extreme learning machine method. In: *2016 IEEE International Conference on Robotics and Biomimetics (ROBIO)* 2016, pp.1349-1354. IEEE.
29. Rosero-Montalvo PD, Godoy-Trujillo P, Flores-Bosmediano E, et al. Sign language recognition based on intelligent glove using machine learning techniques. In: *2018 IEEE Third Ecuador Technical Chapters Meeting (ETCM)* 2018, pp.1-5. IEEE.
30. Kılıboz NÇ, Güdükbay UJJoVC and Representation I. A hand gesture recognition technique for human–computer interaction. 2015; 28: 97-104.
31. Huang Xa, Wang Q, Zang S, et al. Tracing the motion of finger joints for gesture recognition via sewing RGO-coated fibers onto a textile glove. 2019; 19: 9504-9511.
32. Bai VZ, Tan J, Chen A, et al. Enhancing the wearablity and accessibility of illuminated POF garment. 2019.
33. Bai Z-q, Tan J, Johnston C, et al. Enhancing the functionality of traditional interior textiles with integration of optical fibers. *Research journal of textile and apparel* 2012.
34. Bai Z-q, Tan J, Johnston CF, et al. Connexion. *International Journal of Clothing Science and Technology* 2015.

35. Chen A, Tan J, Henry P, et al. The design and development of an illuminated polymeric optical fibre (POF) knitted garment. 2020; 111: 745-755.
36. Ge L and Tan JJTJoTTI. Development of three-dimensional effects and stretch for polymeric optical fiber (POF) textiles with double weave structure containing spandex. 2021; 112: 398-405.
37. Tan J. Photonic fabrics for fashion and interiors. Springer Reference, 2015.
38. Hillesund T. Digital reading spaces: How expert readers handle books, the Web and electronic paper. 2010.
39. Kurtenbach G and Hulteen E. The art of human-computer interface design. In: Laurel B and Mountford SJ (eds). Addison-Wesley Longman Publishing Co., Inc., 1990, pp.309-317.
40. Kendon A. How gestures can become like words. In: *This paper is a revision of a paper presented to the American Anthropological Association, Chicago, Dec 1983* 1988, Hogrefe & Huber Publishers.
41. Orth M. Firefly dress and necklace. *ACM SIGGRAPH 98 Electronic art and animation catalog*. 1998, pp.37.
42. Orth M, Post R and Cooper E. Fabric computing interfaces. In: *CHI 98 conference summary on Human factors in computing systems* 1998, pp.331-332.
43. Wu T, Fukuhara S, Gillian N, et al. ZebraSense: A Double-sided Textile Touch Sensor for Smart Clothing. In: *Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology* 2020, pp.662-674.
44. Karrer T, Wittenhagen M, Lichtschlag L, et al. Pinstripe: eyes-free continuous input on interactive clothing. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* 2011, pp.1313-1322.
45. Parzer P, Sharma A, Vogl A, et al. SmartSleeve: real-time sensing of surface and deformation gestures on flexible, interactive textiles, using a hybrid gesture detection pipeline. In: *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology* 2017, pp.565-577.
46. Schneegass S and Voit A. GestureSleeve: using touch sensitive fabrics for gestural input on the forearm for controlling smartwatches. In: *Proceedings of the 2016 ACM International Symposium on Wearable Computers* 2016, pp.108-115.
47. Olwal A, Moeller J, Priest-Dorman G, et al. I/O Braid: Scalable touch-sensitive lighted cords using spiraling, repeating sensing textiles and fiber optics. In: *Proceedings of the 31st Annual ACM Symposium on User Interface Software and Technology* 2018, pp.485-497.
48. Wu H, Guo H, Su Z, et al. Fabric-based self-powered noncontact smart gloves for gesture recognition. 2018; 6: 20277-20288.
49. Wen F, Sun Z, He T, et al. Machine Learning Glove Using Self-Powered

Conductive Superhydrophobic Triboelectric Textile for Gesture Recognition in VR/AR Applications. 2020: 2000261.
50. Khan RZ, Ibraheem NAJC and science i. Survey on gesture recognition for hand image postures. 2012; 5: 110.
51. Rautaray SS and Agrawal A. Vision based hand gesture recognition for human computer interaction: a survey. *Artificial intelligence review* 2015; 43: 1-54.
52. Zhou Q, Xing J, Li J, et al. A device-free number gesture recognition approach based on deep learning. In: *2016 12th International Conference on Computational Intelligence and Security (CIS)* 2016, pp.57-63. IEEE.
53. Dinh D-L, Lee S and Kim T-S. Hand number gesture recognition using recognized hand parts in depth images. *Multimedia Tools and Applications* 2016; 75: 1333-1348.
54. Islam MM, Siddiqua S and Afnan J. Real time hand gesture recognition using different algorithms based on american sign language. In: *2017 IEEE international conference on imaging, vision & pattern recognition (icIVPR)* 2017, pp.1-6. IEEE.
55. Gong Z, Xiang Z, OuYang X, et al. Wearable fiber optic technology based on smart textile: A review. *Materials* 2019; 12: 3311.
56. Lin M-T. The chameleonic garment integrated POF fabric with a tricolour LED and wearable device technology. *International Journal of Clothing Science and Technology* 2021.
57. Yang J-H, Cho H-S, Kwak H-K, et al. Influence of Detailed Structure and Curvature of Woven Fabric on the Luminescence Effect of Wearable Optical Fiber Fabric. *Science of Emotion and Sensibility* 2018; 21: 55-62.
58. Kim H, Tan J and Toomey A. Co-designing Interactive Textile for Multisensory Environments. In: *International Conference on Artificial Intelligence on Textile and Apparel* 2018, pp.205-211. Springer.
59. Kim H, Tan J, Toomey AJIJoDM, et al. User experience and interactive textiles: A textile designer's perspective. 2019; 13: 1-10.
60. Kim J-E, Kim Y-H, Oh J-H, et al. Interactive Smart Fashion Using User-Oriented Visible Light Communication: The Case of Modular Strapped Cuffs and Zipper Slider Types. 2017; 2017.
61. McCann J. The garment design process for smart clothing: from fibre selection through to product launch. *Smart clothes and wearable technology*. Elsevier, 2009, pp.70-94.
62. Garg P, Aggarwal N and Sofat S. Vision based hand gesture recognition. *World academy of science, engineering and technology* 2009; 49: 972-977.
63. Ullah A, Ahmad J, Muhammad K, et al. Action recognition in video sequences using deep bi-directional LSTM with CNN features. 2017; 6: 1155-1166.
64. RaspberryPi. Raspberry Pi 4: Completely upgraded, re-engineered Faster, more

powerful, https://www.raspberrypi.org/products/raspberry-pi-4-model-b/ (2019, 2020).
65. RaspberryPi. Raspberry Pi 4 Tech Specs, https://www.raspberrypi.org/products/raspberry-pi-4-model-b/specifications/ (2019).
66. Raspberrypi. Raspberry Pi 4 Model B product brief, https://static.raspberrypi.org/files/product-briefs/200521+Raspberry+Pi+4+Product+Brief.pdf (2019).
67. BaiduAICloud. Gesture Recognition Python SDK Document, https://cloud.baidu.com/doc/BODY/s/Yk3cpymjy (2019).
68. BaiduAICloud. Gesture Recognition: The Main Page, https://cloud.baidu.com/product/body/gesture (2019).