(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) World Intellectual Property Organization
International Bureau

(43) International Publication Date
29 September 2016 (29.09.2016)

WIPO | PCT

(10) International Publication Number
WO 2016/153620 A1

(51) **International Patent Classification**:
G06F 3/01 (2006.01)

(21) **International Application Number**:
PCT/US2016/017413

(22) **International Filing Date**:
10 February 2016 (10.02.2016)

(25) **Filing Language**: English

(26) **Publication Language**: English

(30) **Priority Data**:
14/665,536 23 March 2015 (23.03.2015) US

(71) **Applicant**: **INTEL CORPORATION** [US/US]; 2200 Mission College Boulevard, Santa Clara, California 95054 (US).

(72) **Inventors**: **ALCOCER OCHOA, Alberto**; Av Patria 3117 Int 41, Rinconada de la Calma, 45601 Zapopan (MX). **ARDITTI ILITZKY, David**; Carlos F. Landeros No. 335, 44600 Guadalajara (MX). **CORDOURIER MARURI, Hector A.**; Topacio 2821-6 Col. Sta. Eduwiges, 44580 Guadalajara (MX). **CAMACHO PEREZ, Jose R.**; Privada Jazmin 12 Col. Las Amapas, 45640 Tlajomulco de Zuniga (MX).

(74) **Agents**: **MALLIE, Michael J.** et al.; Blakely Sokoloff Taylor & Zafman LLP, 1279 Oakmead Parkway, Sunnyvale, California 94085 (US).

(81) **Designated States** *(unless otherwise indicated, for every kind of national protection available)*: AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IR, IS, JP, KE, KG, KN, KP, KR, KZ, LA, LC, LK, LR, LS, LU, LY, MA, MD, ME, MG, MK, MN, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SA, SC, SD, SE, SG, SK, SL, SM, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, ZA, ZM, ZW.

[Continued on next page]

(54) **Title**: GESTURE RECOGNITION MECHANISM

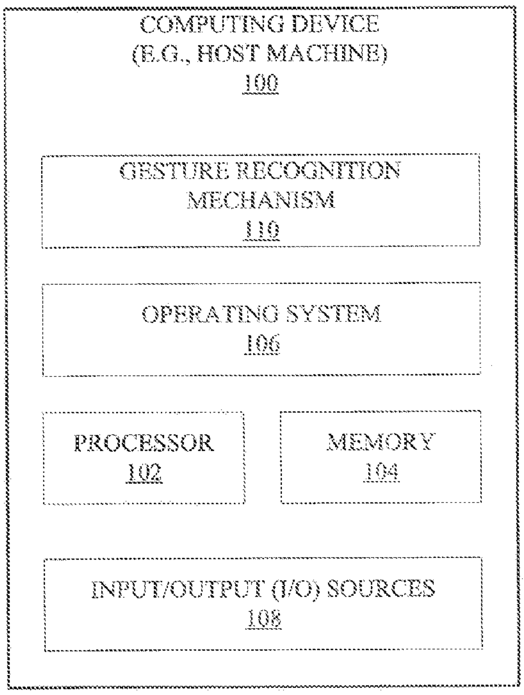

FIG. 1

(57) **Abstract**: A method is described including performing gestural training to extract training signals representing a gesture from each sensor in a sensor array, storing the training signals for each signal corresponding to the gesture in a library, receiving real time signals from the sensor array and comparing the real time output signals to corresponding training signals within the library to determine if a gesture has been recognized.

WO 2016/153620 A1

(84) Designated States *(unless otherwise indicated, for every kind of regional protection available)*: ARIPO (BW, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SD, SL, ST, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, KM, ML, MR, NE, SN, TD, TG).

Published:

— *with international search report (Art. 21(3))*

GESTURE RECOGNITION MECHANISM

FIELD

Embodiments described herein generally relate to wearable computing. More particularly, embodiments relate to identifying gestures using a wearable device.

BACKGROUND

Modern clothing and other wearable accessories may incorporate computing or other advanced electronic technologies. Such computing and/or advanced electronic technologies may be incorporated for various functional reasons or may be incorporated for purely aesthetic reasons. Such clothing and other wearable accessories are generally referred to as "wearable technology" or "wearable computing devices."

Wearable devices often include Small Form Factor (SFF) devices, which are becoming prevalent for enabling users to accomplish various tasks while on the go. However, as SFF devices become smaller typical input/output (I/O) interfaces (e.g., keyboard and/or mouse) have become impracticable. Thus, speech or gesture commands may be implemented to interact with SFF computing devices to overcome interface problems. A gesture is defined as any type of movement of part of the body (e.g., a hand, head, facial expression, etc.) to express an idea or meaning. Additionally, the way gestures are interpreted depend on transducers implemented to measure the gesture. Therefore a gesture being measured through a digital camera, piezoelectric transducer or several accelerometers will provide different signal representations. However when a new input mechanism to interface with SFF devices is introduced, new challenges arise since there is no initial information regarding how to interpret input signals from the device.

BRIEF DESCRIPTION OF THE DRAWINGS

Embodiments are illustrated by way of example, and not by way of limitation, in the figures of the accompanying drawings in which like reference numerals refer to similar elements.

Figure 1 illustrates a gesture recognition mechanism at a computing device according to one embodiment.

Figure 2 illustrates one embodiment of a gesture recognition mechanism.

Figure 3 illustrates one embodiment of a device.

Figures 4A-4D illustrates embodiments of gestures implemented with a device.

Figure 5 illustrates one embodiment of a linear time-invariant (LTI) system.

Figure 6 is a block diagram illustrating one embodiment of a process performed by an LTI system.

Figure 7 illustrates one embodiment of a receiver operating characteristic curve of a gesture recognition mechanism.

Figure 8 illustrates one embodiment of a computer system.

DETAILED DESCRIPTION

Embodiments may be embodied in systems, apparatuses, and methods for gesture recognition, as described below. In the description, numerous specific details, such as component and system configurations, may be set forth in order to provide a more thorough understanding of the present invention. In other instances, well-known structures, circuits, and the like have not been shown in detail, to avoid unnecessarily obscuring the present invention. Embodiments provide for a gesture recognition mechanism that implements a time domain methodology to perform gesture identification and recognition. In such an embodiment, the gesture recognition mechanism is unaware of either a particular gesture, or specifics regarding one or more device sensors, prior to interfacing with the device. In one embodiment, the gesture recognition mechanism includes a training mode that extracts noiseless output signals (training signals) representing a gesture whenever a new user or gesture is added. In one embodiment, the training signals are generated during activation of each of one or more of the sensors during the training mode. Subsequently, training signals for each sensor corresponding to each performed gesture is stored in a library for future gesture recognition. During operation of the gesture recognition mechanism, real time output signals received for each sensor are compared to corresponding training signals within the library to determine if a gesture has been recognized. In various embodiments, the gesture recognition mechanism is integrated into a wearable device.

Figure 1 illustrates a gesture recognition mechanism 110 at a computing device 100 according to one embodiment. In one embodiment, computing device 100 serves as a host machine for hosting gesture recognition mechanism ("recognition mechanism") 110 that includes a combination of any number and type of components for facilitating dynamic identification of gestures at computing devices, such as computing device 100. In one embodiment, computing device 100 includes a wearable device. Thus, implementation of recognition mechanism 110 results in computing device 100 being an assistive device to identify gestures of a wearer of computing device 100.

In other embodiments, gesture recognition operations may be performed at a computing device 100 including large computing systems, such as server computers, desktop computers, etc., and may further include set-top boxes (e.g., Internet-based cable television set-top boxes, etc.), global positioning system (GPS)-based devices, etc. Computing device 100 may include mobile computing devices, such as cellular phones including smartphones (e.g., iPhone® by Apple®, BlackBerry® by Research in Motion®, etc.), personal digital assistants (PDAs), tablet computers (e.g., iPad® by Apple®, Galaxy 3® by Samsung®, etc.), laptop computers (e.g., notebook, netbook, Ultrabook^{TM}, etc.), e-readers (e.g., Kindle® by Amazon®, Nook® by Barnes and Nobles®, etc.), etc.

Computing device 100 may include an operating system (OS) 106 serving as an interface between hardware and/or physical resources of the computer device 100 and a user.

Computing device 100 may further include one or more processors 102, memory devices 104, network devices, drivers, or the like, as well as input/output (I/O) sources 108, such as touchscreens, touch panels, touch pads, virtual or regular keyboards, virtual or regular mice, etc.

Figure 2 illustrates a gesture recognition mechanism 110 employed at computing device 100. In one embodiment, gesture recognition mechanism 110 may include any number and type of components, such as: training engine 201, library 202 and recognition logic 203. In one embodiment, training engine 201 performs gestural training by implementing an algorithm that identifies the response of one or more sensors in sensor array 220 due to a body gesture without being previously aware of either a gesture (mechanical or electrical) signal waveform or the sensors (e.g., mechanical-to-electrical or electrical-toelectrical) transfer function. Accordingly, training engine 201 identifies a linear and time invariant response of each sensor to a gesture (e.g., input signal), without the previous knowledge of the gesture or the sensor's natural transfer function.

In embodiments, gesture recognition mechanism 110 receives input data from sensor array 220, where the image data may be in the form of a sequence of images or frames (e.g., video frames). Sensor array 220 may include an image capturing device, such as a camera. Such a device may include various components, such as (but are not limited to) an optics assembly, an image sensor, an image/video encoder, etc., that may be implemented in any combination of hardware and/or software. The optics assembly may include one or more optical devices (e.g., lenses, mirrors, etc.) to project an image within a field of view onto multiple sensor elements within the image sensor. In addition, the optics assembly may include one or more mechanisms to control the arrangement of these optical device(s). For example, such mechanisms may control focusing operations, aperture settings, exposure settings, zooming operations, shutter speed, effective focal length, etc. Embodiments, however, are not limited to these examples.

Image sources may further include one or more image sensors including an array of sensor elements where these elements may be complementary metal oxide semiconductor (CMOS) sensors, charge coupled devices (CCDs), or other suitable sensor element types. These elements may generate analog intensity signals (e.g., voltages), which correspond to light incident upon the sensor. In addition, the image sensor may also include analog-to-digital converter(s) ADC(s) that convert the analog intensity signals into digitally encoded intensity values. Embodiments, however, are not limited to these examples. For example, an image sensor converts light received through optics assembly into pixel values, where each of these pixel values represents a particular light intensity at the corresponding sensor element. Although these pixel values have been described as digital, they may alternatively be analog. As described above, the image sensing device may include an image/video encoder to encode and/or compress pixel values. Various techniques, standards, and/or formats (e.g., Moving Picture Experts Group (MPEG), Joint Photographic Expert Group (JPEG), etc.) may be employed for this encoding and/or compression.

In a further embodiment, sensor array 220 may include other types of sensing components, such as context-aware sensors (e.g., myoelectric sensors, temperature sensors, facial expression and feature measurement sensors working with one or more cameras, environment sensors (such as to sense background colors, lights, etc.), biometric sensors (such as to detect fingerprints, facial points or features, etc.), and the like.

According to one embodiment, training engine 201 extracts training responses (or eigensignals) of the gesture signals received from sensor array 220. In one embodiment, the extraction is performed by estimating cross-correlation functions from a reduced set of gesture realizations and applying a Karhunen–Loève Eigendecomposition (KLE) decomposition, wherein a training set per gesture is implemented to begin the process. In a further embodiment, the KLE process provides a criteria to select a minimum number of eigensignals to use once a predefined error is chosen. In such an embodiment, the error is user defined and is integral to the accuracy of the gesture recognition process. Once the set of eigensignals is calculated, then they are used by recognition logic 203 at the recognition stage.

Figure 3 illustrates one embodiment of a device 300, representative of computing device 100. In one embodiment, device 300 is a wearable device worn around the wrist of a user. Device 300 includes processor 310, battery 320, sensors (or transducers) 330 and antenna 340. **Figures 4A-4D** illustrates embodiments of gestures that may be implemented at device 300. **Figure 4A** shows a user wearing device 300 performing a gesture of touching a semi-rigid surface with the index finger, while **Figure 4B** shows the user performing a gesture of sliding the index finger on the semi-rigid surface in a downward manner. Meanwhile, **Figures 4C and 4D** show gestures being made to the hand/arm wearing device 300. In response to the gestures, sensors 330 transmit data to processor 310 which performs gesture recognition mechanism 110. Referring back to **Figure 2**, training engine 201 extracts and processes recognition information from the sensor data responsive to the gestures. **Figure 5** illustrates one embodiment of a linear time-invariant (LTI) system implemented by training engine 201 to process the sensor data. In one embodiment, training engine 201 implements a Single–Input to Multiple–Output (SIMO) LTI system since the input data includes a single gesture and the output data corresponds to multiple sensors. From the output signals (e.g., including one set per gesture), training engine 201 synthetizes the responses of each sensor to the gesture (e.g., eigensignals) that is used by recognition logic 203 during a recognition stage. In one embodiment, the eigensignals are calculated from the bi-dimensional cross-correlation functions estimated from a number of repetitions (one per gesture) as represented by:

$$R_{p,q}(t_1,t_2) = E\{X^p(t_1)X^q(t_2)\},$$

where $X^p(t)$ represents a training signal at the output of the p^{th} sensor. Further, a reduced set of orthogonal eigensignals is obtained (e.g., one per gesture) by applying the KLE process to the cross-correlation function.

Figure 6 is a block diagram illustrating one embodiment of a process performed by the training engine 201 LTI system. For every gesture, several realizations (K) are tossed to have a representative sample of the process. At the p^{th} sensor, every realization of the output signal, $\{X^p(t)\}_k = 1, 2, \ldots, K,\}$ is time–aligned prior to the cross-correlations estimations (1). **Figure 6** shows the the realizations in the discrete time domain rather than in the continuous time domain, i.e., $t = nT$, where $T = 1/Fs$ and Fs denotes the sampling frequency of the analog to digital converter. The KLE (e.g., eigendecomposition block in **Figure 6**) is applied to every cross-correlation function, and is provided with a set of eigensignals, denoted as $\{\varphi_l(n)\}$, and eigenvalues, denoted as $\{\lambda_l\}$, such that $R_{p,q} = \mathbf{\Phi\Lambda\Phi}^H$, where $\mathbf{\Phi}$ is a matrix built as $\mathbf{\Phi} = [\varphi_1, \varphi_2, \ldots, \varphi_L]$, $\Lambda = \text{diag}\ \{\lambda_1, \lambda_2, \ldots, \lambda_L\}$, L is the cardinality of the set and (⍰)^H denotes the Hermitian operator. In alternative embodiments, other basis such that $\Theta^H\ \mathbf{R}p,q\ \Theta$ is approximately a diagonal matrix can be used to perform gesture recognition. However, such embodiments do not perform as well as the KLE implementation.

In the KLE implementation, the cardinality of the set depends on a predefined representation error represented by:

$$E = 1 - \sum_{l=1}^{L} \lambda_l$$

Having a low representation error improves the recognition process. However, a low representation error increases the size of library 202, which may be undesirable in application with limited memory. According to one embodiment the cross-correlations process provide a less noisy measurement of the test signal responses (e.g., several realizations of the output signal are averaged together) when the output signals exhibit symmetrical additive noise PDF. Therefore the additive noise tends to its mean. In a further embodiment, a single eigensignal is typically implemented to represent a gesture per sensor.

In one embodiment, the eigensignal set is stored in library 202 for use by recognition logic 203 to perform gesture recognition. In this embodiment, recognition logic 203 implements a matched finite impulse result (FIR) filter to perform gesture recognition. In such an embodiment, a filter, ($\Psi(n)$), is used to maximize the chances for gesture recognition. Such a matched filter is an ideal signal detection criterion in the presence of additive noise with a symmetric Probability Density Function (PDF) (not necessarily Gaussian). Accordingly, form of the matched filter is proposed as:

$$\Psi(n) = \sum_{i=1}^{L} \lambda_i \phi_i(n)$$

Figure 7 illustrates one embodiment of a receiver operating characteristic curve (ROC) graphical plot that illustrates the performance of gesture recognition mechanism 110 system as a discrimination threshold is varied. In one embodiment, the curve is created by plotting a fraction of false acceptance out of a total actual number of trials versus a fraction of false rejects out of total actual negatives at various threshold settings. The performance curves are obtained by changing the threshold of acceptance at the identification stage. Recognition performance can be evaluated easily by detecting how far the curve is from the origin.

Figure 8 illustrates one embodiment of a computer system 800. Computing system 800 includes bus 805 (or, for example, a link, an interconnect, or another type of communication device or interface to communicate information) and processor 810 coupled to bus 805 that may process information. While computing system 800 is illustrated with a single processor, electronic system 800 and may include multiple processors and/or co-processors, such as one or more of central processors, graphics processors, and physics processors, etc. Computing system 800 may further include random access memory (RAM) or other dynamic storage device 820 (referred to as main memory), coupled to bus 805 and may store information and instructions that may be executed by processor 810. Main memory 820 may also be used to store temporary variables or other intermediate information during execution of instructions by processor 810.

Computing system 800 may also include read only memory (ROM) and/or other storage device 830 coupled to bus 805 that may store static information and instructions for processor 810. Date storage device 840 may be coupled to bus 805 to store information and instructions. Date storage device 840, such as magnetic disk or optical disc and corresponding drive may be coupled to computing system 800.

Computing system 800 may also be coupled via bus 805 to display device 850, such as a cathode ray tube (CRT), liquid crystal display (LCD) or Organic Light Emitting Diode (OLED) array, to display information to a user. User input device 860, including alphanumeric and other keys, may be coupled to bus 805 to communicate information and command selections to processor 810. Another type of user input device 860 is cursor control 870, such as a mouse, a trackball, a touchscreen, a touchpad, or cursor direction keys to communicate direction information and command selections to processor 810 and to control cursor movement on display 850. Camera and microphone arrays 890 of computer system 800 may be coupled to bus 805 to observe gestures, record audio and video and to receive and transmit visual and audio commands.

Computing system 800 may further include network interface(s) 880 to provide access to a network, such as a local area network (LAN), a wide area network (WAN), a metropolitan area network (MAN), a personal area network (PAN), Bluetooth, a cloud network, a mobile network (e.g., 3rd Generation (3G), etc.), an intranet, the Internet, etc. Network interface(s) 880 may include, for example, a wireless network interface having antenna 885, which may represent one or more antenna(e). Network interface(s) 880 may also include, for example, a wired network interface to communicate with remote devices via network cable 887, which may be, for example, an Ethernet cable, a coaxial cable, a fiber optic cable, a serial cable, or a parallel cable.

Network interface(s) 880 may provide access to a LAN, for example, by conforming to IEEE 802.11b and/or IEEE 802.11g standards, and/or the wireless network interface may provide access to a personal area network, for example, by conforming to Bluetooth standards. Other wireless network interfaces and/or protocols, including previous and subsequent versions of the standards, may also be supported.

In addition to, or instead of, communication via the wireless LAN standards, network interface(s) 880 may provide wireless communication using, for example, Time Division, Multiple Access (TDMA) protocols, Global Systems for Mobile Communications (GSM) protocols, Code Division, Multiple Access (CDMA) protocols, and/or any other type of wireless communications protocols.

Network interface(s) 880 may include one or more communication interfaces, such as a modem, a network interface card, or other well-known interface devices, such as those used for coupling to the Ethernet, token ring, or other types of physical wired or wireless attachments for purposes of providing a communication link to support a LAN or a WAN, for example. In this manner, the computer system may also be coupled to a number of peripheral devices, clients, control surfaces, consoles, or servers via a conventional network infrastructure, including an Intranet or the Internet, for example.

It is to be appreciated that a lesser or more equipped system than the example described above may be preferred for certain implementations. Therefore, the configuration of computing system 800 may vary from implementation to implementation depending upon numerous factors, such as price constraints, performance requirements, technological improvements, or other circumstances. Examples of the electronic device or computer system 800 may include without limitation a mobile device, a personal digital assistant, a mobile computing device, a smartphone, a cellular telephone, a handset, a one-way pager, a two-way pager, a messaging device, a computer, a personal computer (PC), a desktop computer, a laptop computer, a notebook computer, a handheld computer, a tablet computer, a server, a server array or server farm, a web server, a network server, an Internet server, a work station, a mini-computer, a main frame computer, a supercomputer, a network appliance, a web appliance, a distributed computing system, multiprocessor systems, processor-based systems, consumer electronics, programmable consumer electronics, television, digital television, set top box, wireless access point, base station, subscriber station, mobile subscriber center, radio network controller, router, hub, gateway, bridge, switch, machine, or combinations thereof.

Embodiments may be implemented as any or a combination of: one or more microchips or integrated circuits interconnected using a parentboard, hardwired logic, software stored by a memory device and executed by a microprocessor, firmware, an application specific integrated circuit (ASIC), and/or a field programmable gate array (FPGA). The term "logic" may include, by way of example, software or hardware and/or combinations of software and hardware.

Embodiments may be provided, for example, as a computer program product which may include one or more machine-readable media having stored thereon machine-executable instructions that, when executed by one or more machines such as a computer, network of computers, or other electronic devices, may result in the one or more machines carrying out operations in accordance with embodiments described herein. A machine-readable medium may include, but is not limited to, floppy diskettes, optical disks, CD-ROMs (Compact Disc-Read Only Memories), and magneto-optical disks, ROMs, RAMs, EPROMs (Erasable Programmable Read Only Memories), EEPROMs (Electrically Erasable Programmable Read Only Memories), magnetic or optical cards, flash memory, or other type of media/machine-readable medium suitable for storing machine-executable instructions.

Moreover, embodiments may be downloaded as a computer program product, wherein the program may be transferred from a remote computer (e.g., a server) to a requesting computer (e.g., a client) by way of one or more data signals embodied in and/or modulated by a carrier wave or other propagation medium via a communication link (e.g., a modem and/or network connection).

References to “one embodiment”, “an embodiment”, “example embodiment”, “various embodiments”, etc., indicate that the embodiment(s) so described may include particular features, structures, or characteristics, but not every embodiment necessarily includes the particular features, structures, or characteristics. Further, some embodiments may have some, all, or none of the features described for other embodiments.

In the following description and claims, the term “coupled” along with its derivatives, may be used. “Coupled” is used to indicate that two or more elements co-operate or interact with each other, but they may or may not have intervening physical or electrical components between them.

As used in the claims, unless otherwise specified the use of the ordinal adjectives “first”, “second”, “third”, etc., to describe a common element, merely indicate that different instances of like elements are being referred to, and are not intended to imply that the elements so described must be in a given sequence, either temporally, spatially, in ranking, or in any other manner.

The following clauses and/or examples pertain to further embodiments or examples. Specifics in the examples may be used anywhere in one or more embodiments. The various features of the different embodiments or examples may be variously combined with some features included and others excluded to suit a variety of different applications. Examples may include subject matter such as a method, means for performing acts of the method, at least one machine-readable medium including instructions which, when performed by a machine, cause the machine to performs acts of the method, or of an apparatus or system for facilitating hybrid communication according to embodiments and examples described herein.

Some embodiments pertain to Example 1 that includes an apparatus to facilitate gesture recognition, comprising a sensor array to acquire sensory data, a training engine to extract training signals representing a gesture from each sensor in the sensor array during a training mode, a library to store the training signals for each signal corresponding to the gesture and gesture recognition logic to receive real time signals from the sensor array and to compare the real time output signals to corresponding training signals within the library to determine if a gesture has been recognized.

Example 2 includes the subject matter of Example 1, wherein the training engine identifies a response of each sensor in the sensor array due to the gesture without previous awareness of a signal waveform for the gesture or the sensors.

Example 2 includes the subject matter of claims 1 and 2, wherein the training engine implements a linear and time invariant (LTI) system to extract the training signals by identifying a response of each sensor to a gesture.

Example 4 includes the subject matter of Example 3, wherein the LTU system is a Single–Input to Multiple–Output (SIMO) system.

Example 5 includes the subject matter of Example 3, wherein the training engine synthetizes input signal responses of each sensor to the gesture.

Example 6 includes the subject matter of Example 5, wherein the training engine calculates the training signals from bi-dimensional cross-correlation functions estimated from a number of repetitions of the gesture.

Example 7 includes the subject matter of Example 1-6, wherein the training engine applies a Karhunen–Loève Eigendecomposition to the cross-correlation function to obtain a reduced set of orthogonal training signals.

Example 8 includes the subject matter of Example 7, wherein the recognition logic perform gesture recognition using a matched finite impulse result (FIR) filter.

Some embodiments pertain to Example 9 that includes a method to facilitate gesture recognition comprising performing gestural training to extract training signals representing a gesture from each sensor in a sensor array, storing the training signals for each signal corresponding to the gesture in a library receiving real time signals from the sensor array and comparing the real time output signals to corresponding training signals within the library to determine if a gesture has been recognized.

Example 10 includes the subject matter of Example 9, wherein performing gestural training comprises identifying a response of each sensor in the sensor array due to the gesture without previous awareness of a signal waveform for the gesture or the sensors.

Example 11 includes the subject matter of Examples 9 and 10, wherein performing gestural training comprises implementing a linear and time invariant (LTI) system to extract the training signals by identifying a response of each sensor to a gesture.

Example 12 includes the subject matter of Example 11, wherein the LTU system is a Single–Input to Multiple–Output (SIMO) system.

Example 13 includes the subject matter of Example 11, wherein performing gestural training further comprises synthetizing input signal responses of each sensor to the gesture.

Example 14 includes the subject matter of Example 13, further comprising calculating the training signals from bi-dimensional cross-correlation functions estimated from a number of repetitions of the gesture.

Example 15 includes the subject matter of Examples 10-14, further comprising applying a Karhunen–Loève Eigendecomposition to the cross-correlation function to obtain a reduced set of orthogonal training signals.

Example 16 includes the subject matter of Example 15, wherein gesture recognition is performed using a matched finite impulse result (FIR) filter.

Some embodiments pertain to Example 17 that includes at least one machine-readable medium comprising a plurality of instructions that in response to being executed on a computing device, causes the computing device to carry out the method of claims 9-16.

Some embodiments pertain to Example 18 that includes a system to facilitate gesture recognition comprising means for performing gestural training to extract training signals representing a gesture from each sensor in a sensor array, means for storing the training signals for each signal corresponding to the gesture in a library and means for receiving real time signals from the sensor array and means for comparing the real time output signals to corresponding training signals within the library to determine if a gesture has been recognized.

Example 19 includes the subject matter of Example 18, wherein the means for performing gestural training comprises implementing a linear and time invariant (LTI) system to extract the training signals by identifying a response of each sensor to a gesture.

Example 20 includes the subject matter of Example 19, wherein the means for performing gestural training further comprises synthetizing input signal responses of each sensor to the gesture.

Example 21 includes the subject matter of Example 20, further comprising means for calculating the training signals from bi-dimensional cross-correlation functions estimated from a number of repetitions of the gesture.

Example 22 includes the subject matter of Example 21, further comprising means for applying a Karhunen–Loève Eigendecomposition to the cross-correlation function to obtain a reduced set of orthogonal training signals.

Example 23 includes the subject matter of Example 18, wherein the means for gesture recognition is performed using a matched finite impulse result (FIR) filter.

Some embodiments pertain to Example 24 that includes a gesture recognition computing device comprising a sensor array to acquire sensory data, a memory device to store a library and a processor to execute a training engine to extract training signals representing a gesture from each sensor in the sensor array during a training mode and store the training signals for each signal corresponding to the gesture in the library and gesture recognition logic to receive real time signals from the sensor array and to compare the real time output signals to corresponding training signals within the library to determine if a gesture has been recognized.

Example 25 includes the subject matter of Example 24, wherein the training engine calculates the training signals from bi-dimensional cross-correlation functions estimated from a number of repetitions of the gesture.

Some embodiments pertain to Example 26 that includes at least one machine-readable medium comprising a plurality of instructions that in response to being executed on a computing device, causes the computing device to carry out operations comprising performing gestural training to extract training signals representing a gesture from each sensor in a sensor array, storing the training signals for each signal corresponding to the gesture in a library receiving real time signals from the sensor array and comparing the real time output signals to corresponding training signals within the library to determine if a gesture has been recognized.

Example 27 includes the subject matter of Example 26, wherein performing gestural training comprises implementing a linear and time invariant (LTI) system to extract the training signals by identifying a response of each sensor to a gesture.

Example 28 includes the subject matter of Example 27, wherein performing gestural training further comprises synthetizing input signal responses of each sensor to the gesture.

Example 29 includes the subject matter of Example 28, comprising a plurality of instructions that in response to being executed on a computing device, causes the computing device to further carry out operations comprising calculating the training signals from bi-dimensional cross-correlation functions estimated from a number of repetitions of the gesture.

Example 30 includes the subject matter of Example 29, comprising a plurality of instructions that in response to being executed on a computing device, causes the computing device to further carry out operations comprising applying a Karhunen–Loève Eigendecomposition to the cross-correlation function to obtain a reduced set of orthogonal training signals.

Example 31 includes the subject matter of Example 30, wherein gesture recognition is performed using a matched finite impulse result (FIR) filter.

The drawings and the forgoing description give examples of embodiments. Those skilled in the art will appreciate that one or more of the described elements may well be combined into a single functional element. Alternatively, certain elements may be split into multiple functional elements. Elements from one embodiment may be added to another embodiment. For example, orders of processes described herein may be changed and are not limited to the manner described herein. Moreover, the actions of any flow diagram need not be implemented in the order shown; nor do all of the acts necessarily need to be performed. Also, those acts that are not dependent on other acts may be performed in parallel with the other acts. The scope of embodiments is by no means limited by these specific examples. Numerous variations, whether explicitly given in the specification or not, such as differences in structure, dimension, and use of material, are possible. The scope of embodiments is at least as broad as given by the following claims.

CLAIMS

What is claimed is:

1. An apparatus to facilitate gesture recognition, comprising:

a sensor array to acquire sensory data;

training engine to extract training signals representing a gesture from each sensor in the sensor array during a training mode;

a library to store the training signals for each signal corresponding to the gesture; and

gesture recognition logic to receive real time signals from the sensor array and to perform gesture recognition.

2. The apparatus of claim 1, wherein the training engine identifies a response of each sensor in the sensor array due to the gesture without previous awareness of a signal waveform for the gesture or the sensors.

3. The apparatus of claims 1 and 2, wherein the training engine implements a linear and time invariant (LTI) system to extract the training signals by identifying a response of each sensor to a gesture.

4. The apparatus of claim 3, wherein the LTU system is a Single–Input to Multiple–Output (SIMO) system.

5. The apparatus of claim 3, wherein the training engine synthetizes input signal responses of each sensor to the gesture.

6. The apparatus of claim 5, wherein the training engine calculates the training signals from bidimensional crosscorrelation functions estimated from a number of repetitions of the gesture.

7. The apparatus of claims 1-6, wherein the training engine applies a Karhunen–Loève Eigendecomposition to the crosscorrelation function to obtain a reduced set of orthogonal training signals.

8. The apparatus of claim 7, wherein the recognition logic perform gesture recognition using a matched finite impulse result (FIR) filter.

9. A method to facilitate gesture recognition, comprising:

performing gestural training to extract training signals representing a gesture from each sensor in a sensor array;

storing the training signals for each signal corresponding to the gesture in a library; and

performing gesture recognition upon receiving real time signals from the sensor array.

10. The method of claim 9, wherein performing gestural training comprises identifying a response of each sensor in the sensor array due to the gesture without previous awareness of a signal waveform for the gesture or the sensors.

11. The method of claims 9 and 10, wherein performing gestural training comprises implementing a linear and time invariant (LTI) system to extract the training signals by identifying a response of each sensor to a gesture.

12. The method of claim 11, wherein the LTU system is a Single–Input to Multiple–Output (SIMO) system.

13. The method of claim 11, wherein performing gestural training further comprises synthetizing input signal responses of each sensor to the gesture.

14. The method of claim 13, further comprising calculating the training signals from bidimensional crosscorrelation functions estimated from a number of repetitions of the gesture.

15. The method of claims 10-14, further comprising applying a Karhunen–Loève Eigendecomposition to the crosscorrelation function to obtain a reduced set of orthogonal training signals.

16. The method of claim 15, wherein gesture recognition is performed using a matched finite impulse result (FIR) filter.

17. At least one machine-readable medium comprising a plurality of instructions that in response to being executed on a computing device, causes the computing device to carry out the method of claims 9-16.

18. A system to facilitate gesture recognition comprising:

means for performing gestural training to extract training signals representing a gesture from each sensor in a sensor array;

means for storing the training signals for each signal corresponding to the gesture in a library; and

means for performing gesture recognition upon receiving real time signals from the sensor array.

19. The system of claim 18, wherein the means for performing gestural training comprises implementing a linear and time invariant (LTI) system to extract the training signals by identifying a response of each sensor to a gesture.

20. The system of claim 19, wherein the means for performing gestural training further comprises synthetizing input signal responses of each sensor to the gesture.

21. The system of claim 20, further comprising means for calculating the training signals from bidimensional crosscorrelation functions estimated from a number of repetitions of the gesture.

22. The system of claim 21, further comprising means for applying a Karhunen–Loève Eigendecomposition to the crosscorrelation function to obtain a reduced set of orthogonal training signals.

23. The system of claim 22, wherein the means for gesture recognition is performed using a matched finite impulse result (FIR) filter.

24. A gesture recognition computing device, comprising:

a sensor array to acquire sensory data;

a memory device to store a library; and

a processor to execute:

a training engine to extract training signals representing a gesture from each sensor in the sensor array during a training mode and store the training signals for each signal corresponding to the gesture in the library; and

gesture recognition logic to receive real time signals from the sensor array and to perform gesture recognition.

25. The computing device of claim 24, wherein the training engine calculates the training signals from bidimensional crosscorrelation functions estimated from a number of repetitions of the gesture.

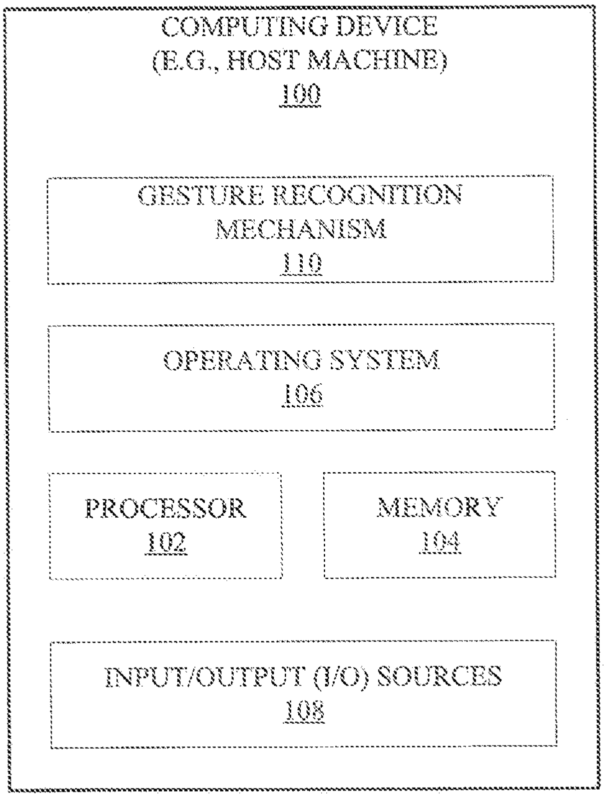
COMPUTING DEVICE
(E.G., HOST MACHINE)
100
GESTURE RECOGNITION
MECHANISM
110
OPERATING SYSTEM
106
PROCESSOR
102
MEMORY
104
INPUT/OUTPUT (I/O) SOURCES
108

FIG. 1

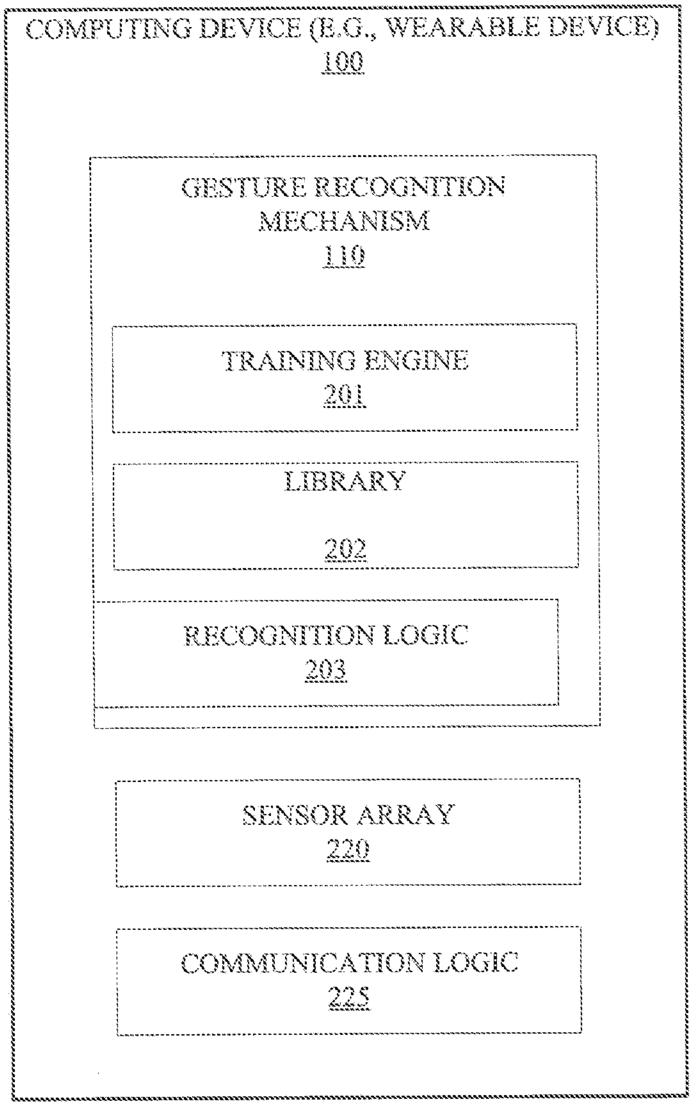
COMPUTING DEVICE (E.G., WEARABLE DEVICE)
100
GESTURE RECOGNITION
MECHANISM
110
TRAINING ENGINE
201
LIBRARY
202
RECOGNITION LOGIC
203
SENSOR ARRAY
220
COMMUNICATION LOGIC
225

FIG. 2

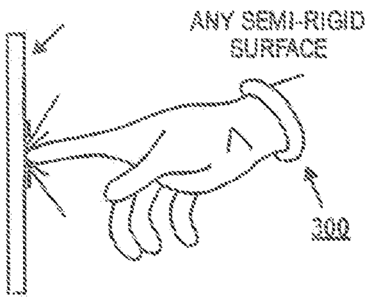

FIG. 4A

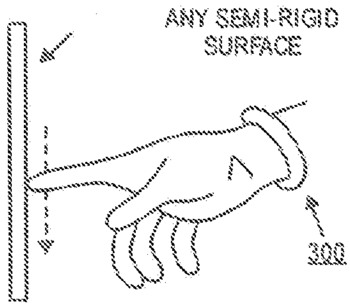

FIG. 4B

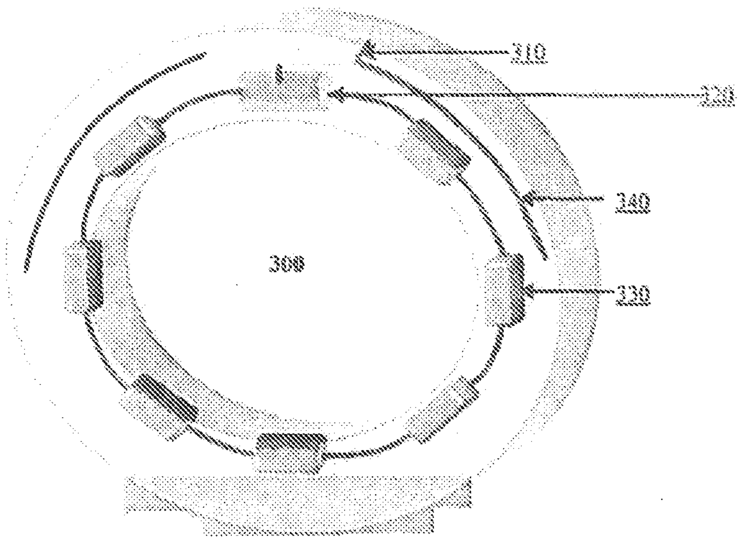

FIG. 3

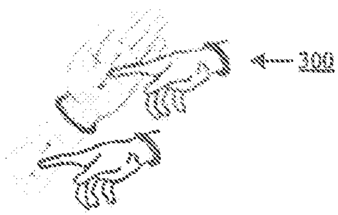

FIG. 4C

FIG. 4D

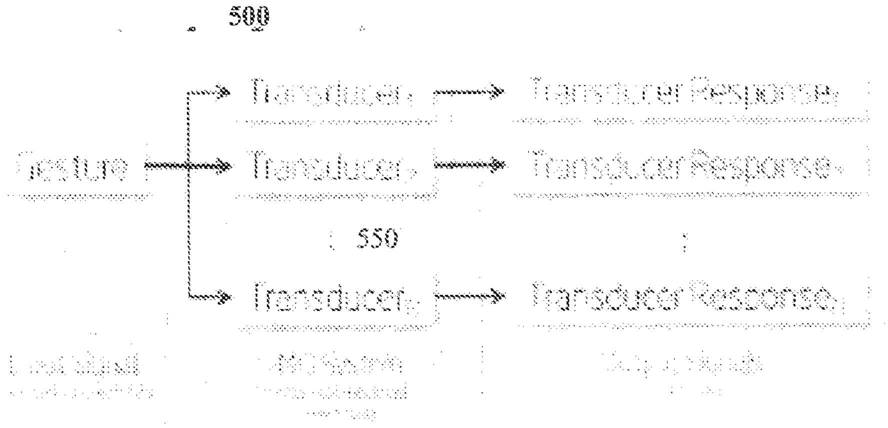
500
Gesture
Transducer
Transducer Response
Transducer
Transducer Response
550
Transducer
Transducer Response

FIG. 5

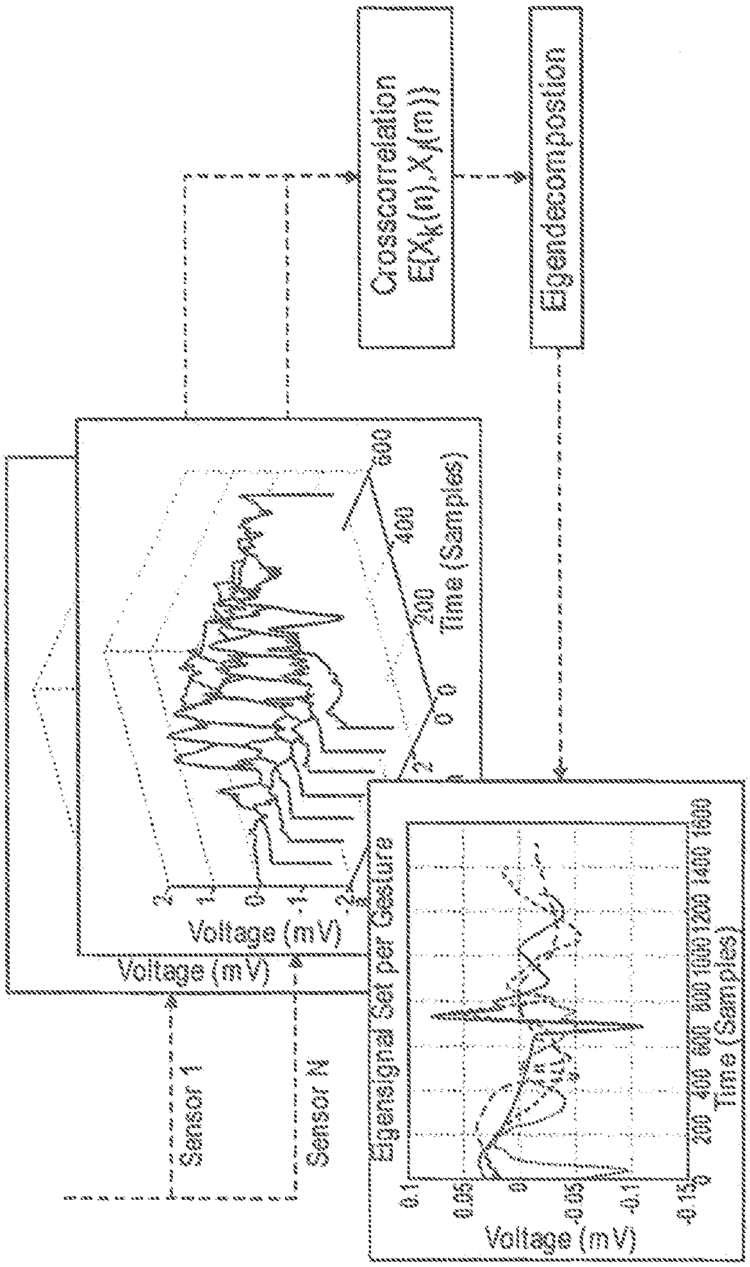
Crosscorrelation
$E\{X_k(n), X_j(m)\}$
Eigendecomposition
Sensor 1
Sensor N
Voltage (mV)
Time (Samples)
Eigensignal Set per Gesture
Voltage (mV)
Time (Samples)

FIG. 6

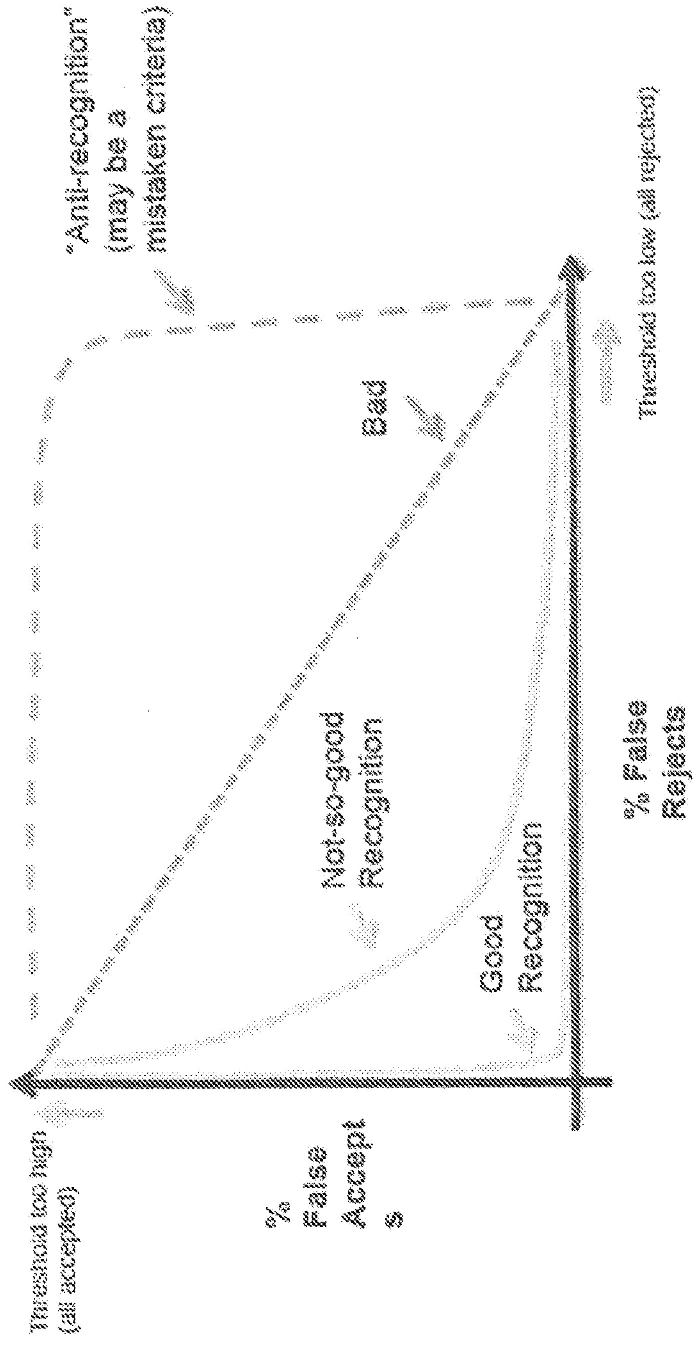
"Anti-recognition" (may be a mistaken criteria)
Threshold too low (all rejected)
Bad
Not-so-good Recognition
Good Recognition
% False Rejects
% False Accept s
Threshold too high (all accepted)

FIG. 7

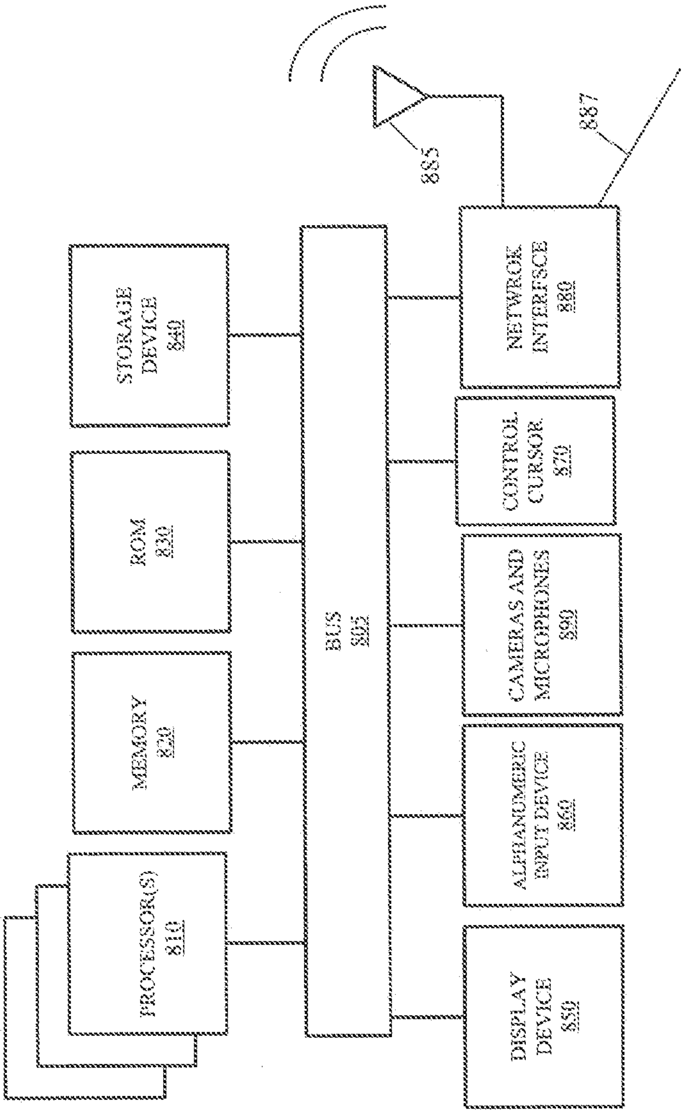
PROCESSOR(S)
810
MEMORY
820
ROM
830
STORAGE
DEVICE
840
BUS
805
DISPLAY
DEVICE
850
ALPHANUMERIC
INPUT DEVICE
860
CAMERAS AND
MICROPHONES
890
CONTROL
CURSOR
870
NETWROK
INTERFSCE
880
885
887

FIG. 8

INTERNATIONAL SEARCH REPORT

International application No.
PCT/US2016/017413

A. CLASSIFICATION OF SUBJECT MATTER

G06F 3/01(2006.01)i

According to International Patent Classification (IPC) or to both national classification and IPC

B. FIELDS SEARCHED

Minimum documentation searched (classification system followed by classification symbols)
G06F 3/01; G06F 3/033; A63F 9/24; G01B 11/14; H04B 1/10; G06F 7/04; G01V 1/00

Documentation searched other than minimum documentation to the extent that such documents are included in the fields searched
Korean utility models and applications for utility models
Japanese utility models and applications for utility models

Electronic data base consulted during the international search (name of data base and, where practicable, search terms used)
eKOMPASS(KIPO internal) & Keywords: sensor, acquire, training signal, gesture, library, store, gesture recognition

C. DOCUMENTS CONSIDERED TO BE RELEVANT

Category*	Citation of document, with indication, where appropriate, of the relevant passages	Relevant to claim No.
X	US 2012-0007713 A1 (STEVE NASIRI et al.) 12 January 2012 See paragraphs [0006], [0039]-[0045], [0059]-[0060], [0102]; claims 1, 15, 20; and figures 1, 7.	1-2,9-10,17-18,24
Y		3-8,11-16,19-23,25
Y	US 2003-0091134 A1 (CHONG-YUNG CHI et al.) 15 May 2003 See paragraphs [0004], [0036], [0044]; and figure 1.	3-6,11-14,19-23
Y	US 2007-0064535 A1 (ROY MATTHEW BURNSTAD) 22 March 2007 See paragraph [0019]; claim 10; and figures 3-4.	6-8,14-16,21-23,25
A	WO 2011-094366 A1 (INTERSIL AMERICAS INC.) 04 August 2011 See paragraphs [0028]-[0037]; and figures 3-4.	1-25
A	US 2012-0306745 A1 (CHRISTOPHER MOORE et al.) 06 December 2012 See paragraphs [0003]-[0005]; and figures 1, 8.	1-25

☐ Further documents are listed in the continuation of Box C. ☒ See patent family annex.

* Special categories of cited documents:
"A" document defining the general state of the art which is not considered to be of particular relevance
"E" earlier application or patent but published on or after the international filing date
"L" document which may throw doubts on priority claim(s) or which is cited to establish the publication date of another citation or other special reason (as specified)
"O" document referring to an oral disclosure, use, exhibition or other means
"P" document published prior to the international filing date but later than the priority date claimed
"T" later document published after the international filing date or priority date and not in conflict with the application but cited to understand the principle or theory underlying the invention
"X" document of particular relevance; the claimed invention cannot be considered novel or cannot be considered to involve an inventive step when the document is taken alone
"Y" document of particular relevance; the claimed invention cannot be considered to involve an inventive step when the document is combined with one or more other such documents,such combination being obvious to a person skilled in the art
"&" document member of the same patent family

Date of the actual completion of the international search	Date of mailing of the international search report
05 July 2016 (05.07.2016)	**06 July 2016 (06.07.2016)**

Name and mailing address of the ISA/KR
International Application Division
Korean Intellectual Property Office
189 Cheongsa-ro, Seo-gu, Daejeon, 35208, Republic of Korea
Facsimile No. +82-42-481-8578

Authorized officer
BYUN, Sung Cheal
Telephone No. +82-42-481-8262

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
US 2012-0007713 A1	12/01/2012	CN 102725712 A	10/10/2012
		EP 2499552 A1	19/09/2012
		EP 2499552 A4	22/07/2015
		JP 2013-510381 A	21/03/2013
		JP 5882220 B2	09/03/2016
		TW 201140386 A	16/11/2011
		US 2016-018902 A1	21/01/2016
		US 9144735 B2	29/09/2015
		US 9174123 B2	03/11/2015
		WO 2011-057287 A1	12/05/2011
US 2003-0091134 A1	15/05/2003	TW 544997 B	01/08/2003
		US 7050490 B2	23/05/2006
US 2007-0064535 A1	22/03/2007	CA 2622961 A1	29/03/2007
		CN 101310196 A	19/11/2008
		CN 101310196 B	07/03/2012
		EP 1934635 A2	25/06/2008
		EP 1934635 A4	08/08/2012
		NO 20081324 A	17/06/2008
		US 7333392 B2	19/02/2008
		WO 2007-035787 A2	29/03/2007
		WO 2007-035787 A3	29/11/2007
		WO 2007-035787 A8	08/05/2008
		WO 2007-035787 B1	20/03/2008
WO 2011-094366 A1	04/08/2011	CN 102822691 A	12/12/2012
		CN 102822759 A	12/12/2012
		CN 102822759 B	20/08/2014
		TW 201145075 A	16/12/2011
		TW 201202730 A	16/01/2012
		TW 201202731 A	16/01/2012
		TW 201203008 A	16/01/2012
		TW 201205047 A	01/02/2012
		TW 201432283 A	16/08/2014
		TW I439716 B	01/06/2014
		TW I445993 B	21/07/2014
		TW I448871 B	11/08/2014
		US 2011-0180693 A1	28/07/2011
		US 2011-0180709 A1	28/07/2011
		US 2011-0181254 A1	28/07/2011
		US 2011-0181861 A1	28/07/2011
		US 2011-0181892 A1	28/07/2011
		US 2011-0182519 A1	28/07/2011
		US 2014-327900 A1	06/11/2014
		US 8274037 B2	25/09/2012
		US 8530819 B2	10/09/2013
		US 8760631 B2	24/06/2014
		WO 2011-094360 A1	04/08/2011

INTERNATIONAL SEARCH REPORT

Information on patent family members

International application No.

PCT/US2016/017413

Patent document cited in search report	Publication date	Patent family member(s)	Publication date
		WO 2011-094361 A1	04/08/2011
		WO 2011-094362 A1	04/08/2011
		WO 2011-094364 A1	04/08/2011
		WO 2011-094365 A1	04/08/2011
US 2012-0306745 A1	06/12/2012	TW 201303656 A	16/01/2013
		TW I493385 B	21/07/2015
		US 2015-355721 A1	10/12/2015
		US 9110510 B2	18/08/2015
		WO 2012-166354 A2	06/12/2012
		WO 2012-166354 A3	28/03/2013