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GripLaunch: a Novel Sensor-Based Mobile User Interface with Touch Sensing Housing

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Abstract

This paper describes a novel way of applying capacitive sensing technology to a mobile user interface. The key idea is to use grip-pattern, which is naturally produced when a user tries to use the mobile device, as a clue to determine an application to be launched. To this end, a capacitive touch sensing system is carefully designed and installed underneath the housing of the mobile device to capture the information of the user's grip-pattern. The captured data is then recognized by dedicated recognition algorithms. The feasibility of the proposed user interface system is thoroughly evaluated with various recognition tests.

Key words : Capacitive touch sensing, mobile terminal, recognition, grip-pattern recognition, accelerometer, motion sensing.

1. Introduction

The rapid advance of technology redirects computing power away from the desktop and into mobile devices. In these days, users of mobile devices can perform many tasks which could be done only on the desktop computing environments in the past. Therefore, now, the interactivity of buttons and keypads are not sufficient to guarantee the usability of multi-function mobile devices.

In an effort to resolve this problem, several approaches have been taken in the industrial and academic fields. The classical main stream in the design of mobile user interface is to refine physical and graphical interfaces or improve the menu navigation structures while sticking to conventional input devices such as buttons, keyboards, mice, touch screens, etc. The second approach, which is relatively immature, is to totally redesign or invent an input device by employing additional sensors to increase the number of interaction channels [1–5].

The major role of input systems is to robustly deliver user's intention to the device, which is not problematic for the first case since the user's actions and the responses of input systems of the devices are well defined. In addition, users are already familiar with those traditional input systems. The second approaches, however, suffers from many technical and non-technical barriers. First, one has to implement reliable hardware and software systems, which are mainly issues of sensing technology. It is also required to have intelligent sensor data fusion and processing algorithms to deal with the ill-defined user's actions. Regarding another critical issue, the user acceptance of the developed interface cannot be guaranteed.

Turning to the issues regarding human-computer interaction, our hands are undoubtedly dominant tools to use our devices. Especially, every mobile device has some sensing means on the specific area of their housings to get information from hands. The sensed signals, which partially represent the user's intention, are then processed to provide machine-understandable information with the devices. Those sensing means and surfaces are collectively called control surface [6]. Therefore, many of user interfaces assume that the interaction is performed directly between the user's

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bare-hands and control surfaces

Interaction with bare hand and/or finger has long been pursued in the literature of human-computer interaction due to its naturalness and intuitiveness. Except for buttons and keypads, touch sensor-based user interfaces are most successful examples of bare *finger*-based interaction [7–9]. However, they are inherently designed to detect a single finger and be placed on the front face of the device, although some researchers suggested some variations [9].

To the contrary, interaction techniques based on the information from multiple fingers and the hand or part of the body are also well pursued topics in human-machine interfaces for desktop computing, ubiquitous computing and robotics [10]. To cite a few, various body or bare hand interaction system have been implemented based on pressure sensing and image processing technologies [11, 12]. Tactapad from Tactiva (http://www.tactiva.com) provides two-handed interaction with desktop users by the combination of pressure sensitive touch sensing system and a camera. JazzMutant (http://www.jazzmutant.com) suggests a multi-touch input device called Lemur, whose main interaction is performed with the movement user's multiple fingers by using resistive sensing technique. Rekimoto *et al.* and Dietz *et al.* proposed a desktop multi-user collaboration interface with variations of capacitive touch sensing technology [4, 13, 14]. Morrison described a user interface for large displays with optical multi-touch input device [15].

The above mentioned multiple touch and hand-based interaction schemes are not viable interface solution for mobile devices due to their limited size. However, the grip-pattern, which is inevitably produced when a user tries to use his/her mobile device, can be a good alternative for mobile bare-hand interaction. Several Japanese and US patents claim the idea of applying sensor information generated by user's grip to the mode change [16, 17], power control [18, 19], and device control [20]. However, most systems described in those patents are equipped with only a few sensors and the interaction is just performed through the combination of signals form the sensors, which limits the usability and feasibility of the claimed systems. Turning to the academic field, the relevant issues has been rarely dealt with. Until only very recently, Veldhuis *et al.* presented an authentication system for a gun to prevent accidental firing by using pressure sensors wrapped around the gun's butt [21].

Based on the aforementioned observations, this paper aims at developing a new sensor-based user interface system for mobile devices with touch sensing technology. To this end, we proceed by describing GripLaunch. As illustrated in Fig. 1, GripLaunch utilizes grip-pattern information to provide quick and easy access to embedded applications of the mobile devices without multi-step menu navigation.

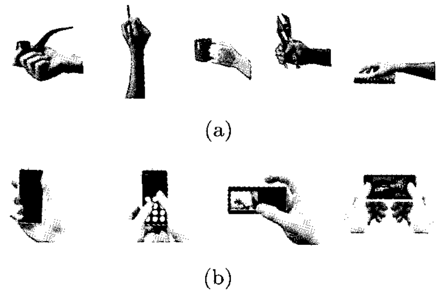


Figure 1: Grip patterns and their relevant functions (a) each tool requires its own grip-pattern. (b) each function in a multi-function mobile device requires its own grip-pattern.

In order to realize the concept of GripLaunch, we first develop a capacitive touch sensor system, whose sensing portion is made by a flexible printed circuit board (FPCB) to be easily installed beneath the housing of the device. In addition, the sensor system is designed to detect multi-point touch for sensing the grip-pattern. Totally 64 electrodes are arranged on the FPCB and the size of each electrode is designed to be 8 mm by 8 mm. Thus, the synthesized mobile device can sense the user's grip with sufficient resolution. Since the capacitive touch sensor has a feature of non-contact sensing, the system also detect the user's grip without revealed sensing portions on the surface of the device. During the synthesis of the whole system, the authors equip the system with a trial-axis accelerometer as an auxiliary orientation sensing mean. The obtained sensor data is then mapped to an appropriate application by an embedded recognizer system. We constructed the recognition system with three popular classifiers, i.e., a minimum distance classifier (MDC), naive Bayes classifier, and a support vector machine (SVM) classifier.

The main contributions of this paper are the design and implementation of touch sensing system, which allows the whole surface of the housing of the mobile device to operate as a sensing mean. In specific, the array of capacitive sensors distributed on the FPCB efficiently detects the touch of user's hand without disclosure. Although pressure sensors [11, 22] can be considered as an alternative approach, we adopt capacitive sensing because pressure sensors severely degrade the quality of the form factor of the device due to the exposed sensing portions. Using the developed *sensing housing* and the relevant recognition algorithms, we propose a novel mobile user interface which proactively responses to the user's grip which is naturally produced when the user tries to use the device. The interaction method proposed in this paper should be expressly distinguished from other research works in that the presented interface takes into account the grip-pattern, which has been ignored in the mobile human-computer interaction.

This paper is organized as follows. Section 2.1 briefly introduces the concept of the proposed interface system. In section 2, the implementation of GripLaunch system is discussed. Experimental results, primarily focused on the recognition rate, are included in Section 3. This paper concludes with section 4.

2. Implementation of GripLaunch system

In this section, we attempt to show that the proposed concept can be implemented with current available components with reasonable size, cost and performance. We describe the hardware and software systems in detail to provide a foundation for the next-level of touch sensor-based user interface.

2.1 Interaction Architecture

Before going further, an ideal usage scenario with the proposed GripLaunch is briefly discussed. Figure 2 (a) shows a mobile device with a touch-sensitive screen and housing with no externally disclosed buttons or switches. Although the system is literally touch-sensitive, it does not respond to the unintentional touch signals. In other words, a user can hold or put the system in his/her pocket without worrying about false operation of the system.

When a specific function of the device is required, the user simply takes hold of the device. The embedded recognizer classifies the sensed grip-pattern to launch an appropriate application as shown in Fig. 2.

Since the whole surface of the device except for the display portion senses the contact of the human body, the unintentional touch can trigger the system to falsely operate, which leads to degraded reliability of the system. However, the system is equipped with a dedicated preprocessing and postprocessing procedures to reject signals from the unintentional touch actions.

During the use of the service, the part of the housing and screen is assigned as a control surface. For example, in the camera mode, the half of the right side of the device becomes a linear slider and a switch with slight illumination for feedforward guide as shown in Fig. 3. In this paper, the control surface is defined as a portion of the housing of the device through which

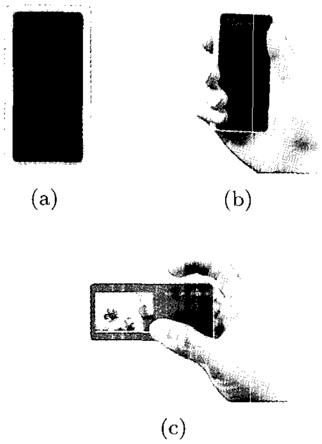


Figure 2: (a) A mobile device with GripLaunch system in idle mode (b) When a user holds the device to make a call, the system automatically launches the voice dialing service (c) A user just grasps the device to take a picture, then the device is functioned as a camera. The internal gravity sensor (accelerometer) further determines the proper orientation of the display.

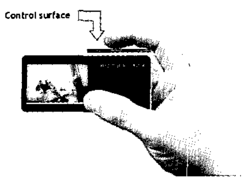


Figure 3: The parts of the device becomes control surfaces and light feedforward is generated as a guide for users.

a user deliver his/her control actions to the device [6].

Figure 4 illustrates the brief overview of the data flow for GripLaunch system. Based on the ideal usage scenario of GripLaunch, this paper is devoted to the design and synthesis of supporting hardware systems and essential recognition algorithm.

2.2 Hardware of GripLaunch

Unlike the traditional touch sensor interface, sensing portion of our prototype is not confined within a specific region. Ideally speaking, a user just need to naturally grip the device to transfer his/her control intention to the device. Then, system automatically launch a desirable application. In order to implement a hardware system to support the proposed interaction scheme, we focus on developing a sensor system

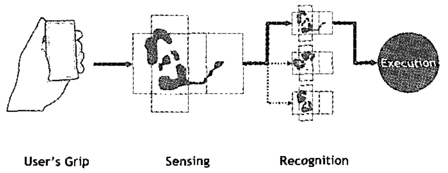


Figure 4: Brief data flow of GripLaunch system.

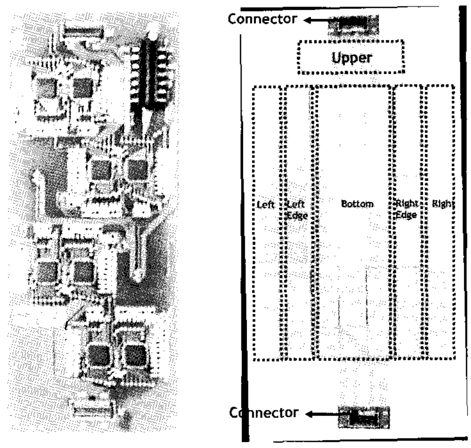
that has the following characteristics.

- Multi-point touch: This feature is required to capture user's hand image.
- Easy to manufacture: The system is aimed to be installed in the mobile device. Therefore, the whole sensing system should be reasonably small and easy to assemble.

Here, we note that other pressure sensing technologies [11, 22] can be used to implement the proposed interface system. However, pressure sensors severely restrict the material and form factor of target mobile device because they require the sensing parts should be revealed outside. Therefore, we adopt the capacitive sensing technology which can detect the touch of human body without contact [10]

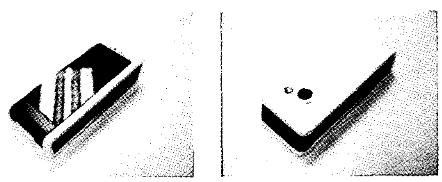
Figure 5 shows the block diagram of the system. The system hardware is composed of the main board and the separate sensor board. The touch electrode array (TEA), i.e. touch pad, is made of a flexible printed circuit board and consists of 64 square electrodes so that the single flexible TEA (FTEA) is enough to make a touch-sensitive housing. The size of each electrode is 8 mm by 8 mm, which is sufficient to sense the contact of the human body through 1.8 mm thickness housing. Totally eight 8 channel ESSD SS01 touch sensor ICs are deployed and two 32 channel ADG732 multiplexors are used to transfer the sensed data to the CPU through two analogue input ports of the CPU. The CPU controls the two multiplexors simultaneously with five GPIO ports. Figure 6 shows photos of the sensor board and the FTEA. Since capacitive touch sensors are inherently analogue electric circuits, one has to pay careful attention to the design and assembly of the sensor system. In this paper, we deployed a standardized Kyocera 14-5602-020-001 connector to relieve the possible analogue noises.

Samsung S3C2410X01 ARM-compatible CPU is used as a main processing unit. Recognition software and user interface programs are stored in the 2 MB flash memory area and loaded to 16 MB SDRAM during the execution. In the current version, the user interface is in charge of guiding users the grip-pattern and notifying recognition results. We virtually implement the 1:2 ratio screen with two Samsung LTS180S3-H1 1.8 inch TFT LCDs. In addition, we adopt Kionix KXM52 accelerometer and the measured motion information by the KXM52 is used as auxiliary information for the recognizer. Figure 7 shows the final working prototype. The size of the system is 105 (L) $\times$ 48 (W) $\times$ 23 (H) (mm).



(a) (b)

Figure 6: Sensor System (a) Sensor board with eight ESSD SS01 touch sensor ICs. (b) Flexible Touch Electrode Array (FTEA).



(a) (b)

Figure 7: External appearances of the final prototype system (a) Front. (b) Rear.

2.3 Data Processing

For the measurements, a Java-based data acquisition program is used to collect the sensor data from the presented system. An experimental environment called touch interface development environment (TIDE) is built with Python language. Figure 8 shows the experimental environment.

The developed hardware system is attached to a PC through the RS232C serial interface. The sensor signals are captured and transmitted to the PC and saved to the database.

All of outputs from the capacitive sensors and accelerometer is acquired by 10 bit A/D converters. The

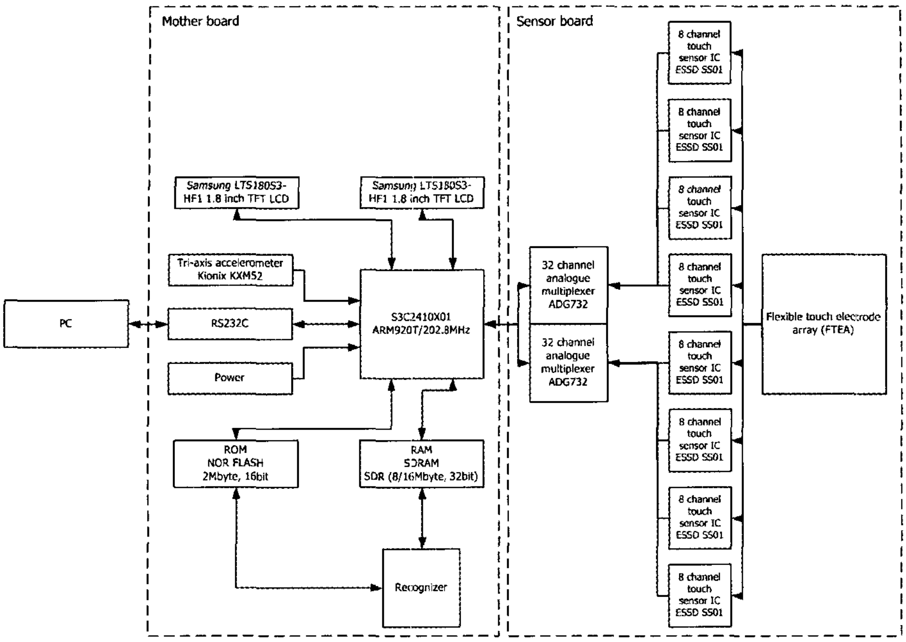


Figure 5: GripLaunch architecture. Most of the hardware is installed on the motherboard including the CPU and LCDs. Touch sensor ICs and multiplexers are implemented on a separate sensor board and wired to FTEA via dedicated connector. The whole system communicates with a PC through an RS232C cable.

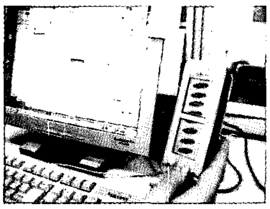


Figure 8: Photograph of collecting user data using the developed system.

system internally binarize the A/D values of capacitive sensors with threshold value 512, which is the half of the maximum value of 10 bit A/D converters.

Therefore, the sensor data is composed of 64 binary touch sensor outputs and three analogue accelerometer outputs. Each touch sensor output corresponds to a single bit. For the accelerometer, each axis occupies double bytes. Therefore, totally 14 bytes are required to deliver the sensor information to the PC system, which are sufficient to be transferred via RS232C communication protocol.

On the PC side, the acclerometer measurements are converted to their physical values by:

$$\begin{aligned} A_{bx} &= -\frac{A^{AD}_{bx}-\alpha_x}{\beta_x} \\ A_{by} &= -\frac{A^{AD}_{by}-\alpha_y}{\beta_y} \\ A_{bz} &= -\frac{A^{AD}_{bz}-\alpha_z}{\beta_z} \end{aligned} \tag{1}$$

where, A_{bx}, A_{by}, and A_{bz} are accelerations along the x, y, and z axis of the accelerometer. A^D_{bx}, A^D_{by}, and A^D_{bz} are A/D converted output of the accelerometer, $\alpha_x = \frac{A^{AD1}_{bx}+A^{AD2}_{bx}}{2}$, $\alpha_y = \frac{A^{AD1}_{by}+A^{AD2}_{by}}{2}$, $\alpha_z = \frac{A^{AD1}_{bz}+A^{AD2}_{bz}}{2}$, $\beta_x = \frac{A^{AD1}_{bx}-A^{AD2}_{bx}}{2g}$, $\beta_y = \frac{A^{AD1}_{by}-A^{AD2}_{by}}{2g}$, and $\beta_z = \frac{A^{AD1}_{bz}-A^{AD2}_{bz}}{2g}$. $A^{AD1}_{bx} = 308$, $A^{AD2}_{bx} = 722$, $A^{AD1}_{by} = 716$, $A^{AD2}_{by} = 300$, $A^{AD1}_{bz} = 727$, and $A^{AD2}_{bz} = 317$ are experimentally obtained calibration parameters.

2.4 Recognition

The purpose was to infer the correct grip-pattern of the user with the given set of the accelerometer and capacitive sensor outputs. Figure 9 shows the overall structure of the recognition system.

In the preprocessing stage, the time average of each variable in the data set is taken and the data set is normalized to have means of zero and standard deviation of one. Therefore, the dimension of the resulting data set is 67, which is composed of three acceleration measurements and 64 capacitive sensor outputs.

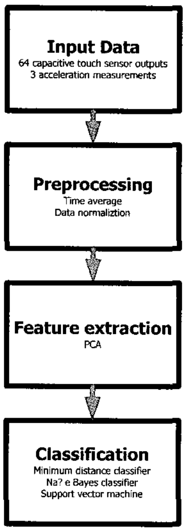


Figure 9: Overall structure of the recognition system

The feature extraction block reduces the dimension of the data set by applying the well-known principal component analysis (PCA) method.

Finally, the classifiers determines the class that the obtained grip-pattern data belongs to. In this paper, we construct three classifiers for the grip-pattern recognition; a minimum distance classifier (MDC) [23], a naive Bayes classifier (NBC) [24], and a support vector machine (SVM) classifier. In the MDC, the Euclidean distance between an unknown data and the mean value of data sets of each class is used to assign the new data to the appropriate class. Since the naive Bayes classifier assumes that the features of the data sets are probabilistically independent to the given classes, the structure and learning of Bayes classifiers are very simple and efficient [25, 26]. For the SVM classifier, we adopt pairwise classification technique with maximum-voting method since a single SVM classifier can deal with binary classification problems only [27, 28]. In addition, we train the SVM with the linear kernel.

3. Experimental Results

The recognition performance of the proposed system is evaluated using the grip-pattern data collected from 50 users. Users were guided to take hold of the device according to examples shown in Fig. 10. The services or situations for the defined modes include call, one-handed SMS, two-handed SMS, camera function with horizontal pose, two camera functions with vertical pose, digital contents management (DCM), and gaming. Four grip-pattern data sets was collected

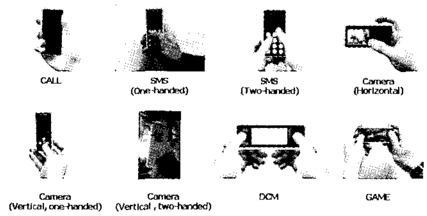


Figure 10: Examples of grip-pattern for data collection.

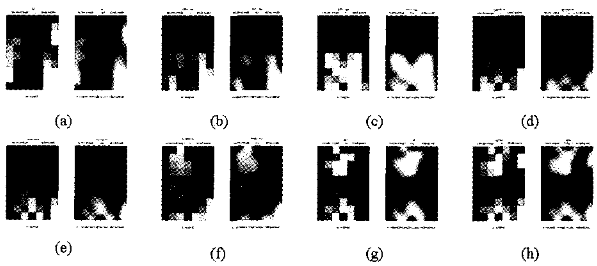


Figure 11: Averaged images of grip-patterns (a) Call (b) SMS (one-handed) (c) SMS (two-handed) (d) Camera (horizontal) (e) Camera (vertical, one-handed) (f) Camera (vertical, two-handed) (g) DCM (h) Game.

for each of eight modes. The number of grip-pattern data sets were 1600. However, the last eight grip-pattern data sets of seventh user is removed from the database due to the failure in the system. Therefore, we used 1592 data sets for evaluation of classification systems.

Before training classifier, we qualitatively evaluate the reliability of the sensor system by displaying the captured grip-pattern. Due to the low resolution of the capture images grip-patterns, we resize the images by using bicubic interpolation algorithm [14] for the reader's convenience. Averaged images of each mode are shown in Fig. 11, which clearly indicate that the performance of the sensor system is acceptable.

For thorough investigation of the feasibility of the proposed interaction system, the following steps are selectively activated and totally four different types of data sets are provided.

1. Inclusion of accelerometer outputs in the preprocessing stage.

2. Feature extraction using principal component analysis (PCA).

It is noted that principal component analysis (PCA) method [29] is used in the feature extraction stage, where we chose principal components that contributes

Table 1: Classification results.

Case	Acclerometer data	PCA	Recall (%)			Cross validation (%)		
			MDC	NBC	SVM	MDC	NBC	SVM
1	Excluded	Deactivated	82.8	84.4	94.0	81.7	81.1	83.5
2	Excluded	Activated	78.6	80.5	88.8	78.1	78.8	84.0
3	Included	Deactivated	91.8	93.7	98.9	91.1	90.8	94.0
4	Included	Activated	89.3	91.1	96.9	89.2	89.8	93.6

more than 2% to the total variation in the given data set.

The performance of classifiers are evaluated based on recall rate test and ten-fold cross validation test. In the ten-fold cross validation test, data set of 50 users are divided into ten partitions. At the first time, The first nine subsets are used to train classifiers and the remaining set is used for testing. Secondly, the next nine subsets and the remained set are used for training and testing, respectively. In this way, ten different configurations of training and test sets are constructed to measure the classification performance.

The evaluation is performed under the Matlab environment. We used the `Bayes Net Toolbox` for Matlab (http://bnt.sourceforge.net/) and `SVM Toolbox` for Matlab (http://ida.first.fraunhofer.de/ anton/software.html) for the grip-pattern recognition.

The classification results are shown in Table 1. The `Deactivated` case in the column with heading of PCA means the original data is directly given to classifiers.

The best recognition rate is obtained when all of the sensor data is used and PCA is not applied. The best recognition rates from the view point of cross validation test are 91.1%, 90.8%, and 94% for the minimum distance classifier, naive Bayes classifier, and SVM classifier, respectively. Since the accelerometer can effectively describes the orientation of the device, the inclusion of accelerometer data reduces the confusion between the two vertical camera modes and the horizontal camera mode, which results in the improved recognition results. The claim can be justified the confusion matrices in Tables 2 – 5. In Tables 2 and 3, the class 4 (`Camera`, horizontal) and class 5 (`Camera`, vertical, one-handed) are severely confused. However, as shown in Tables 4 and 5, those two classes are well classified with the orientation information given by the accelerometer.

In this experiments, the features extracted by PCA method does not contribute to the performance of the classifiers. It only made the performance of classifiers worse. It may be claimed that the dimension reduction by PCA method just results in the loss of useful information since the dimensions of the data set is relatively small compared with other applications such as image and voice recognition.

In addition, except for the pair of `Camera` (horizontal) and `Camera` (vertical, one-handed), the pair of `SMS`

Table 2: Confusion matrices for Case 1 (1 = Call, 2 = SMS (one-handed), 3 = SMS (two-handed), 4 = Camera (horizontal), 5 = Camera (vertical, one-handed), 6 = Camera (vertical, two-handed), 7 = Game, 8 = DCM).

(a)

Class	1	2	3	4	5	6	7	8	Total
1	188	0	0	0	0	0	0	0	188
2	1	157	22	2	5	0	2	1	190
3	1	22	163	3	2	0	0	0	191
4	0	2	0	149	54	9	0	3	217
5	9	18	13	45	138	4	5	25	257
6	0	0	0	0	0	169	0	3	172
7	0	0	0	0	0	3	179	10	192
8	0	0	1	0	0	14	13	157	185
Total	199	199	199	199	199	199	199	199	1592

(b)

Class	1	2	3	4	5	6	7	8	Total
1	192	4	5	0	2	2	0	4	209
2	0	140	28	2	3	0	1	1	175
3	1	22	141	2	0	0	1	0	167
4	0	1	1	166	82	0	0	1	251
5	5	31	24	29	112	0	0	2	203
6	0	0	0	0	0	188	8	11	207
7	0	0	0	0	0	0	182	10	192
8	1	1	0	0	0	9	7	170	188
Total	199	199	199	199	199	199	199	199	1592

(c)

Class	1	2	3	4	5	6	7	8	Total
1	190	2	3	0	1	1	0	2	199
2	3	155	21	2	8	0	2	1	192
3	4	24	161	2	7	0	1	2	201
4	1	4	4	161	58	1	0	2	231
5	1	13	9	33	125	0	2	7	190
6	0	0	0	0	0	186	0	8	194
7	0	1	0	0	0	1	185	10	197
8	0	0	1	1	0	10	9	167	188
Total	199	199	199	199	199	199	199	199	1592

Table 3: Confusion matrices for Case 2 (1 = Call, 2 = SMS (one-handed), 3 = SMS (two-handed), 4 = Camera (horizontal), 5 = Camera (vertical, one-handed), 6 = Camera (vertical, two-handed), 7 = Game, 8 = DCM).

(a)

Class	1	2	3	4	5	6	7	8	Total
1	187	0	1	0	0	0	0	0	188
2	0	155	25	2	7	0	3	1	193
3	2	22	153	3	4	0	0	1	185
4	0	5	0	129	62	11	1	2	210
5	10	15	17	65	126	3	2	25	263
6	0	0	0	0	0	165	0	4	169
7	0	2	0	0	0	4	173	10	189
8	0	0	3	0	0	16	20	156	195
Total	199	199	199	199	199	199	199	199	1592

(b)

Class	1	2	3	4	5	6	7	8	Total
1	185	0	2	1	0	0	0	0	188
2	2	155	17	1	10	0	3	1	189
3	3	26	167	4	12	1	0	1	214
4	0	5	0	119	48	1	0	1	174
5	5	11	9	74	129	0	2	20	250
6	2	0	0	0	0	174	3	9	188
7	0	2	0	0	0	4	172	14	192
8	2	0	4	0	0	19	19	153	197
Total	199	199	199	199	199	199	199	199	1592

(c)

Class	1	2	3	4	5	6	7	8	Total
1	191	0	5	1	1	0	0	4	202
2	2	164	19	2	12	0	3	1	203
3	4	25	172	3	9	1	1	0	215
4	1	1	2	148	56	0	1	0	209
5	1	7	1	45	120	0	1	5	180
6	0	0	0	0	0	185	2	11	198
7	0	2	0	0	0	1	186	7	196
8	0	0	0	0	1	12	5	171	189
Total	199	199	199	199	199	199	199	199	1592

Table 4: Confusion matrices for Case 3 (1 = Call, 2 = SMS (one-handed), 3 = SMS (two-handed), 4 = Camera (horizontal), 5 = Camera (vertical, one-handed), 6 = Camera (vertical, two-handed), 7 = Game, 8 = DCM).

(a)

Class	1	2	3	4	5	6	7	8	Total
1	188	0	0	0	0	0	0	0	188
2	1	166	23	0	4	0	2	0	196
3	2	23	170	1	1	0	0	0	197
4	0	0	0	198	0	13	6	0	217
5	8	10	6	0	194	0	1	27	246
6	0	0	0	0	0	181	0	2	183
7	0	0	0	0	0	3	188	4	195
8	0	0	0	0	0	2	2	166	170
Total	199	199	199	199	199	199	199	199	1592

(b)

Class	1	2	3	4	5	6	7	8	Total
1	194	4	5	4	2	3	2	7	221
2	1	153	34	0	2	0	0	0	190
3	1	22	145	1	0	0	1	0	170
4	0	0	0	194	0	0	0	0	194
5	3	19	15	0	195	0	0	3	235
6	0	0	0	0	0	194	9	4	207
7	0	0	0	0	0	0	186	0	186
8	0	1	0	0	0	2	1	185	189
Total	199	199	199	199	199	199	199	199	1592

(c)

Class	1	2	3	4	5	6	7	8	Total
1	191	2	3	0	1	0	0	0	197
2	2	165	24	0	6	0	0	0	197
3	4	29	170	1	1	0	1	2	208
4	0	0	0	198	0	2	1	0	201
5	1	3	2	0	191	0	0	7	204
6	0	0	0	0	0	197	1	0	198
7	0	0	0	0	0	0	196	1	197
8	1	0	0	0	0	0	0	189	190
Total	199	199	199	199	199	199	199	199	1592

Table 5: Confusion matrices for Case 4 (1 = Call, 2 = SMS (one-handed), 3 = SMS (two-handed), 4 = Camera (horizontal), 5 = Camera (vertical, one-handed), 6 = Camera (vertical, two-handed), 7 = Game, 8 = DCM).

(a)

Class	1	2	3	4	5	6	7	8	Total
1	187	0	1	0	0	0	0	0	188
2	0	165	25	0	5	0	2	0	197
3	2	24	160	1	1	0	0	1	189
4	0	0	0	194	6	16	4	0	220
5	10	10	13	4	187	0	4	27	255
6	0	0	0	0	0	175	0	1	176
7	0	0	0	0	0	6	186	4	196
8	0	0	0	0	0	2	3	166	171
Total	199	199	199	199	199	199	199	199	1592

(b)

Class	1	2	3	4	5	6	7	8	Total
1	187	0	1	1	1	0	0	0	190
2	5	159	19	0	8	0	3	0	194
3	2	29	172	1	7	0	0	0	211
4	0	0	0	190	7	3	1	0	201
5	3	9	5	5	176	0	1	22	221
6	1	0	0	1	0	189	1	3	195
7	0	2	0	1	0	5	188	6	202
8	1	0	2	0	0	2	5	168	178
Total	199	199	199	199	199	199	199	199	1592

(c)

Class	1	2	3	4	5	6	7	8	Total
1	193	1	6	0	2	0	0	3	205
2	2	166	19	2	7	0	2	3	201
3	3	26	170	2	2	0	0	1	204
4	0	2	0	195	0	0	0	0	197
5	1	3	4	0	185	0	0	3	196
6	0	0	0	0	0	199	2	1	202
7	0	1	0	0	0	0	194	0	195
8	0	0	0	0	3	0	1	188	192
Total	199	199	199	199	199	199	199	199	1592

(one-handed) and SMS (two-handed) is still confused. Since the two classes are seldom confused with other classes, the most direct way of improving the performance of the system is to regard them as a single SMS class.

4. Conclusions

In this article, we presented an innovative mobile user interface using the information of grip-pattern. The working implementation of GripLaunch is constructed and its feasibility is evaluated through recognition rate test.

The key contributions of the developed GripLaunch system can be summarized as follows:

1. It adopts the capacitive-type touch sensing technique to capture the image of the user's grip-pattern. Due to the non-contact sensing feature of the capacitive-type touch sensors, the housing of the device itself works as a sensing mean and the resulting user interface does not require separate control surface. In addition, the single FTEA allows the sensor system to be easily installed inside the mobile device.

2. Unlike most commercial and/or academic works on the mobile touch-based user interface, it addresses the effective way of utilizing multi-touch information. The grip, which is the inevitable action in using mobile devices, seamlessly integrated in the flow of interaction between the user and the device.

The authors admit that there are plenty amount of industrial and research works on capacitive touch sensing techniques, touch-based user interfaces, and bare-hand human-computer interaction schemes. However, it is worth while to note that the proposed system is one of the very few systems that offer an systematically organized framework to fusing those two items for the mobile human-computer interaction.

However, we have several open questions for further research and development to improve the performance, usability, and user acceptance of the proposed system.

First, we still need to improve the overall specification of the sensor system. The number of sensor ICs used should be reduced to be easily installed in the extremely small mobile devices such as mobile phones, PDAs, etc. In addition, the output of the sensor system should be continuous (multi-valued) to provide more information with the recognizer system. For example, with the continuous sensor output, the sensor system can indirectly discriminate different pressure levels of the user's grip, which can be used as alternative input to the recognizer.

Secondly, more improved pre-processing and post-processing algorithms are required. Since the whole surface of the device except for the display portion senses the contact of the human body, the unintentional touch can trigger the system to falsely operate, which leads to degraded reliability of the system.

Thirdly, the proposed GripLaunch system have used raw sensor data for classification. In order to enhance robustness and generalization performance of the system, the recognizer should use features rather than raw sensor data like other hand gesture recognition systems. Additionally, the best time instant of initiating recognition should be also investigated.

Finally, the designer of the user interface should consider that the task success rate cannot be 100% due the the involved sensor system and recognizer.

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