Multi Touch Shape Recognition for Projected Capacitive Touch Screen

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Abstract: Devices equipped by touch screens are nowadays widely diffused. One of the most meaningful factor which leads to this success is their easy and intuitive interface which allows a friendly user-device interaction. Touch shape recognition is a topic which has contributed to the realization of these types of interfaces. In this paper we propose a solution able to discriminate among different classes of touch shapes. We focus on the problem of recognizing typical touches performed in mid-sized devices as tablets and phablets. The proposed solution discriminates among single finger, multiple fingers and palm by reaching high recognition accuracy and maintaining a low computational complexity.

1 INTRODUCTION

In the last decade the sale of the hand held devices has reached high volumes and the diffusion of these devices has increased the need to improve the user-device interaction through simple and intuitive interfaces. The great revolution in this field has been determined by the introduction of the touch screen in the market. The selection of a functionality by touching the screen is a natural gesture which allows the user to interact with the device in a more easy and clear way. The effort of researchers is to further improve the touch screen functionalities by developing new algorithms to support the human-device interaction.

Some of the classic touch based functions are the zooming, the rotation of images and the scrolling of web pages. However, with the wide diffusion of high screen size (from 5” to 10”) new problems must be solved in performing the recognition of the touch. Due to the screen size, it can happen that some conductive human parts can touch the screen together with the fingers. For example, a desirable feature is the recognition of the palm touching the panel; this involuntary touch usually inhibits other touch functionalities such as the selection of an icon or scrolling of pictures, etc. Another example is the keyboard device tapping with fingers and simultaneously touching the screen with the palm. To effectively use the device, the touch recognition engine should be able to recognize the palm touches and reject them.

Another shape to be recognized, to improve the interface interaction, is the ear touch (Guarneri et al., SPIE 2013). The presence of this shape is possible in phablets (having around a 5” screen size) and for devices having lower panel resolution. The recognition of this class could allow the elimination of the proximity sensor used for switching from the touch to the talk functionality.

Although the shape recognition is a key topic discussed in different application context (Escalera et al., 2011; Azzaro et al., 2011; Zhang et al., 2004; Daliri et al., 2008; Belongie et al., 2002; Battiato et al., 2012; Farinella et al., 2006), it is not yet widely discussed in the context of touch screens and few works have been proposed in literature. Zhang et al. (2011) proposed a technique able to discriminate among different shapes acquired by touching displays. The authors exploit the integral image obtained by summing the signals data along rows and columns. The obtained x and y curves are segmented into peaks and valleys and the finger identification is obtained by applying a threshold on peaks values. Despite the method is fast, it cannot guarantee robustness when shapes are obtained in critical conditions, such as in the case of slightly wet fingers (Guarneri et al. ICCE 2013). Westermann (2008) identifies and discriminates between fingertips, thumbs, palms and cheeks. In order to

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extracts all simultaneous touches the input capacitive map is firstly segmented. Then a measure of the regularity of each patch is computed as the ratio of a patch's spatial energy minus its peak energy to the patch's total energy. The eccentricity of the shape is also computed for each patch. The shape discrimination is mainly based on two parameters: the eccentricity and the regularity. Thumb contacts are distinguished from fingertip contacts using the patch eccentricity feature; the *cheek* is discriminated from the *ear* because the former is considered a regular shape, while the latter is considered a not regular shape.

Guarneri et al. (SPIE 2013) proposed a shape recognition engine to discriminate typical shapes in devices equipped by a touch panel lower than 5" size: *finger*, *ear*, *cheek*, *hand held*. The authors presented a technique which exploits different shape descriptors such as the area, the connections degree, the filling degree, the central and peripheral number of not touched lines. Another work of Guarneri et al. (ICCE 2013) proposed a shape recognition method based on Principal Component Analysis transformation coupled with decision tree for classification. This approach regards mainly devices with a panel up to 4" size. It is a multi-touches technique focused on the discriminations of finger/s versus palm. The authors also investigated cases of recognition wet panel.

This paper proposes a solution for multi touch shape recognition built on Guarneri et al. (SPIE 2013, ICCE 2013). With respect to the previous solution the technique proposed here has a low computational complexity and takes into account more shape classes. Moreover, temporal check is introduced to have a more robust recognition engine.

The paper is organized as follows: Section 2 details the proposed multi touches recognition system. In Section 3 the HW prototype used in the experiments is briefly summarized. Section 4 reports the experimental results. Finally, Section 5 concludes the paper.

2 PROPOSED MULTI TOUCHES RECOGNITION

The proposed solution takes into account the following ten classes of touches: one or more isolated fingers (up to five fingers), two or more fingers touching each other (up to five fingers) and the palm. The involved technique can be easily extended to more than five touching fingers; this value has been chosen just because it is usually the maximum number of fingers used to perform typical gestures as scrolling or flipping. Conversely, for isolated fingers there is not a limited number.

Three main steps are involved in the proposed pipeline: capacitance map segmentation, shape representation, and shape recognition.

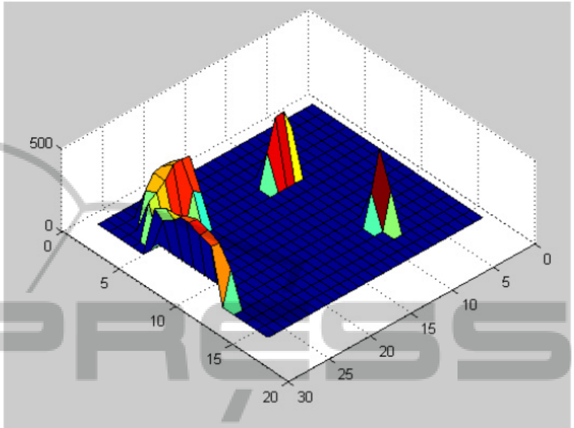

Figure 1: The capacitance map presents three touches: two fingers and a palm.

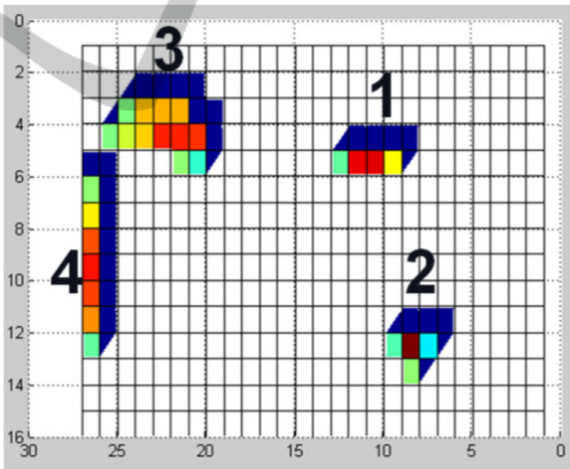

Figure 2: 2D representation of the capacitance map showed in Figure 1; two fingers (patches 1 and 2) and a palm (patches 3 and 4).

2.1 Capacitance Map Segmentation

To deal with noisy spikes, a noise removal filter is applied to each acquired capacitance matrix (i.e., a 16×27 matrix containing raw data). The filtered frames are then analysed and cells are aggregated into a patch using a watershed like algorithm (Gonzalez, 2008). Through the patches aggregation step, the number of sensed capacitive nodes is

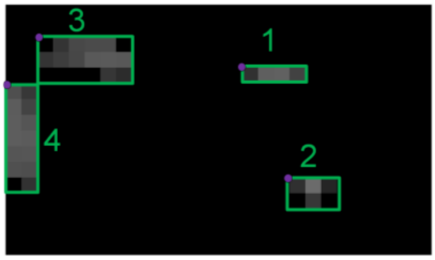

Figure 3: Representation of the four extracted patches. The bounding box, with highlighted the left- up vertex point, is shown for each patch.

computed, and we used this value to perform a first selection of patches to be classified. Differently than previous work (Guarneri et al., ICCE 2013), we don't need to normalize and rotate each single shape considering the shape representation described in Section 2.2. Figure 1 shows the 3D plot of the capacitance map relative to three contemporary touches: two fingers and a palm. It should be noticed that the palm is constituted by two predominant parts, which are correctly extracted as two patches by the watershed algorithm. Considering as example the map reported in Figure 1, after the segmentation step four patches are extracted: two relative to fingers and two constituting the palm touch. Figure 2 shows the 2D representation of the map reported in Figure 1 with over-imposed the labels of the four extracted patches. After the segmentation step, the patch is described to recognize the patch 1 and 2 as *fingers* whereas the patch 2 and 3 as *palm (not fingers)*.

2.2 Shape Representation

Each patch can be considered as a group of nodes with a maximum and the remaining nodes with lower values. The first feature of the patch relates the area in terms of number of nodes. Patches formed by a single node are not processed for the final recognition. This minimum area size has been fixed taking into account the resolution and the sensibility of the used panel, but it can be modified depending on different hardware settings. The shape size, in term of nodes number, is used to fix the minimum finger size. We represent a patch by using two descriptors, the height and the width of the bounding box containing the patch. The computation of the contouring box is based on the comparison of x and y values of all nodes forming the shape. Through this fast comparison we compute two points: the first one having as abscissa the lower x-value of all expressed nodes and as ordinate, the minimum y-value of all expressed nodes. The coordinate pair of the second point is found by looking for the maxima x and y of all expressed nodes. Hence, for each box patch we compute its width, its height, its area and the coordinate pair of its left-up corner (Figure 3). The area is used as first filtering: patches too small are excluded for final recognition. The width and the height are used to identify a potential finger. The left-up corner, together with the width and the weight of the bounding box, are used for the temporal check described in the Section 2.4. Figure 3 shows the graphical representation of the four boxes computed for each patch showed in Figure 2.

2.3 Shape Recognition

The recognition of different classes is performed by a decision tree (Quinlan, 1993) trained on a set of capacitive maps manually labeled. The discrimination is based on the width and height of the bounding box. In order to have a more effective classification, a further check is performed to verify the adjacency between patches. So, width and height of the boxes are used to discriminate *finger* from others. These information are also used to verify if a patch is overlapping/adjacent with other patches. This last check is performed by comparing the intersection of the box contours of all patches and it is done to verify if a patch is completely isolated from others or if it is in touch with other patches. In case of two or more adjacent or overlapped patches, the presence of a *not finger* patch forces to be the classification of all other adjacent patches in the same class.

Figure 4 shows a map representing a palm touch. After the segmentation, two bounding boxes have been extracted. In this case one of the two boxes (the little/blue one) is a potential finger, as well as it is verified the overlapping with other non-finger patches.

Since the bigger/yellow one does not satisfy the constraints of finger for width and height, it is a

0	33	296	302	314	346	123
0	0	289	336	339	319	0
0	0	132	342	339	165	0
0	0	0	237	324	66	0
0	0	0	0	93	134	32
0	0	0	0	0	0	0

Figure 4: Map showing a palm touch. Two patches have been extracted. The patches have an overlap and, due to the fact that one of them is a potential *not finger* (the yellow/bigger one), also the other patch (the blue/little one) is classified as *not finger (i.e., a palm)*.

0	96	349	165	0	0	0	0	0	0	0
0	277	441	289	39	0	0	0	0	0	0
0	96	269	306	380	101	70	80	305	211	0
0	0	0	269	336	309	373	272	378	181	0
0	0	0	0	31	106	222	58	94	0	0

Figure 5: Map showing four fingers touching each other. The patches are all overlapping and since each patch is classified as *finger* (i.e., no one is classified as *not finger*), the final class will be "4 finger".

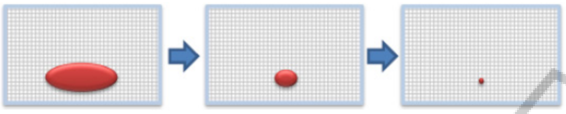

Figure 6: Three toy frames representing a stylized palm touching the panel during its removal from the screen. Due to reduction of the shape size it can happen that the latest two frames can be wrongly classified as a finger.

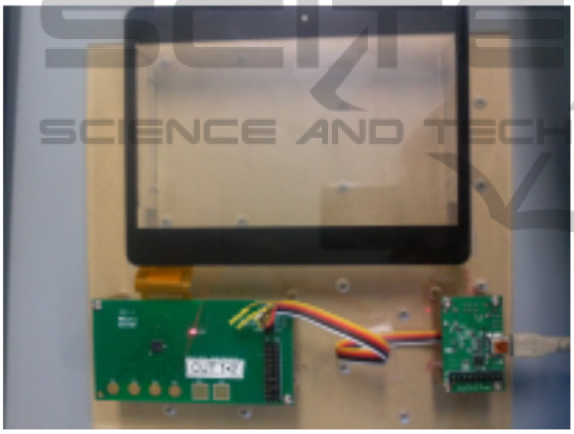

Figure 7: Board prototype equipped by a 7" screen size.

potential *not finger (i.e., a palm)*, and the final classification for the little patch is also a not finger (i.e., a palm).

Figure 5 reports an example of four fingers and their relative boxes touching each other. For each box, the intersection with the other patches is verified. Since all of them are potential fingers their final classification is "4 fingers". In order to reduce the false finger rate, we perform a further check on the potential finger patches. This analysis aims to take into account the history (in time) of a touch shape classification. Details about that temporal check are reported in the following section.

2.4 Temporal Analysis

One of the most critical conditions for shape recognition regards the moment when a palm is removed from the display. A toy example showing this condition is reported in Figure 6, where it is represented a stylized palm removed from the panel. From the first to the third frame the palm changes its shape. In these transition steps, the touch of the palm changes in terms of area size, from a big to a small one. This induces a wrong classification of the palm shape because its shape becomes more similar to a finger. To reduce the rate of wrong classifications relative to this specific condition, a temporal analysis has been introduced into the classification process. Each time a patch is a potential *finger* a check taking into account the touched area in previous classified frames is performed. In case of intersection/overlaying with a patch which was classified as *not finger* in previous frames, than the current potential *finger* patch is classified as a *not finger*. This allows a better classification accuracy of the palm when is it removed from the screen.

The temporal check can introduce an unwished behaviour. When the algorithm wrongly classifies a *finger* touch as a *not finger* (just because it does not pass the width and height test), then it can happen that the temporal analysis will propagate this error through the next successive frames, so we lose many right finger classifications. To avoid that propagation a counter has been introduced to force a reset, in this way a too old shape classification cannot lead to a wrong classification.

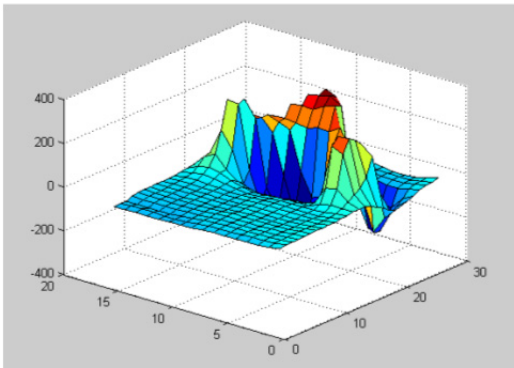

Figure 8: Capacitive map related to a palm touch.

3 HARDWARE PROTOTYPE

To acquire the capacitive maps for testing purposes we have used the board prototype shown in Figure 7.

The board is equipped with a 7" capacitive screen size, STM32 processor and STMT05 microcontroller.

The board is connected to the PC through a USB cable. The developed embedded software allows to store sequence of frames, each frames is a matrix of 16x27 capacitive nodes. The maps show the presence of spike noise due to the high sensitive of nodes. To handle this type of noise the capacitive values are filtered by applying a threshold at the beginning of the software pipeline. The threshold value has been fixed by considering the range of capacitive node magnitudes. A too low threshold value guarantees the elimination of noise spikes but it can cause the loosing of important data relative to touches. On the contrary a too high threshold could not eliminate the noisy data.

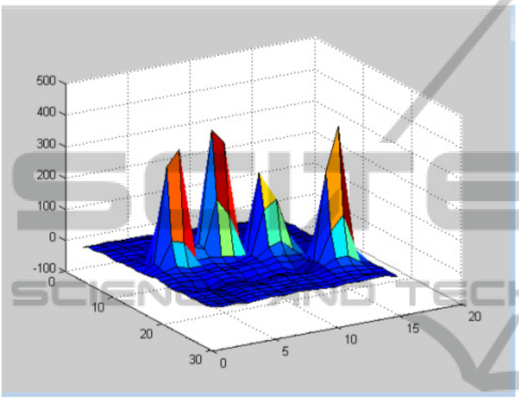

Figure 9: Capacitive map related to four separated fingers.

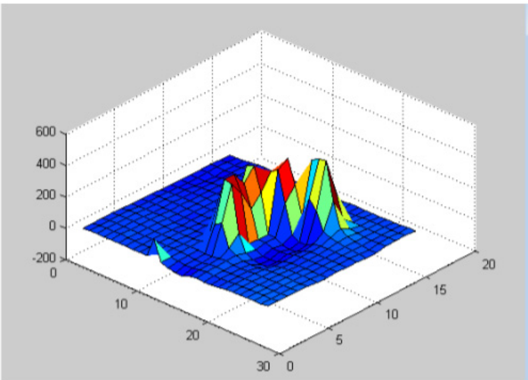

Figure 10: Capacitive map related to four touching finger.

4 EXPERIMENTAL RESULTS

The proposed technique has been tested on a dataset of 3000 capacitive maps related the following ten classes involved in the experiments: single finger, two separated fingers, two touching fingers, three separated fingers, three touching fingers, four separated fingers, four touching fingers, five separated fingers, five touching fingers, palm. The palm shape is strongly deformable because it changes in size and also it can be split in two o or more subparts. In case of multi split division the algorithm must be able to classify each single part as belonging to the palm shape.

Figure 8 shows an example of a palm touching the panel and producing two separated touched area on the screen device. Figure 9 shows an example of four separate fingers, whereas Figure 10 shows a capacitance map related to four touching fingers. As first, we tested the proposed solution without temporal checking. Each frame has been classified independently without considering the classification of the previous frames. The results have been collected in the confusion matrix reported in Table 1. The test has been then repeated enabling the temporal analysis. The results obtained in this last experiment are reported in Table 2.

Analyzing the results reported in the two confusion matrixes (Table 1 and 2) it can be observed that the palm class is the one which reaches an improvement around of 50% when the temporal check is performed. This improvement is due to the fact the palm changes its area size whether the palm is removed from the screen. In these two critical steps many palm shapes are wrongly classified as fingers. By using the temporal check many palm maps wrongly classified are correctly classified. Due to its simple implementation, the temporal check requires a low computational complexity (it is performed by storing three binary labels with the classification type, palm or finger, of the current patch in the three previous frames).

5 CONCLUSIONS

In this paper we proposed a solution for multi touches recognition for capacitive displays. The main aim is the discrimination of multi touch fingers against the palm touch. The representation of shapes through the presented simple features allows the recognition of the different classes of touches. The proposed technique obtains good performances in terms of classification accuracy. Future works will be devoted to increase the recognition accuracy, augmenting also the number of classes to be recognized. Moreover, algorithms to recognize multi-fingers gestures could be useful for application such as zooming, rotation and flipping of pictures.

Table 1: Results obtained by the proposed approach without temporal check.

	1Finger	*2 Separate Fingers*	*3 Separate Fingers*	*4 Separate Fingers*	*5 Separate Fingers*	*2 United Fingers*	*3 United Fingers*	*4 United Fingers*	*5 United Fingers*	*Palm*
1Finger	**100,00%**	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
2 Separate Fingers	0,33%	**98,67%**	0,00%	0,00%	0,00%	0,33%	0,67%	0,00%	0,00%	0,00%
3 Separate Fingers	0,00%	0,33%	**98,00%**	0,00%	0,00%	0,00%	1,67%	0,00%	0,00%	0,00%
4 Separate Fingers	0,00%	0,33%	1,33%	**90,33%**	0,33%	0,00%	0,33%	7,33%	0,00%	0,00%
5 Separate Fingers	0,00%	0,00%	0,00%	5,67%	**89,67%**	0,00%	0,00%	0,33%	4,33%	0,00%
2 United Fingers	2,33%	3,00%	0,00%	0,00%	0,00%	**94,33%**	0,33%	0,00%	0,00%	0,00%
3 United Fingers	0,33%	1,33%	1,00%	0,00%	0,00%	9,67%	**87,67%**	0,00%	0,00%	0,00%
4 United Fingers	0,00%	0,00%	1,67%	0,67%	0,00%	1,33%	17,33%	**76,00%**	0,00%	3,00%
5 United Fingers	0,00%	0,00%	0,67%	5,00%	0,00%	0,00%	1,00%	28,67%	**63,33%**	1,33%
Palm	10,67%	0,00%	0,00%	0,00%	0,00%	22,33%	14,67%	2,00%	0,67%	**49,67%**

Table 2: Results obtained by the proposed approach considering temporal check.

	1Finger	*2 Separate Fingers*	*3 Separate Fingers*	*4 Separate Fingers*	*5 Separate Fingers*	*2 United Fingers*	*3 United Fingers*	*4 United Fingers*	*5 United Fingers*	*Palm*
1Finger	**100,00%**	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
2 Separate Fingers	0,33%	**98,67%**	0,00%	0,00%	0,00%	0,33%	0,67%	0,00%	0,00%	0,00%
3 Separate Fingers	0,00%	0,33%	**98,00%**	0,00%	0,00%	0,00%	1,67%	0,00%	0,00%	0,00%
4 Separate Fingers	0,00%	0,33%	1,33%	**90,33%**	0,33%	0,00%	0,33%	7,33%	0,00%	0,00%
5 Separate Fingers	0,00%	0,00%	0,00%	5,67%	**89,67%**	0,00%	0,00%	0,33%	4,33%	0,00%
2 United Fingers	2,33%	3,00%	0,00%	0,00%	0,00%	**94,33%**	0,33%	0,00%	0,00%	0,00%
3 United Fingers	0,33%	1,33%	1,00%	0,00%	0,00%	9,67%	**87,67%**	0,00%	0,00%	0,00%
4 United Fingers	0,00%	0,00%	1,67%	0,33%	0,00%	1,33%	15,33%	**76,00%**	0,00%	11,00%
5 United Fingers	0,00%	0,00%	0,67%	5,00%	0,00%	0,00%	1,00%	28,67%	**63,33%**	1,33%
Palm	3,67%	0,00%	0,00%	0,00%	0,00%	0,33%	0,00%	0,67%	0,00%	**95,33%**

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