1. Oleksandr Karpin[1,2], 2. Volodymyr Brygilevych[3], 3. Zinovii Liubun[1], 4. Vasyl Mandziy[1,2]

Ivan Franko National University of Lviv (1), Infineon Technologies, Lviv, Ukraine (2), State Academy of Applied Sciences in Jarosław, Poland (3)

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Processing of capacitive sensor signal profile for enhancing gestures detection

***Abstract**. The article considers the usage of one sensor button to identify signals triggered by Type 1. clicking the button and Type 2. swiping at the button surface. The developed algorithm of the sensor signal analysis features: high-accuracy identification of signals, minimal processing time, easy definition of the classification algorithm optimal parameters for a definite type of the sensor button due to the usage of neural networks.*

***Streszczenie.** W artykule rozważono wykorzystanie jednego przycisku sensorycznego do identyfikacji sygnałów wyzwalanych przez kliknięcie przycisku w trybie 1 i przesunięcie po powierzchni przycisku w trybie 2. Opracowany algorytm analizy sygnałów czujnika charakteryzuje się: dużą dokładnością identyfikacji sygnałów, minimalnym czasem przetwarzania, łatwym zdefiniowaniem algorytmu klasyfikacji optymalnymi parametrami dla określonego typu przycisku czujnika ze względu na wykorzystanie sieci neuronowych. (**Przetwarzanie profilu sygnału czujnika pojemnościowego w celu zwiększenia wykrywania gestów**)*

Keywords: capacitive sensor, signal profile, gesture detection, neural network.
Słowa kluczowe: czujnik pojemnościowy, profil sygnału, detekcja gestów, sieć neuronowa.

Introduction

The usage of the hand gestures is one of the most natural ways to interact with the device. Moreover, the accurate interpretation of hand gestures in real time has many applications [1-5]. Therefore, the interaction of a human with many technical devices requires developing software-hardware methods to identify signals in real time [1-5]. The development of the structure and algorithms of these devices in combination with the advantages of Infineon microcontrollers [6] and the use of neural networks will allow the realization of simple, cheap, efficient and reliable control devices.

Fig. 1 shows the CY8CKIT-040T PSoC™ 4000T CAPSENSE™ Evaluation Kit [7, 8] that was used for developing and testing algorithm. The kit contains capacitive button, which allows obtaining a signal to be analyzed and process identification result.

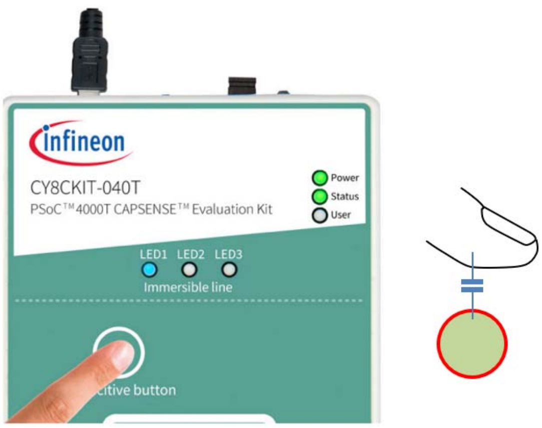


Fig.1. Capacitive button of CY8CKIT-040T Evaluation Kit

An algorithm must be developed for identification of the two types of signals:

1. The signal of the sensor resulting from clicking a button (Touch).
2. The signal of the sensor resulting from swiping a finger at the button surface (Swipe).

To solve the task of the classification, the attributes of the signals with which the task can be implemented must be defined. Fig. 2 shows a pair of examples of real signals that differ significantly visually (a), and similar ones that are not easy to distinguish even visually (b).

The red graph – signal; the green graph – the gesture indicator.

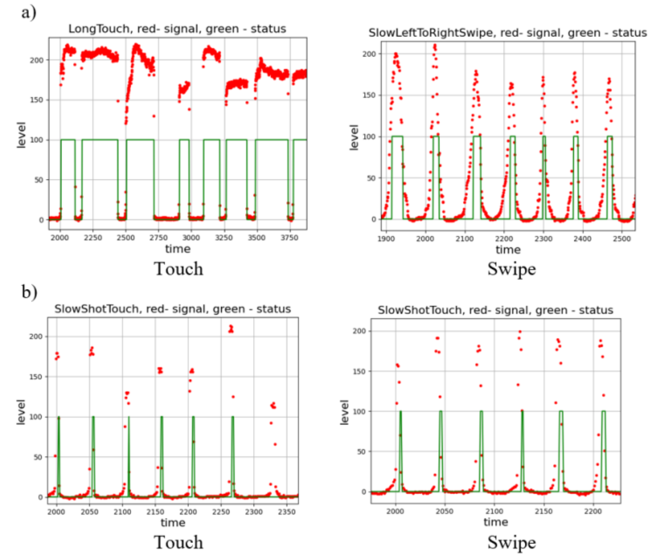


Fig.2. Signals (red) and gesture indicator (green)

The requirements for the identification system performance: the classification must be performed as soon as a signal becomes available, and must provide high effectivity of the task algorithm. Therefore, for example, the analysis of the signal spectrum cannot be used because it requires: a) the entire signal (from beginning to end); b) much processing time; c) many resources while transiting to another frequency domain.

Analysis of classification attributes

Identification requires simple attributes. The level of the signal and its duration cannot be used because their changes ranges overlap significantly for both types of signals.

1. Signal shape attribute

Only the attribute of the signal shape can be used as a simple attribute. For a Touch event, the signal in most cases is close to the P-shape; for a Swipe gesture, it looks more like the Gauss function. Unfortunately, short-duration signals cannot be identified even visually (Fig. 2. b). The conclusion is that there is no chance that any identification algorithm based on the shape of the signal will yield a

100%-true result. For such a complicated boundary of the allocation with the overlapping, to solve the task of the classification, the usage of a neural network of a definite structure would be appropriate.

Similar to any other classification algorithm, the neural network approach requires the selection of the classification attributes. As mentioned before, most signals can be classified based on their shape and the signal derivative depends strongly on the shape (Fig. 3 (Touch)) and (Fig. 4 (Swipe)), the blue graph. Therefore, to do the signal shapes analysis, it is logical to analyze the signal derivative values in the frame of the time function.

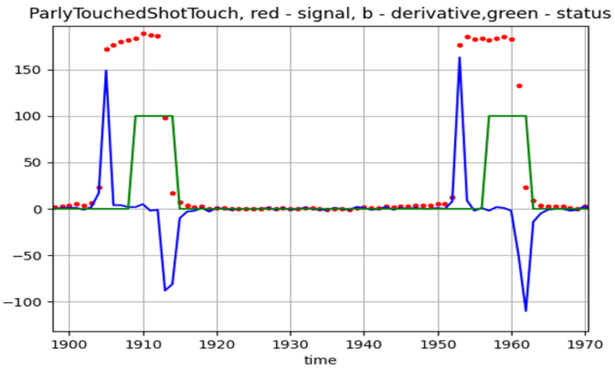


Fig.3. Touch signal – red; derivative – blue

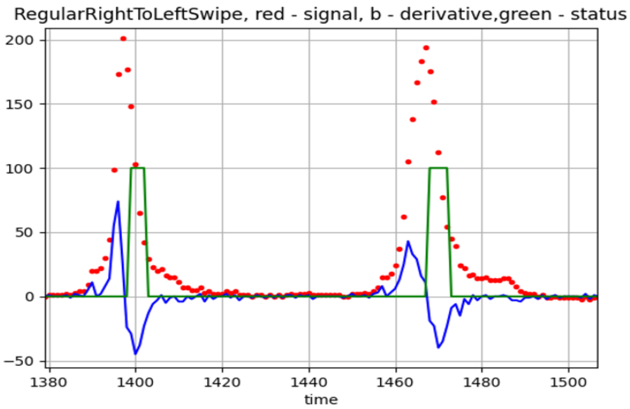


Fig.4. Swipe signal – red; derivative – blue

P-shape signal – usually rises between two spikes defined by the signal front lines, and this signal time interval derivative is close to zero. For Swipe signal, such an interval is either not present or the minimal.

This difference between the signal types can be used as an attribute for classification performance.

2. Speed of increment of signal front line

The second attribute can be the speed of the increment of the signal front line. In many cases, this speed is significantly bigger for the Touch type signal than for the Swipe type signal. So, the maximal value of the derivative at the signal front line can be used as the second attribute.

A possible classification algorithm is shown in Fig. 5, where:

x_0=25 points at the signal arrival

d_0=20 points at the derivative value close to zero

d_k – the signal derivative on the k-th step

Nmax1=4 the limit number of signals close to zero, this number is sufficient for assigning the signal to the Touch type, further analysis will not be performed.

Nmax2=3 the limit number of signals close to zero, this number is sufficient for assigning the signal to the Touch type, the analysis is performed until the moment when a derivative negative value less than d_0 appears

Na=0 indicates whether to perform or not the signal analysis (when the signal level is bigger than x0)

ind=0 the analysis step meter

N_0=0 the meter of points where the derivative is close to zero

T, S – the signal type identified

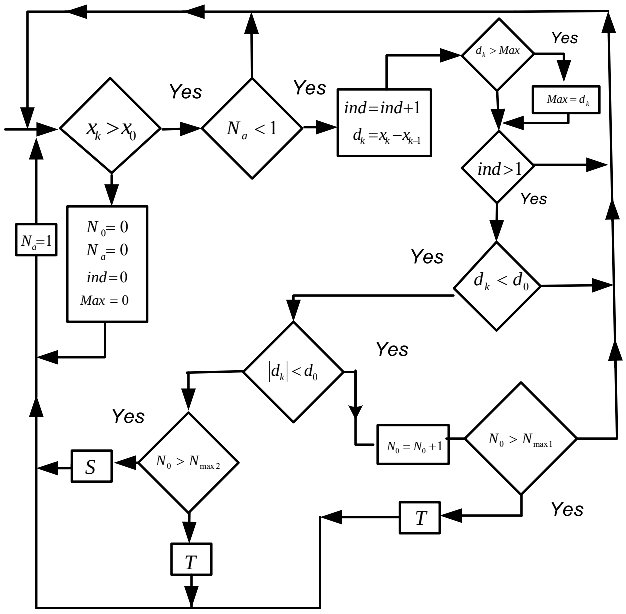


Fig.5. Algorithm of signal identification

It is worth noting that these attributes values are obtained before the signal completion – at the moment of the arrival of the signal front line decrement.

Unfortunately, there are cases when these signal attributes are very close. For example, Fig. 6 shows the signal when the button is pressed shortly, where the number of intervals when the derivative is close to zero is small (2-4 points).

The given algorithm has drawbacks:

1. The large number of constants that define the result of classification (x_0, d_0).
2. To better classify, another algorithm is required to define the optimal values of the parameters (Nmax1, Nmax2).
3. The given algorithm does not consider the non-linearity of the distribution boundary among signals sets of different types.

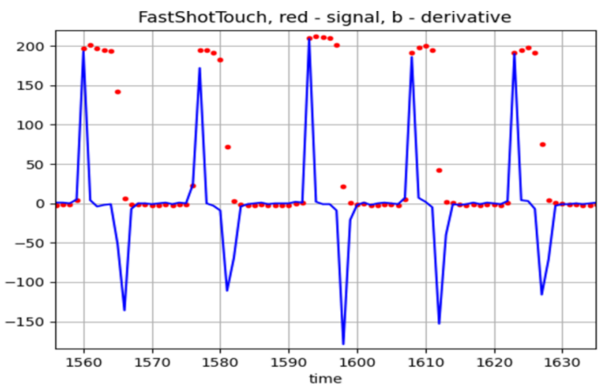


Fig.6. Short touch: signal – red, derivative – blue

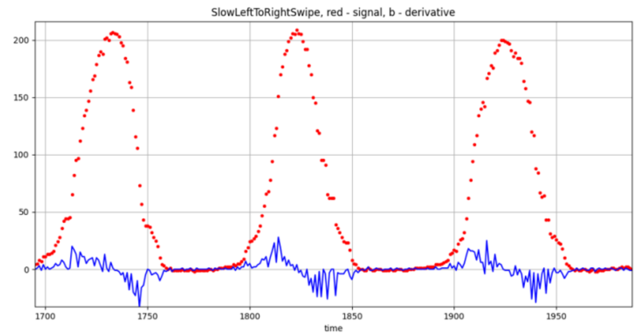


Fig.7. Slow Swipe: signal – red, derivative – blue

Apparently, the boundaries of signals sets are blurred. There are a) Touch type signals and b) Swipe type signals.
a) these signals under a short touch have a small value of intervals with the derivative close to zero, so, the can be identified as Swipe signal (Fig. 6)
b) the number the derivative's zero is great (Fig. 7).

Results

The decreasing of the constants number and definition of their optimal values is possible with the usage of the neural network to solve the task of the classification.

Two values of the classification criteria provide the possibility of visualization used for defining the optimal structure of the neural network and optimal values of the constants.

To train the neural network, an array of training pairs is required obtained from the measurements results. Fig. 8 shows the algorithm of modelling an array of attributes of the two types of signals. The signal attribute is defined as the maximal value of the derivative at the front line of the signal and the number of zeroes before the arrival of the descending front line of the signal.

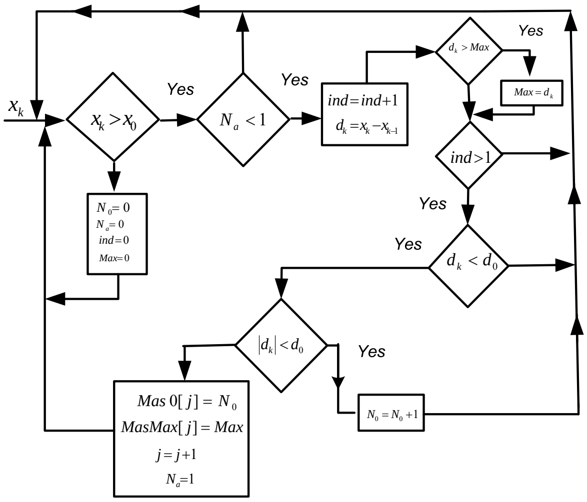


Fig.8. Algorithm of definition of signal attribute array

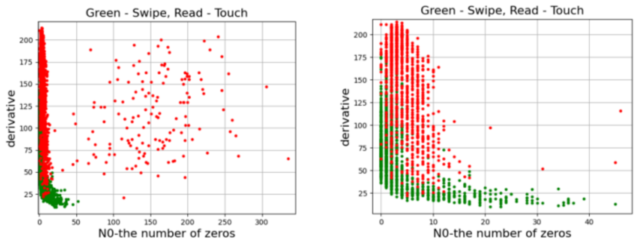
To perform, the algorithm requires only two constants: x_0 the minimal level of the signal; d_0 the maximal value of the signal derivative, which indicates that the derivative is deemed to be equal to zero.

Fig. 9a and 9b show the attributes values obtained based on this algorithm.

Before the neural network training, the normalization of the input vectors was performed. The number of neurons in the input layer will define the accuracy of the reproduction of the boundaries between two sets. The error coefficient was used to assess the classification quality:

$$K = (ERswipe + ERtouch)/Nnp$$

where:
$ERswipe$ the number of incorrectly identified signals of Swipe type
$ERtouch$ the number of incorrectly identified signals of Touch type
Nnp the summative number of signals



a) complete data   b) zoomed boundary region

Fig.9. Attributes for classification

Due to the complicity of the distribution boundaries, a two-layer neural network of the direct distribution was chosen with the sigmoidal function of activation to solve the task of classification.

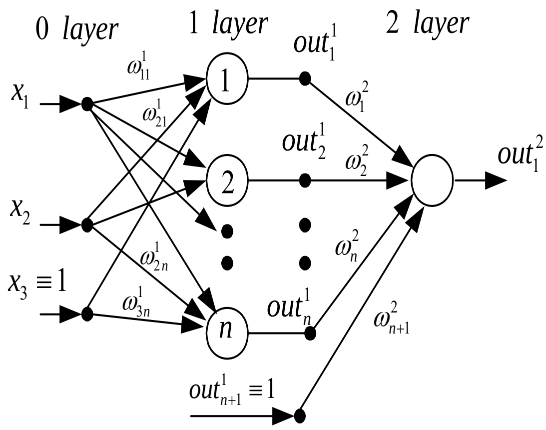


Fig.10. Neural network structure

Table 1. Results of classification with different numbers of signals in input layer

№	Number of neurons in input layer	Error coefficient (%)
1	2	8.2
2	3	7.1
3	4	6.5
4	6	6.4

Further increasing of the number of neurons in the input layer does not yield better results because the boundary between the two types of signals is blurred. The only way to improve the accuracy of the classification is the increasing of the number of the classification attributes. The given selected classification attributes proved to the best whereas adding other attributes, for example, the value of the signal amplitude did not bring significant improvement.

Conclusions

The proposed algorithm of classification performs the identification of two signals with quite good precision. During the minimal processing time, the algorithm uses the minimal calculation resources. Therefore, the algorithm can be used to enhance the capabilities if sensor panels at the minimal costs.

Authors

***Authors**: dr. Oleksandr Karpin, [1] Ivan Franko National University of Lviv, Department of Sensory and Semiconductor Electronics, 2Infineon Technologies, Lviv, Ukraine, Oleksandr.Karpin@infineon.com; dr. Volodymyr Brygilevych, State Academy of Applied Sciences in Jarosław, Poland, Faculty of Technical Engineering, vbrygilevych@pwste.edu.pl; dr. Zinovii Liubun, Ivan Franko National University of Lviv, Department of Radio Physic and Computer Technologies, zinovijlyubun@gmail.com; Vasyl Mandziy, Ivan Franko National University of Lviv, Faculty of Electronics and Computer Technologies, Vasyl.Mandzii@lnu.edu.ua*

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