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### **ENHANCEMENT OF SENSOR PANEL TACTILE TOUCH INTERFACE**

Oleksandr Karpin<sup>1,2</sup> O, Zinovii Liubun<sup>1</sup> O, Vasyl Mandziy<sup>1,2</sup> O, Oleh Tereshchuk<sup>1</sup> O, Nestor Hotsiy<sup>2,3</sup> O Department of RadioPhysics and Computer Technologies, Department of Sensor and Semiconductor Electronics, Ivan Franko National University of Lviv 107 Tarnavsky Str., 79017 Lviv, Ukraine Infineon Technologies, Lviv, Ukraine, 20 Luhanska Str., 79048 Lviv, Ukraine Department of Information Technologies and Electronic Communications Systems, Lviv State University of Life Safety, 35 Kleparivska Str., 79007 Lviv, Ukraine

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#### **ABSTRACT**

**Introduction**. The article explores the possibility of utilizing a touch-sensitive button for the identification of two types of signals – a button press signal and a finger swipe signal across the button. This concept has the potential to revolutionize the way we interact with electronic devices, making them more intuitive and user-friendly. The ability to detect different types of gestures using a single button can also lead to a more compact and cost-effective design.

**Materials and Methods**. To address the classification task, an algorithm has been proposed for the identification of signal characteristics upon which recognition will be conducted. The algorithm is based on a neural network architecture, which is trained on a dataset of signals collected from a touch-sensitive button. The dataset includes a variety of signals, each corresponding to a specific gesture, such as a button press or a swipe in different directions. The neural network is designed to learn the patterns and characteristics of the signals, allowing it to accurately classify new, unseen signals. The algorithm is optimized to minimize processing time and computational resources, making it suitable for real-time applications.

**Results**. Using neural networks to solve the recognition task allows for the easy determination of optimal classification algorithm parameters for a specific type of touch button. The results show that the proposed algorithm achieves high accuracy in identifying two types of gestures, with a minimal error rate.

**Conclusions**. The proposed classification algorithm exhibits satisfactory accuracy in identifying the two signals within a minimal timeframe and requires minimal computational resources. Therefore, it can be employed cost-effectively to enhance the functionality of touch panels. The algorithm's ability to detect gestures using a single button makes it an attractive solution for applications where space is limited, such as in wearable devices or mobile phones. Additionally, the algorithm's low computational requirements make it suitable for use in low-power devices, such as those powered by batteries or energy harvesting systems. Future work can focus on improving the algorithm's accuracy and robustness, as well as exploring its application in different domains.

**Keywords**: gesture detection, neural network, capacitive sensor, signal profile.



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#### INTRODUCTION

Using gestures is one of the most convenient ways of interaction with gadgets. Therefore, gesture real time detection has many applications [1-6], including gaming, virtual reality, and smart home devices. The ability to detect gestures in real-time enables users to interact with devices in a more natural and intuitive way, enhancing the overall user experience.

Development of structures and algorithms of such gadgets combined with the advantages of microcontrollers Infineon Technologies [7] and neural networks shall allow realizing simple, cheap, effective, and reliable gadgets. The integration of Infineon's microcontrollers with neural networks can provide a powerful platform for gesture detection, enabling the development of a wide range of innovative applications.

The use of neural networks can improve the accuracy and robustness of gesture detection, while Infineon's microcontrollers can provide the necessary processing power and low power consumption. This combination can enable the creation of gesture-based devices that are not only effective but also energy-efficient and cost-effective.

#### **MATERIALS AND METHODS**

Figure 1 shows a panel prototype with three buttons. Only signal from one of them (middle button) was used for the algorithm development. A button press is identified as a certain command.

An algorithm shall be developed to differentiate the two types of signal:

- 1. The sensor signal resulted from a button press (Touch).
- 2. The sensor signal resulted from a finger swiping on the button surface (Swipe).

To correctly classify signals, signal attributes are required. Figure 2a and 2b shows pairs of real-signals examples that differ visually while Fig. 2c and 2d – similar examples that can hardly be differed visually.

The requirements to the identification system productivity: the classification shall be executed immediately after the signal start and ensure the algorithm high efficiency. Therefore, for example, the signal spectrum analysis cannot be used due to its inherent features:

- the need to process the entire signal (from start to end);
- · significant amount of processing time;
- significant amount of calculation resources for the transition to the frequency domain.
  So, simple attributes are required. Neither the signal level nor its duration is applicable.

They may change in a wide range for both signal types. Only the signal shape is applicable.

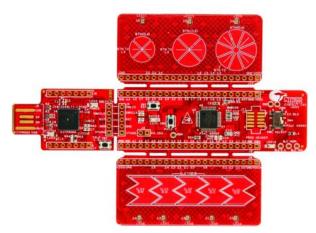


Fig. 1. PSoC 4000S Prototyping Board

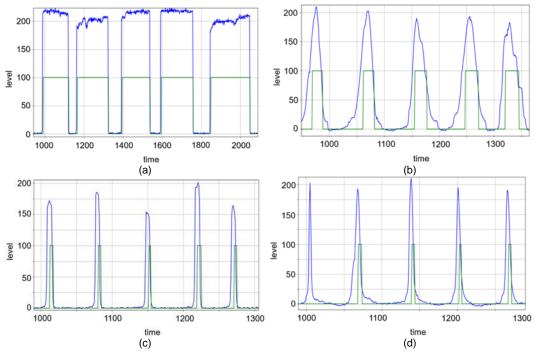


Fig. 2. Real signals: long touch (a); slow right to left swipe (b); short touch (c) and regular right to left swipe (d). Signals are depicted by blue lines, whereas device-identified results – by green lines.

Touch-type signal is close to the  $\Pi$ -shaped in most cases. Swipe-type signal is more similar to the Gauss function.

Unfortunately, short-duration signals in fact cannot be differentiated even visually (Fig. 2c and 2d). This leads to the consideration that any identification algorithm will not yield a 100% correct result. In such cases, the classification issue can be resolved with the neural network solution.

Similar to any classification algorithms, the neural network approach requires the selection of the classification attributes. As mentioned above, most signals can be differentiated based on their shape and the signal derivative depends significantly on the shape (see Figures 3, 4). Therefore, the analysis of the signal shape transits to the analysis of values of the signal derivative, where the derivative is the time function.

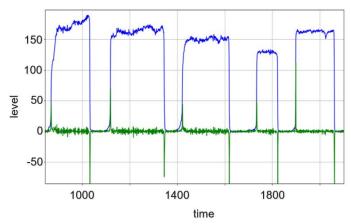


Fig. 3. Long touch signals. Blue line - real signal, green line - signal derivative.

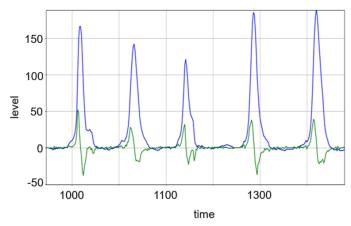


Fig. 4. Regular left to right swipe signals. Blue line – real signal, green line – signal derivative.

The Π-shaped signal may appear suddenly between two peaks determined by the edges of the time interval signal for which the derivative is close to zero. For the Swipe type of signal, such an interval is either absent or minimal. This difference can be used as one of the attributes for the classification. Another attribute can be the speed of the increasing of the leading-edge signal. In many cases, this speed is significantly bigger for the Touch type signal than for the Swipe type signal. Therefore, the maximal value of the derivative on the leading-edge signal can be taken as the second attribute.

#### **RESULTS AND DISCUSSION**

The two attributes are selected for the classification:

- 1. The maximal value of the derivative on the leading-edge signal.
- 2. The number of zeros on the signal top.

Figure 5 shows the flowchart for signal attributes determination.

To make the algorithm work, the two constants are required: the signal minimal level, the maximal value of the signal derivative, where the derivative shall be equal to zero.

Figure 6a demonstrates the results obtained by the program for button press (Touch signal). Figure 6b – same results for button surface (Swipe signal). Figure 6 confirms that the attributes values are different. On the other hand, there is a significant overlapped area (see Fig. 7).

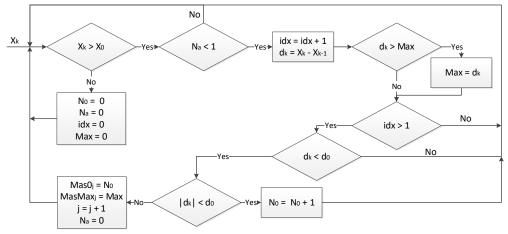


Fig. 5. Algorithm for determination of signal attributes.

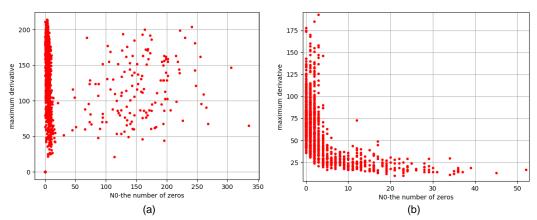


Fig. 6. Signals attributes values for Touch signal (a) and Swipe signal (b).

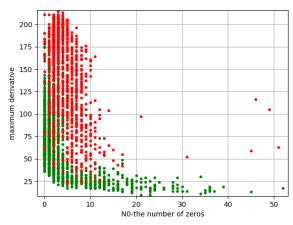


Fig. 7. Normalized attributes values for two types of signals: green dots – Swipe, red dots – Touch.

Due to the difficulty of the signal's boundary determination, as the solution for the classification task, it was selected the forward propagation two-layer neural network with the sigmoidal function of activation, which structure is depicted on the Fig. 8.

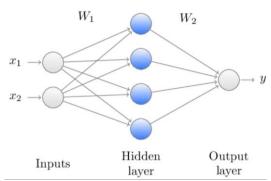


Fig. 8. Neural network structure.

Before the neural network training, the input vectors were normalized. The number of neurons in the input layer shall determine the accuracy of reproducing the boundary between the two sets. To assess the quality of the classification, the error coefficient K was used:

$$K = (ER_{swine} + ER_{touch})/N_{nn}, \tag{1}$$

where:

*ER*<sub>swipe</sub> is the number of incorrectly determined signals of the Swipe type;

 $\mathit{ER}_{touch}$  – the number of incorrectly determined signals of the Touch type;

 $N_{np}$  – the summative number of signals.

Table 1 contains the results of the classification with different quantities of neurons in the input layer.

The further increase of the number of neurons in the input layer shall not yield better results because the boundary between the two types of signals is blurry. The only way to improve the classification accuracy is to increase the number of the classification attributes. The selected here attributes worked the best. Whereas, additional attributes, for example, the signal amplitude value did not show significant improvement.

Table 1. Results of the classification with different quantities of neurons in the input layer

#	Number of neurons in the input layer	Error coefficient (%)
1	2	8.2 – 9.0
2	3	7.1
3	4	6.5
4	6	6.4
5	8	6.3

Figure 9 shows the offset limit of the signals obtained by the trained neural network with six neurons in the input layer.

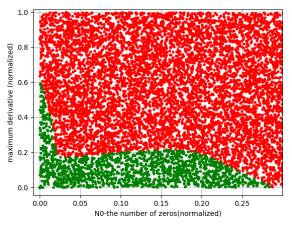


Fig. 9. Boundary between the signals (green dots – Swipe signal, red dots – Touch signal).

The further increase of the number of neurons in the input layer shall not yield better results because the boundary between the two types of signals is blurry. The only way to improve the classification accuracy is to increase the number of the classification attributes.

The selected here attributes worked the best. Whereas, additional attributes, for example, the signal amplitude value did not show significant improvement.

#### CONCLUSION

Based on obtained results, we have concluded that the proposed classification algorithm yields quite good accuracy while executing the identification of two signals in the minimal time period and requires minimal calculation resources, so, can be used with minimal cost for the quality enhancement of the sensor panels.

#### **COMPLIANCE WITH ETHICAL STANDARDS**

The author declare that the research was conducted in the absence of any potential conflict of interest.

#### **AUTHOR CONTRIBUTIONS**

Conceptualization, [O.K.]; methodology, [Z.L.]; validation, [O.K.]; formal analysis, [V.M.].; investigation, [O.T.]; resources, [Z.L.]; data curation, [Z.L.]; writing – original draft preparation, [Z.L.]; writing – review and editing, [V.M.]; visualization, [N.H.] supervision, [V.M.]; project administration, [O.K.]; funding acquisition, [O.K.].

All authors have read and agreed to the published version of the manuscript.

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# АНАЛІЗ УДОСКОНАЛЕННЯ ТАКТИЛЬНОГО ІНТЕРФЕЙСУ ДОТИКУ СЕНСОРНОЇ ПАНЕЛІ

# Олександр Карпін<sup>1,2</sup>, Зіновій Любунь<sup>1</sup>, Василь Мандзій<sup>1,2</sup>, Олег Терещук<sup>1</sup>, Нестор Гоцій<sup>2,3</sup>

¹ Кафедра радіофізики та комп'ютерних технологій Кафедра сенсорної та напівпровідникової електроніки, Львівський національний університет імені Івана Франка вул. Тарнавського, 107, м. Львів, 79017, Україна ² Інфінеон Технолоджіс, Львів, Україна вул. Луганська 20, м. Львів, 79048, Україна з Кафедра інформаційних технологій та систем електронних комунікацій Львівський державний університет безпеки життєдіяльності вул. Клепарівська 35, м.Львів, 79007, Україна

## *RIJATOHA*

**Вступ.** В статті розглянуто можливість використання сенсорної кнопки для ідентифікації двох типів сигналів — сигналу від натискання кнопки та сигналу від проведення пальцем по кнопці. Ця концепція має потенціал кардинально змінити спосіб взаємодії з електронними пристроями, зробивши їх більш інтуїтивно зрозумілими та зручними для користувача. Здатність виявляти різні типи жестів за допомогою однієї кнопки також може призвести до більш компактного та економічно ефективного дизайну.

Матеріали та методи. Для вирішення задачі класифікації запропоновано алгоритм визначення ознак сигналів на основі яких буде проводитись розпізнавання. Алгоритм базується на використанні нейронної мережі, яка навчається на наборі даних сигналів, зібраних із сенсорної кнопки. Набір даних містить різноманітні сигнали, кожен з яких відповідає певному жесту, наприклад натискання кнопки або проведення пальцем у різних напрямках. Нейронна мережа розроблена для вивчення шаблонів і характеристик сигналів, що дозволяє їй точно класифікувати нові, невідомі сигнали. Алгоритм оптимізовано для мінімізації часу обробки та обчислювальних ресурсів, що робить його придатним для детектування жестів в режимі реального часу.

**Результати.** Використання нейромереж для вирішення задачі розпізнавання дозволяє легко визначити оптимальні параметри алгоритму класифікації для конкретного типу сенсорної кнопки. Результати показують, що запропонований алгоритм забезпечує високу точність ідентифікації двох типів жестів з мінімальною кількістю помилок.

Висновки. Запропонований алгоритм класифікації дає досить добру точність при виконанні ідентифікації двох сигналів за мінімальний проміжок часу та вимагає мінімальних обчислювальних ресурсів. Таким чином, він може бути використаний з мінімальними витратами для збільшення функціональності сенсорних панелей. Здатність алгоритму виявляти жести за допомогою однієї кнопки робить його привабливим рішенням для додатків, де простір обмежений, наприклад, у переносних пристроях або мобільних телефонах. Крім того, низькі обчислювальні вимоги алгоритму роблять його придатним для використання в малопотужних пристроях, наприклад тих, що живляться від батареї. Майбутня робота може бути зосереджена на покращенні точності та стійкості алгоритму, а також на дослідженні його застосування в різних областях.

*Ключові слова*: Ємнісний сенсор, профіль сигналу, індикація, нейронна мережа.