Sensors & Transducers, Vol. 238, Issue 11, November 2019, pp. 1-7

Sensors & Transducers

Published by IFSA Publishing, S. L., 2019
http://www.sensorsportal.com

Data Analysis of Frequency-analog Signals of a Humidity Sensor to Improve the Detection of Fakes

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Received: 30 August 2019 /Accepted: 15 October 2019 /Published: 30 November 2019

Abstract: The aim of the described solution is to detect the vitality of presented measurement objects. Therefore, a capacitive sensor is used. The output signal of the sensor is a frequency. The frequency-analog output signal is depending on the humidity of the measurement object. The sampled frequencies data, monitored like dynamic time series data, have been analyzed to develop an efficient binary classifier. The classifier functions as a vitality checker. Vitality checkers are useful additional tools in the field of biometric applications to improve the security of such systems.

Keywords: Analysis of frequency-analog time series data, Vitality checker, Binary classifier.

Preface

This is an extended paper of a work which was discussed at the first IFSA Frequency & Time Conference (IFTC´2019) [1]. It is supplemented by some specific results of analysing the scattering and the temporal change of the time series data.

Whereas in [1] representative qualitative time series of period values were published, in this paper raw data plots in form of quantitative frequency time series are shown.

1. Introduction

Biometric systems have been gaining in importance for more than two decades. They have been used in different areas of social and economic life, in particular for access control to secured systems. The detection of biometric features works very well in the present. So, biometric systems, especially fingerprint sensors, are very often used for identification and authentication purposes. Especially biometric systems, that meet the challenges of sovereign, protected security areas and the growing security demands of privately run businesses, require constant improvements. The detection of fakes is one of the main focal points of such improvements. An almost absolute reliable control mechanism to differ a real biometric object from a fake is to check its characteristic to be alive. On the one hand, it is possible to produce identical copies of biometric features, but on the other hand, it is nearly impossible to imitate the vitality of a measurement object in a sufficiently realistic way. That is why, vitality checkers are components of modern sophisticated biometric systems [2-4], e.g. in sovereign, protected security systems [5].

In this context, a lot of ideas to check the vitality were developed and published [6-14]. Aside from the measurement of vitality parameters like heart rate and oxygen saturation, the verification of the peripheral blood flow, the detection of temperature and patterns of movements etc. have been discussed so far.

Different from these previous works, in this paper a solution based on data analyses of the signals of a frequency-analogue humidity sensor is described.

2. Solution Approach

Water is a permanent metabolic product of human beings. This effects a measurable ambient humidity of skin, e.g. due to the activity of the sweat glands. State of the art vitality checkers using the activity of the sweat glants are based on image processing solutions [15-16].

Here, a solution approach is shown, that is based on the idea of data analyses of time series signals of a capacitive humidity sensor. The studies do not target on very accurate measurements of humidity.

In a multitude of test cases, a binary classifier works efficient to separate real measurement objects from fakes by a measurement signal which correlates with the humidity.

It suggests that dry measurement objects are most probably fakes and wet measurement objects are very often real biometric objects, which are alive. Furthermore, it hypothesized, that adequately moistened fakes will be classified correctly in most cases by using appropriate methods of data analyses. Therefore, several data analyses methods to classify time series signals are used.

3. Experiments

3.1. Experimental Setup

The most important hardware component of the measurement chain is the primary sensor, because it determines the functional characteristic of the whole solution. The primary sensor is a capacitive humidity sensor. The capacity between interdigital electrodes depends on the ambient humidity in the electrical stray field of the used capacitor. Fig. 1 shows a greatly enlarged photo of the used sensor. It is a dimensioned picture.

The dimensions of the sensor are round about 3 mm × 3 mm. Because of its small dimensions, it is not problematic to integrate this sensor in biometric systems.

In the center is the relevant sensitive area of 1.7 mm × 1.7 mm. There, the planar interdigital electrodes are located.

Fig. 1 includes a zoom of the layout of the planar electrodes. The strips of the electrodes and the gap between the electrodes amount to only a few micrometers (≤ 5 μm).

The output signal of the sensor is converted into a square-wave signal by an integrated electronic based on the 555-timer-circuit (Fig. 2), internally consisting of two comparators and a RS-flipflop.

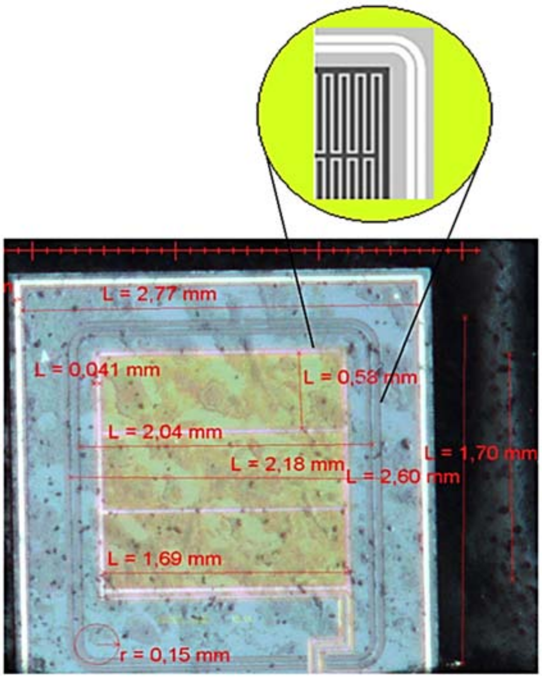

Fig. 1. Greatly enlarged photo of the capacitive humidity sensor (with schematic zoom of planar interdigital electrodes).

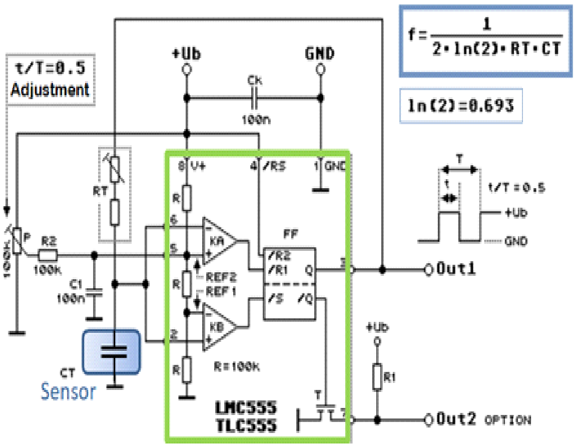

Fig. 2. Capacitance to frequency converter.

The frequency depends directly on the change of capacity caused by the effects of ambient humidity. The square-wave signal has been sampled with a suitable data acquisition device (DAQ), specified by an ADC resolution of 16 Bit and a sample rate of 200 kS/s.

The DAQ has been connected via USB with a computer.

Fig. 3 illustrates the complete measurement chain.

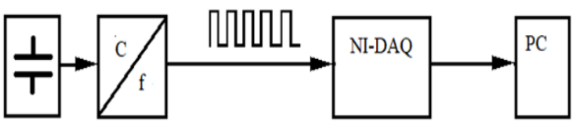

Fig. 3. Measurement chain.

The average frequency respectively the average period of the square-wave signal can be calculated by counting of zero passages. This calculation (Eq. (1)) has been done in timeslots of 7.5 ms:

$$f_i = \frac{N}{7{,}5\,\mathrm{ms}},\ T_i = \frac{1}{f_i} = \frac{7{,}5\,\mathrm{ms}}{\mathrm{N}}, \qquad (1)$$

where f-frequency, T-period, i-count-index: 0…799.

Then, the average values are stored in a raw-data-set.

3.2. Test Objects

The test objects were real alive fingers of more than 70 persons and 180 fakes. The 180 fakes consist of 124 representative dry fake-examples and 56 representative wet fake-examples. The used test-fakes represent the known state of the art of fakes, but details to produce them will not be described in this paper.

While dataset 1 contains only the measurement results of index fingers of the right hand of different persons, dataset 2 contains results of measurements of all ten fingers of both hands from the test persons. In dataset 2 included are repeated measurements of the same fingers at several times. There are more raw-data-sets of index fingers than of the other eight fingers in the dataset 2. It should be noted, that in the presented diagrams, the results of measurements with real alive fingers are called 'Real', all the other ones are called 'Fake'.

4. Results

First, in this section selected raw-data-plots are shown, because significant differences can be observed in these diagrams. Then, in a separate section, results of several data analysis procedures are illustrated.

4.1. Raw-Data-Plots

Figs. 4-6 present representative time series of calculated frequency values (see Eq. (1)). They show the change of the frequency-values in a limited duration.

The frequency values between 55 kHz and 57 kHz of a real alive finger (Fig. 4) are significantly lower than those of dry fakes between 133 kHz and 135 kHz (Fig. 5).

But the frequencies of real fingers and wet fakes may be nearly the same (compare Fig. 4 and Fig. 6).

Furthermore, the diagram quality of real vital objects seems to be 'noisy with a drift', while the diagram quality of the fakes (dry and moist) seems to be 'square-quantized'.

The visual distinguishability of the diagrams is a strong indicator to find a technical opportunity for classifying these objects (Figs. 4-6).

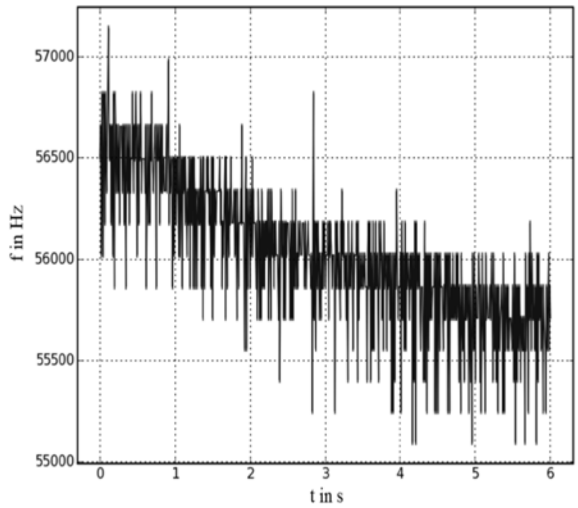

Fig. 4. Frequency-time series of the humidity sensor signal generated by measuring at a real alive index finger.

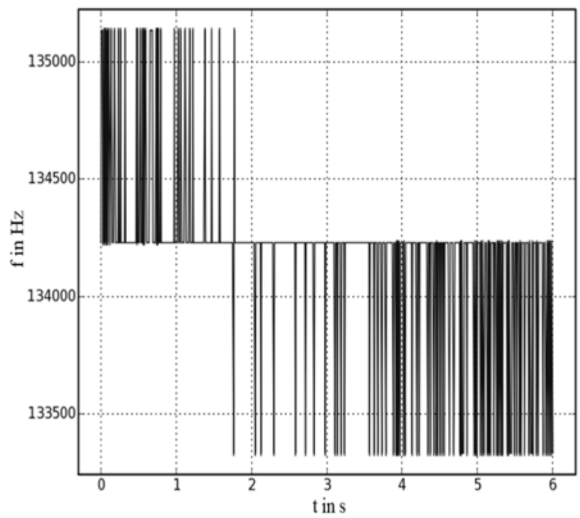

Fig. 5. Frequency-time series of the humidity sensor signal generated by measuring at a dry fake.

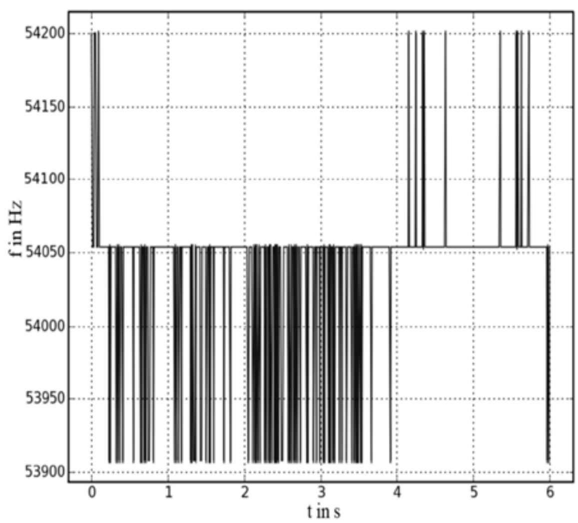

Fig. 6. Frequency-time series of the humidity sensor signal generated by measuring at a wet fake.

4.2. Results of Classification

4.2.1. Frequency-threshold as Separation Criterion

The measured signals of different objects had to be evaluated to develop a reliable binary classifier to separate the real alive biometric objects from fakes.

Typical quantitative criterions to characterize the quality of a classifier are:

$$specifity = \frac{TN}{TN+FP} = \frac{TN}{N}, \tag{2}$$

$$sensitivity = \frac{TP}{TP+FN} = \frac{TP}{P}, \tag{3}$$

$$accuracy = \frac{TP+TN}{TP+FN+TN+FP} = \frac{TP+TN}{P+N}, \tag{4}$$

$$precision = \frac{TP}{TN+FP} = \frac{TP}{N}, \tag{5}$$

$$Youdenindex = \frac{TP}{P} + \frac{TN}{N} - 1, \tag{6}$$

where P is the positive (real alive finger), N is the negative (fakes), TN is the true negative, TP is the true positive, FN is the false negative, FP is the false positive.

That the frequency respectively the period of the square-wave signal of the humidity sensor are expedient separating criterions to detect dry fakes has been illustrated in Fig. 7.

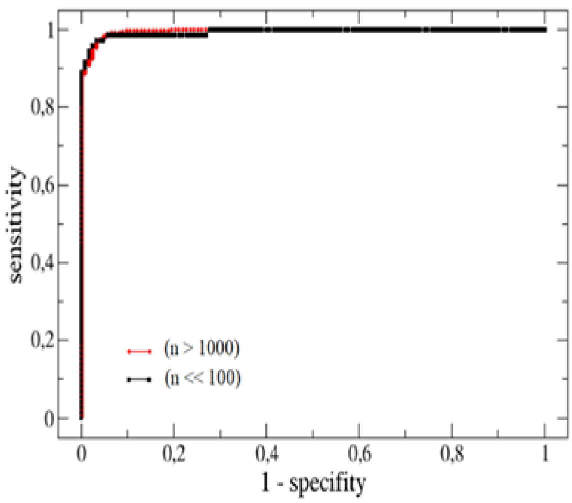

Fig 7. Frequency value as separation criterion (ROC-curves for real fingers vs. dry fakes).

Receiver-Operating-Characteristics (ROC-curves) are shown for detection of dry fakes vs. the real fingers of dataset 1 and dataset 2. Both ROC-curves are nearly identic.

The capacitive humidity sensor is sensitive enough to detect the thin sweat film on the skin of the real fingers.

Ca. 97 % correct classification results for both classes are obtained if only dry fakes are used.

Fig. 8 shows a combination of diagrams to find out the optimal frequency-threshold for separation of real fingers from all kind of suitable fakes.

ROC-curves for real fingers vs. fakes on the left side and Youdenindex-curves and histograms on the right side are shown in Fig. 8. On top are results of dataset 1 vs. all fakes, further below are results of dataset 2 vs. all fakes.

By using wet fakes the performance decreases (Fig. 8), but is good enough by using only one frequency threshold as separating criterion.

Overlaps in both histograms are found for all frequency thresholds in Fig. 8. The best classification results are found for a frequency-threshold at the maximum of the Youdenindex at 0.66 in this study (Eq. (6)). A sensitivity of 96.7% (Eq. (3)) and a specifity of 69.4 % (Eq. (2)) are reached for a threshold of 134 kHz.

To improve the performance, it has to be searched for other separating criterions.

4.2.2. Separation by Scattering of Time Series Signals

It was observed, that the variance of time series values of vitality objects is higher than the variance of dry and wet fakes. Measurement results of real alive fingers were described as ‘noisy with a drift’, the non-vitality objects were characterized as ‘square-quantized’.

The dot plots in Fig. 9(a), Fig. 9(c) illustrate the difference of scattering of both classes.

So, the usability of standard deviation of the time series values as a separation criterion was tested. The results of this idea are plotted in the ROC-curves in Fig. 9(b), Fig. 9(d).

According to expectation, the ROC-curves of both datasets are very similar, like in Fig. 9. But, it seems to be worsening compared with the ROC-curves in Fig. 9.

An expedient separation threshold for the standard deviation couldn’t be found.

4.2.3. Separation by Temporal Change of Time Series Signals

Another difference between vital fingers and non-vital fakes are the temporal change in the raw data plots. The derivation of standard deviation was calculated to characterize the temporal change and a ROC-curve with this parameter as a separation criterion is shown in Fig. 10.

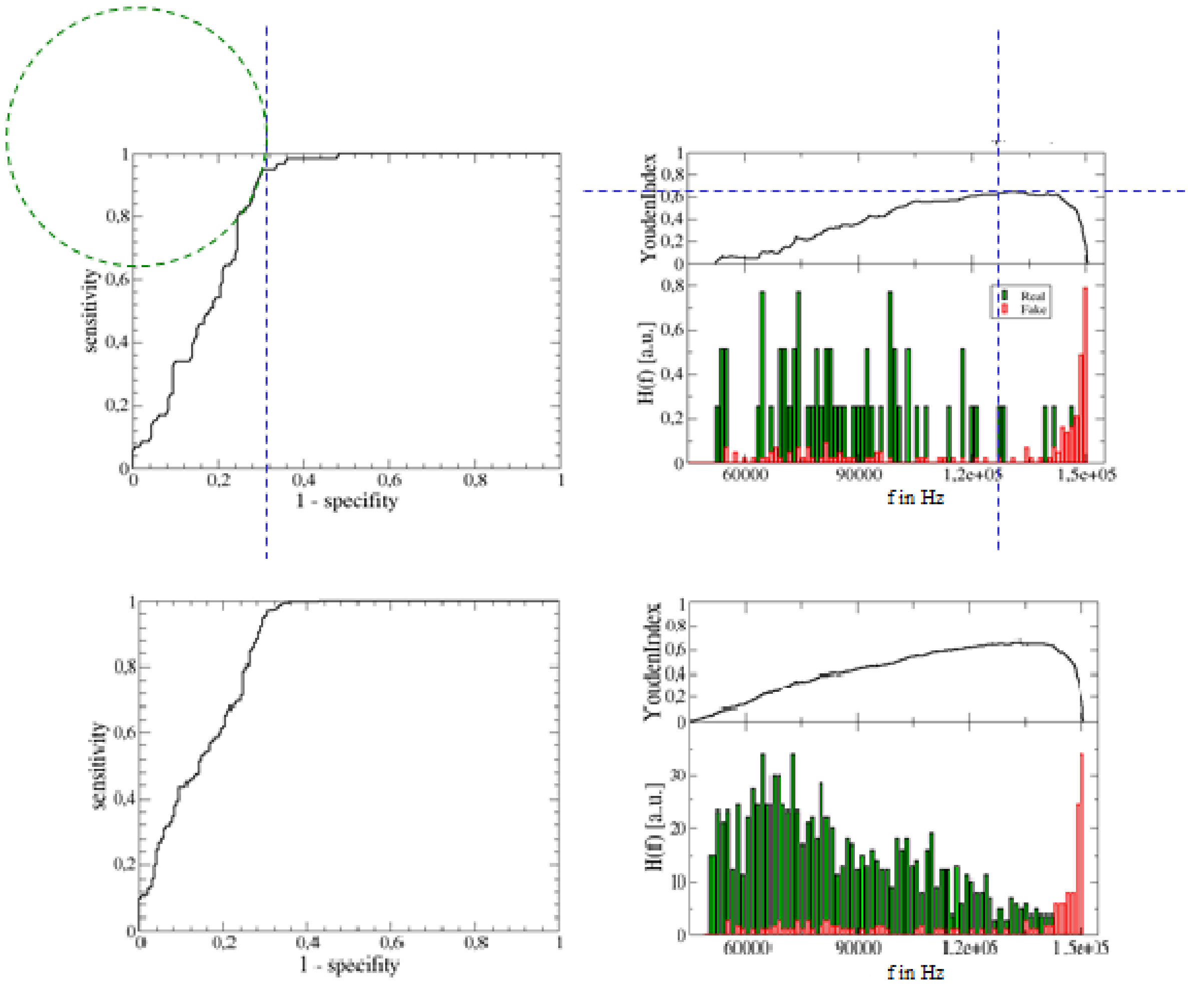

Fig. 8. Frequency threshold in ROC-, YOUDENindex-curves and histograms.

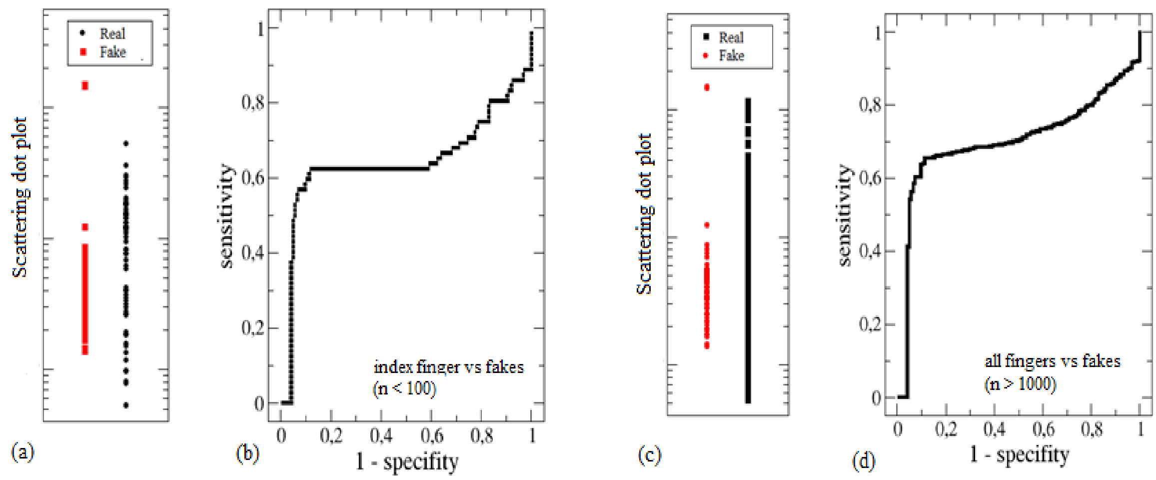

Fig. 9. Standard deviation as separation criterion (Scatter dot plots and ROC-curves.

Approximately 80 % correct classification results for real fingers and all suitable fakes seems to be attainable by using an optimal threshold of the derivation of standard deviation.

The plot in Fig. 11 was created to combine the differences of scattering and drift in one diagram. The result of using the standard deviation and the derivation of standard deviation for dataset 1 are plotted in a full-logarithmic diagram. This idea offers an interesting opportunity for a binary classification.

The line, which is printed into the diagram, shows one successful separation opportunity by combining scattering and drift characteristic.

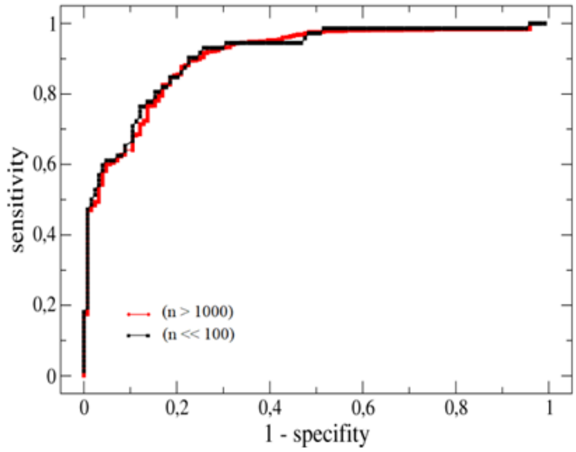

Fig. 10. Derivation of standard deviation as separation criterion (ROC-curves).

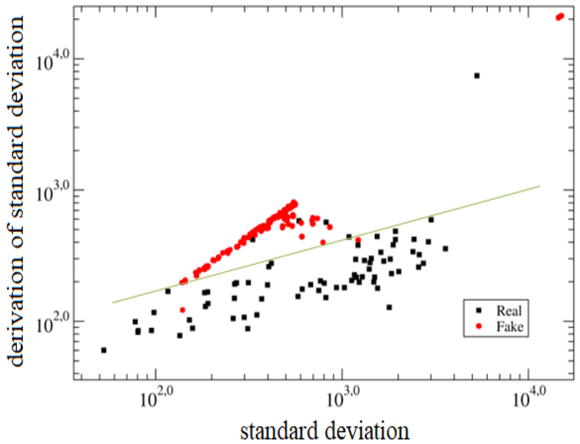

Fig. 11. Separation opportunity by using standard deviation and derivation of standard deviation (log-log-plot).

5. Conclusion

The vitality of presented measurement objects can be detected in a relative simple way by an additional capacitive sensor and the analysing of frequency-output signals. An efficient separating criterion for a binary classifier is a frequency threshold (Figs. 7, 8), but also other separating criterions based on the measurement of the output frequency value and its deviation can be found (e.g. Figs. 10, 11). That's why the described solution is suggested as an additional tool in biometric systems, especially in fingerprint sensors.

By fusion of more than one solution a classification success of more than 95 % seems to be a realistic perspective.

For the reasons mentioned, an implementation of such a relatively simple hardware solution with a planar humidity sensor can be highly recommended for a sensitive detection of fakes in biometric systems like fingerprint sensors. Furthermore, the implementation of other simple coexisting sensors is concurrently recommended to improve the detection of fakes in biometric systems. To create such systems for generic classification tasks by using commercial sensors is one of the research and development fields in the measurement laboratory at the HTW Berlin [17].

The hardware fusion of multifunctional sensors on a chip is an actual trend for more than ten years. So, it may be predicted that such chips [18] are more and more suitable on the market of electronic components.

Acknowledgment

I give big thanks to Thomas Henning for his important input in a lot of relevant scientific discussions. Mr. Henning played a determining part for the success of our project, he realized a lot of data analysing software tools.

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