Signature down-sampling for finger input online signature verification

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Abstract. Online signatures are widely accepted and used for authentication purposes. They are acquired using special devices with different sampling frequencies. A stylus or finger can be used as an input method. This paper studied the minimum sampling frequency required to achieve the best accuracy in online signature verification systems. Three different dynamic time warping-based verifiers were applied on the finger input signatures set of the DeepSignDB database. The results show that we can achieve a highly accurate online signature verification system for finger input signatures using lower sampling frequency, reducing time and computation costs.

Keywords: ×Online signature verification, Sampling frequency, Classification.

1. Introduction

Biometrics are human characteristics, and features such as finger or face print and signatures are used for authentication and identification purposes. Signature verification is a very common method that is used for authentication. Signatures are categorized as offline and online based on the input method. In offline signatures, regular paper and pen are used to draw the signature, later scanned as a digital file.
Online signatures are captured by a special device such as pressure-sensitive tablets or digital pens. Several features are available in online signatures, such as speed, pen pressure, and pen position; see figure 1. These features make the signature unique and harder to forge than offline signatures.

Fig. 1. Wacom Intous 3

The devices used for online signature acquiring have a specific sampling frequency, usually 100–200 Hz. This reflects the number of points contained in each signature. Therefore, the results of the verification might vary when using different devices.
In our previous work, we studied the effect of using a lower sampling rate on the accuracy of online signature verification systems Saleem and Kovari (2021). In this work, we take advantage of the DeepSignDB Tolosana et al. (2021a) database, which includes a special set of finger input signatures to study the minimum sampling frequency that can be used to achieve the best verification accuracy.

There are only a few papers that discussed resampling signature using some interpolation algorithms, but not the direct effect of using lower sampling frequency Martinez-Diaz et al. (2007) Vivaracho-Pascual et al. (2009).
Several verification approaches are commonly used in signature verification system such as multi-layer perceptron (MLP) neural network Al-Shoshan (2006)Hefny and Moustafa (2019), back-propagating recurrent neural network (RNN) Lai and Jin (2018), Hidden Markov Model (HMM) Tolosana et al. (2015), K-Fold Cross-Validation Nilchiyan et al. (2015), Parzen Window Classifier Rashidi et al. (2012), and dynamic time warping (DTW) Yanikoglu and Kholmatov (2009) Sharma and Sundaram (2016) Xia et al. (2017) which is one of the most popular methods for distance-based measurement.

2. Methodology and experimental results

To analyze the effect of the signature down-sampling on the finger input signature, we created several online signature verifiers. The idea behind using different systems is to eliminate the impact that might accrue because of any other factor during the verification process. There are four main stages of any signature verification system, data acquisition, prepossessing, feature extraction, and verification.

For the first step, the finger input set of the DeepSignDB database was selected. More than 70,000 signatures from 1526 signers are available in this database. The signatures were acquired using stylus and fingers; only the finger input signatures are considered in this work. Figure 2 shows the structure of the database. Similar to some previous signature verification competitions Malik et al. (2015)Malik et al. (2013)Yeung et al. (2004), DeepSignDB was also used in a signature verification competition Tolosana et al. (2021b).

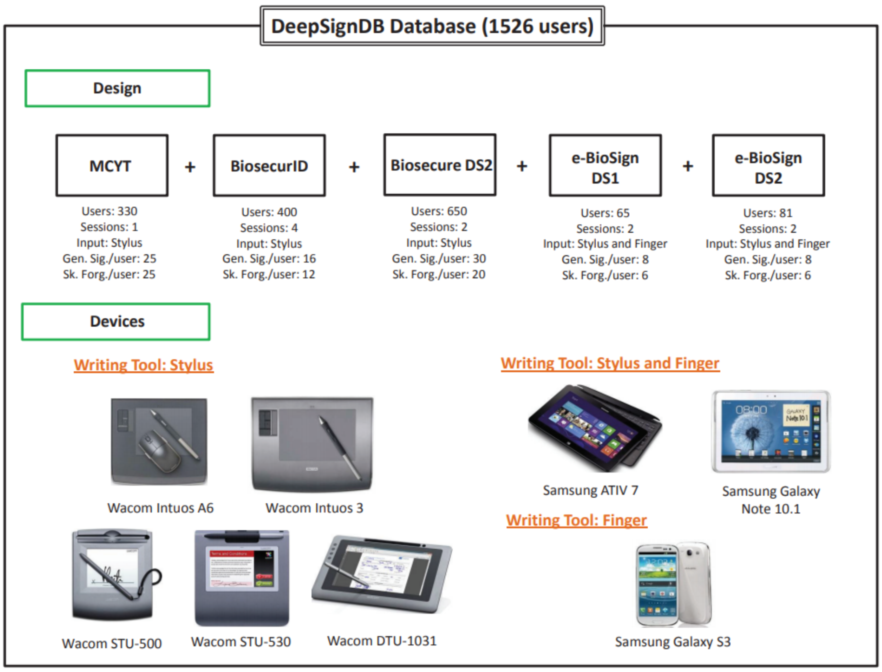

Fig. 2. DeepSignDB Tolosana et al. (2021a).

For the preprocessing phase, four different algorithms were used. The first was to scale the horizontal position values to the range [0,1], then shift the center of gravity of the signature to the origin. The same algorithms were also applied to the vertical position values. Another filtering algorithm was also applied to remove the noise data.

$$\hat{x}(i) = x_{\text{newMin}} + \frac{x(i) - x_{\text{oldMin}}}{x_{\text{oldMax}} - x_{\text{oldMin}}} * (x_{\text{newMax}} - x_{\text{newMin}}) \tag{1}$$

$$\hat{x}(i) = x(i) - \mu_{\text{x}} \tag{2}$$

As several features are available in online signatures, only the horizontal position, vertical position, and pressure features were used. In our previous workSaleem and Kovari (2020), we showed that these are the most efficient features that provide the highest accuracy for dynamic time warping-based verification systems.

We used dynamic time warping (DTW) in the verification phase to calculate the distances between the signatures. Then, we set a lower and an upper threshold for each reference signature.

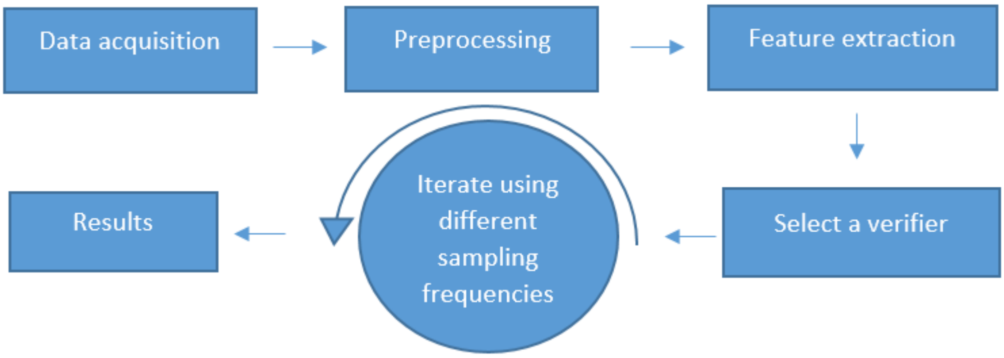

Fig. 3. Proposed method

The distance Dis between the tested signature (S_t) and the reference signature (S_{ref}) is calculated using DTW algorithm. The value is used to calculate the prediction for the tested signature P. Two signer dependent thresholds are also used in the prediction calculations: forgery threshold F_t and genuine threshold G_t.

$$P = \frac{s * F_t - Dis}{s * F_t - G_t} \tag{3}$$

where s is a scaling parameter.

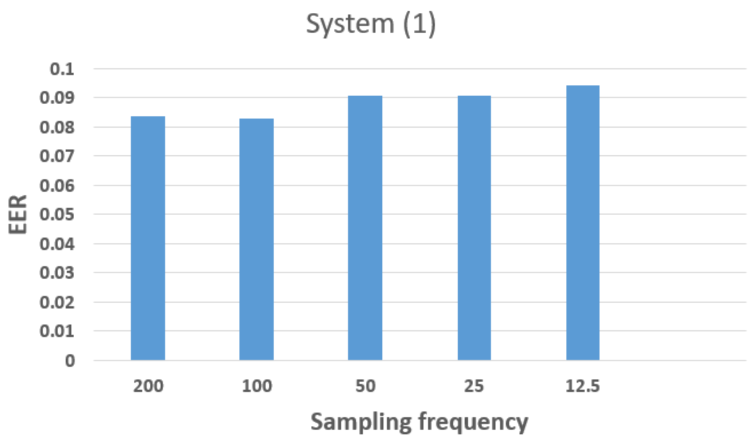

Fig. 4. The results of system(1)

The signatures are classified as genuine or forged based on the prediction value where 0 and 1 represent genuine and forged signatures, respectively, using a signer-dependent threshold.

To evaluate and analyze the effect of the sampling rate on the accuracy of the verification system, each verifier was applied using several sampling frequency rates. In the first iteration, we started by using the original sampling frequency of the database. Then in each iteration, we use a lower sampling frequency. Finally, the verifiers' accuracy using different sample rates is compared and analyzed.

As mentioned before, different verifiers were used to confirming the results. The experiments show that we can achieve the same or very similar results using a lower sampling frequency. In this section, some results of the experiments will be analyzed and discussed. In the following figures, you can see the results of using five different sampling frequencies on three different systems:

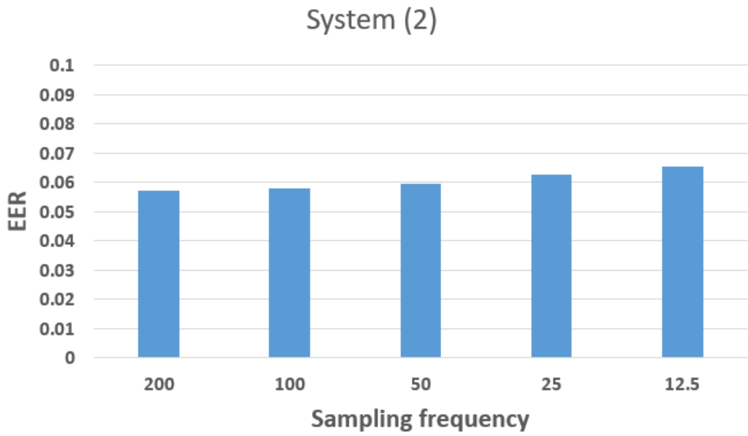

Fig. 5. The results of system(2)

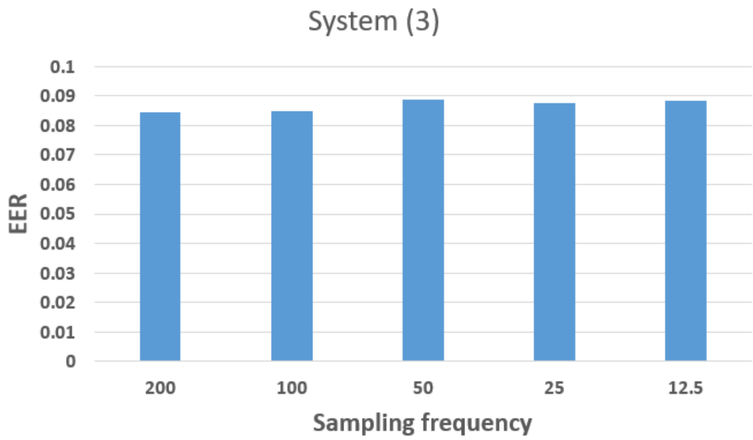

Fig. 6. The results of system(3)

3. Conclusion

In this paper, we studied the minimum sampling frequency that can be used to achieve the best verification accuracy for finger input online signatures. Three different dynamic time warping-based verifiers were used for this purpose. The systems were applied on the finger input set of the DeepSignDB databases. The experiments showed that we could achieve very similar accuracy (less than 1% error rate difference) using a lower sampling frequency. The results were tested using the original sampling frequency (200 Hz), 100Jz, 25Hz, and 12Hz. This shows that we can achieve the same results using faster and cheaper verification systems.

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