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# EVALUATING NEURAL NETWORK MODELS FOR PREDICTING DYNAMIC SIGNATURE SIGNALS

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**Abstract**

A signature is a biometric attribute commonly used for identity verification. It can be represented by a shape created with a classic pen, but it can also contain dynamic information. This information is acquired using a digital input device, such as a graphic tablet or a digital screen and stylus. Information about the dynamics of the signing process is stored in the form of signals that change over time, including pen velocity, pressure, and more. These dynamics are characteristic of an individual and are difficult for a human to forge. However, it is an interesting research issue whether the values of signals describing a dynamic signature can be predicted using artificial intelligence methods. Predicting the dynamics of the signals describing a signature would benefit various scientific problems, including improving the quality of reference signals by detecting anomalies, creating signature templates better suited to individuals, and more effectively detecting potential forgeries by identity verification systems. In this paper, we propose a method for predicting dynamic signature signals using an artificial neural network. The method was evaluated using samples collected in the DeepSignDB database, distributed by BiDA Lab.

**Keywords:** dynamic signature, prediction, neural networks, artificial intelligence, biometrics.

## 1 Introduction

Behavioral biometrics enables the analysis of human behavior to identify patterns characteristic of an individual. Based on these patterns, an individual's identity can be identified or verified. Identification involves determining a person's identity based on their biometric features, while verification involves confirming the claimed identity of the user (see, e.g., [6]).

The literature includes various biometric behavioral attributes, such as gait, keystrokes, mouse movements, and signatures, all of which have strong individual expressions. This paper focuses on the signature biometric attribute, which is commonly used in everyday life, such as in banks, offices, and workplaces. Nowadays, signatures are increasingly created using digital input devices, such as graphic tablets or smartphones. During this process, IT systems can collect information on the dynamics of signing, which is specific to each user. It is noteworthy that identity verification based on dynamic signatures (including information about the signing process's dynamics) is more effective than verification using only a static signature represented by its shape.

A dynamic signature is described by signals that change over time, which can include information about pen position, velocity, and pressure. Therefore, this type of signature is more difficult to forge than a static signature. However, with some information about the signals describing the user's signature, it may be possible to predict the shape of the signals describing the dynamics of other signatures of that user. This is challenging for humans but may be achievable using artificial intelligence methods. This research problem is highly interesting and can be beneficial in many areas of biometrics. For example, it can improve the quality of reference signals by detecting anomalies, allow signature templates to be better suited to individuals, and enable identity verification systems to detect potential forgeries more effectively.

In this paper, we propose a method to predict the values of signals describing the dynamics of a signature based on its previous samples. The method utilizes the potential of artificial neural networks and was tested using the DeepSignDB database, distributed by BiDA Lab.

## 1.1 Related works

In the world literature, one can find methods that use artificial intelligence algorithms for dynamic signature verification. The latest of these are summarized in this section.

In [19], the authors propose a method that transforms the original time-series signature data into stroke images with dynamic-static hybrid information. A new Triplet Supervised Network (TSN), which contains three weight-shared convolutional neural network (CNN) streams, is used as a classifier.

In [15], the authors present a model for dynamic signature verification using network analysis. In this model, signatures are nodes of a complex network, and the existing connection relationship between two signatures is measured through Pearson correlations between time series of signature coordinates that exceed a threshold of comparison. Centrality metrics and entropy of the time series are used as predictive features.

In [8], an extended version of the Dynamic Time Warping (DTW) algorithm is proposed. The paper presents a novel single-template strategy that uses mean templates and local stability-weighted DTW (LS-DTW) distance measures for online signature verification. It uses Euclidean barycenter-based DTW averaging (EB-DBA) to create mean templates that preserve intra-user variability. Moreover, the LS-DTW takes into account local stability in the signature verification process, which improves its accuracy and speed.

In [18], the authors propose an online handwriting signature verification system based on sound and vibration (SVSV) generated during the signing process. The method assumes extraction of the time domain features of the sound signal and then uses the Fast Fourier Transform to extract the frequency domain features of the sound data. Vibration data are processed using Discrete Cosine Transform for dimensionality reduction and feature extraction. In the classification process, a one-class classifier based on a Convolutional Neural Network (CNN) is used.

In [11], the authors note that the signature may change over time, and due to this, the identity of the signature's author could not be properly verified by a qualified expert. They propose a method describing the variation of dynamic features over short and longer periods, defining adequate sample collection strategies and sampling time frames, and laying down the foundation for using time information for comparative analysis of dynamic signatures.

In [20], we propose an interpretable flexible fuzzy system for signature verification. The pre-

sented solution is scalable and can provide independent identity verification for a large number of users in the database, which does not allow for iterative learning. Moreover, the interpretability of the system makes it possible to explain how the similarity of test signatures to reference signature templates is assessed.

In [21], we focus on the prediction of changes in signature descriptors over time. Descriptors of the signature are created based on signals describing its dynamics, but they cannot be used to reconstruct the signal shape. For this purpose, we utilize the capabilities of fuzzy systems and population-based algorithms. An important feature of this algorithm is its ability to interpret changes occurring in signature handwriting because they are represented by the fuzzy rules base.

One can see that dynamic signature verification is a current topic in the world literature.

### 1.2 Motivation

One of the most important features of a dynamic signature as a biometric attribute is the uniqueness of the signals describing its dynamics for each user. The dynamic features of a signature are difficult for humans to reproduce, but with the advancement of artificial intelligence methods, this task may become feasible. This development could significantly impact various aspects of biometric systems for identity verification.

Effective prediction of values describing dynamic signature signals may lead to the creation of more robust identity verification systems that are more resistant to forgery. This could have a significant impact on biometric security, especially in areas such as banking and administration. It is also crucial in the context of changes that may occur in the dynamics of signatures over time for individual users. Predicting dynamic signals can also help filter and improve data quality. For instance, if certain portions of the signal are distorted or missing, the AI model can predict the missing values, thereby enhancing the overall accuracy and reliability of the system.

Moreover, the dynamics of a signature have a strong individual expression for each user, making it a promising area for applying AI models to predict the values of signals describing dynamic signatures. These models can learn and adapt to individual dynamic signature patterns, allowing for the creation of more personalized verification systems that better distinguish real signatures from forgeries. Therefore, in this paper, we propose using artificial neural networks to predict the values of signals describing the dynamics of signatures.

### 1.3 Contribution of the paper

In this paper, we propose a method to predict the values of signals describing the dynamics of the signing process. We use selected neural network models of varying complexity to determine the effectiveness of the prediction process for each model. We evaluate the accuracy of prediction for genuine signatures of individuals and so-called skilled forgeries created by qualified forgers. We also focus on the effectiveness of predicting individual signals describing the dynamics of signature assembly and assess whether the values of each signal can be predicted with similar effectiveness. All simulation results presented in this paper were obtained using the DeepSignDB database, distributed by BiDA Lab.

### 1.4 Structure of the paper

Section 2 describes the proposed approach for predicting the values of signals that characterize dynamic signatures. Section 3 presents the simulation results. Section 4 contains the conclusions and outlines plans for future research.

## 2 Description of the proposed method

The method proposed in this paper is used to predict the values of signals describing dynamic signatures. These signals contain information about the dynamics of an individual's signing process. The proposed method utilizes artificial neural networks to predict these signal values. In the rest of this chapter, we present information on the representation of dynamic signature signal data, the assumptions of the proposed method, and a description of the neural network models used.

### 2.1 Representation of signatures

A dynamic signature can be acquired using a digital input device, such as a graphic tablet. This device can read information about pen position, pressure, and other parameters. In this paper, we consider 10 dynamic signature signals, as presented in Table 1.

**Table 1**. Signals describing the dynamics of the signature used in the proposed method.

| Lp. | Description | Variable |
|---|---|---|
| 1 | $x$-coordinate | $x$ |
| 2 | $y$-coordinate | $y$ |
| 3 | Information on whether the pen is touching the tablet surface | $z$ |
| 4 | Path velocity magnitude | $v$ |
| 5 | Magnitude of the velocity along the coordinate $x$ | $vx$ |
| 6 | Magnitude of the velocity along the coordinate $y$ | $vy$ |
| 7 | Path acceleration magnitude | $a$ |
| 8 | Magnitude of the acceleration along the coordinate $x$ | $ax$ |
| 9 | Magnitude of the acceleration along the coordinate $y$ | $ay$ |
| 10 | Pen pressure | $p$ |

Each dynamic signature $\mathbf{s}_{i,j}$ is represented as follows:

$$\mathbf{s}_{i,j} = \left[s_{i,j,k=1}, s_{i,j,k=2}, \ldots, s_{i,j,k=K}\right], \qquad (1)$$

where $i$ is the index of the user who created the signature, $j$ is the number of the individual's signature, $k$ is the number of the signature sample, $K$ is the total number of signature samples, and $s_{i,j,k}$ is the $k$-th sample of the signature $j$ created by the user $i$.

A sample of the signature contains information about the signature's dynamics and is defined as follows:

$$s_{i,j,k} \in \{x_{i,j,k}, y_{i,j,k}, z_{i,j,k}, v_{i,j,k}, vx_{i,j,k}, vy_{i,j,k}, a_{i,j,k}, ax_{i,j,k}, ay_{i,j,k}, p_{i,j,k}\}. \qquad (2)$$

The artificial neural networks in the proposed method use the signature signals and their samples as described above.

### 2.2 General idea of the method

The proposed method for predicting the values of dynamic signature signals involves using a selected artificial neural network. The network predicts the values of the next signature sample by considering the values of previous samples.

The general idea of the proposed method can be described in the following steps:

- **Step 1. Acquisition of training signatures.** In this step, $J$ training signatures of user $i$ are acquired using a digital input device, e.g., a graphics tablet. These signatures are used to train neural network models.
- **Step 2. Pre-processing of signatures.** All signatures obtained in the previous step have to be pre-processed to enhance data consistency. Signatures can differ, e.g., in size, position, rotation, and number of samples. Pre-processing eliminates these differences. This step is carried out using methods commonly used in the literature (see e.g., [5]).
- **Step 3. Preparation of data.** The proposed method assumes that the neural network uses a set of samples containing information about the signature dynamics to predict the value of the consecutive sample. The data fed to the input of the neural network contain values describing the signature dynamics for $N$ subsequent samples, denoted by indices $n \in \{1,2,\ldots,N\}$, to obtain values for the sample with index $N+1$ at the output of the network.
- **Step 4. Definition of the neural network architecture.** The architecture of the artificial neural network depends on the number of samples $N$ used for prediction and the number of dynamic signals $M$ included in the sample. Details on this step are presented in the next subsection.
- **Step 5. Training of the neural network model.** In this step, training data are used to fit the neural network model. Details on this step are presented in the next subsection.
- **Step 6. Evaluation of the model.** Finally, the created model has to be evaluated to determine the accuracy of the predicted values of the dynamic signature samples, which include infor-

mation about the dynamics of the signing process. Details on this step are provided in Section 3.

The general idea of the proposed method is also presented in Figure 1.

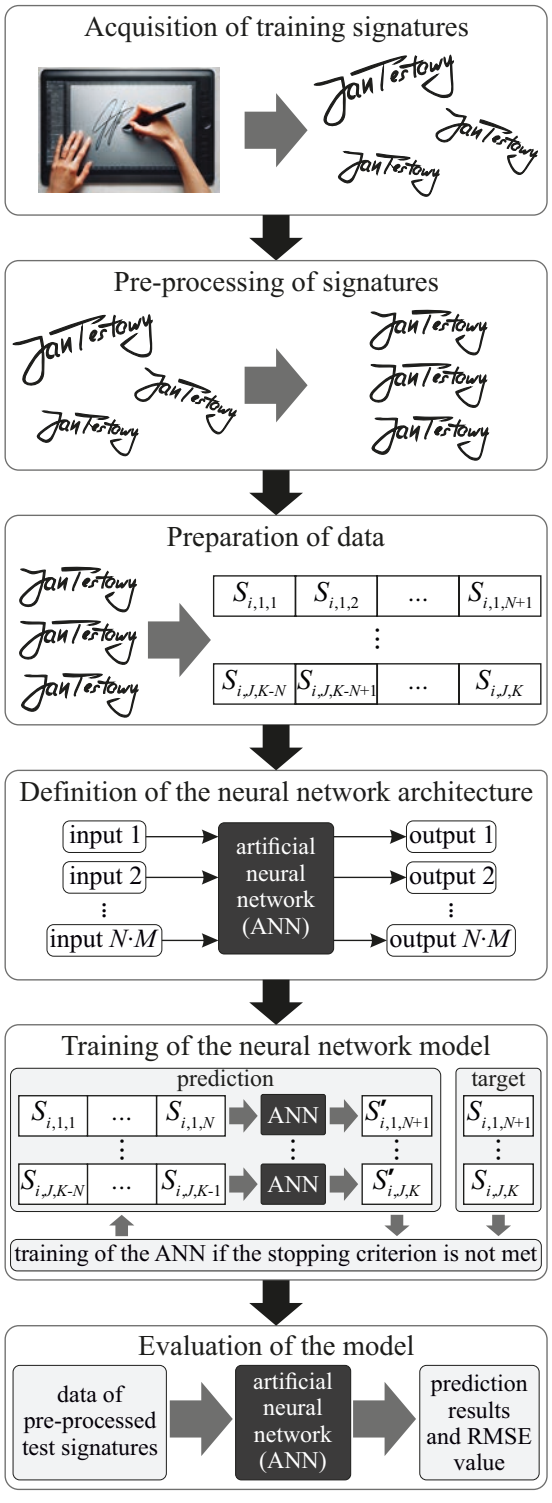


**Figure 1**. Idea of the proposed method.

## 2.3 Description of the neural network models

In this paper, we propose using an artificial neural network (see, e.g., [1, 7, 13]) to predict the values of signals describing dynamic signatures. To make predictions, we tested three neural networks of varying complexity.

The first network is a classic feed-forward fully connected neural network (FFNN), characterized by relatively low computational complexity. This type of ANN is commonly used in classification and regression tasks (see e.g. [2]). However, this type of network does not have internal memory, which affects its effectiveness in tasks requiring the analysis of temporal or contextual sequences.

The second neural network model used is a Gated Recurrent Unit (GRU) (see [3]). It belongs to the group of recurrent neural networks (RNNs), designed to efficiently process sequential data. GRU models consist of memory cells that can store information for a long time and can selectively manage the information they collect. In this model, memory cells are managed by two types of gates: the reset gate, which decides how much information from previous states should be forgotten, and the update gate, which decides how much of the previous state should be transferred to the new state. The architecture of the GRU network is slightly less complex than that of another popular recurrent neural network, the Long Short-Term Memory (LSTM), but it allows for similar response efficiency. This type of network is commonly used in tasks related to natural language processing, time series analysis, and more.

The third neural network model used is the Transformer (see [17]). This model introduces an attention mechanism that identifies relationships between data. The Transformer enables efficient processing of data sequences without needing to process them in order, increasing the network's computational efficiency compared to RNNs. This network model also has encoder and decoder layers that respectively process the input sequence into context vectors and perform the reverse transformation. The use of the attention mechanism allows Transformer networks to effectively process and understand complex data structures. This type of network is used in tasks related to natural language

processing, computer vision, time series analysis, and more.

In the proposed method, the input data for each network consist of $N \cdot M$ feature values, where $N$ is the number of considered training samples and $M$ is the number of dynamic features describing the signature (in this paper, we use the set of features presented in Table 1). We assume that the neural networks used in this method predict the values of $M$ features describing the dynamics of the next sample $N+1$. The input features $\mathbf{X}$ fed into the neural network and the output values $\mathbf{Y}$ representing the predicted values of the next sample are defined as follows:

$$\mathbf{X}_{i,j} = \left\{ \begin{array}{c} x_{i,j,1}, x_{i,j,2}, ..., x_{i,j,N}, \\ y_{i,j,1}, y_{i,j,2}, ..., y_{i,j,N}, \\ z_{i,j,1}, z_{i,j,2}, ..., z_{i,j,N}, \\ v_{i,j,1}, v_{i,j,2}, ..., v_{i,j,N}, \\ vx_{i,j,1}, vx_{i,j,2}, ..., vx_{i,j,N}, \\ vy_{i,j,1}, vy_{i,j,2}, ..., vy_{i,j,N}, \\ a_{i,j,1}, a_{i,j,2}, ..., a_{i,j,N}, \\ ax_{i,j,1}, ax_{i,j,2}, ..., ax_{i,j,N}, \\ ay_{i,j,1}, ay_{i,j,2}, ..., ay_{i,j,N}, \\ p_{i,j,1}, p_{i,j,2}, ..., p_{i,j,N}, \end{array} \right\}, \quad (3)$$

$$\mathbf{Y}_{i,j} = \left\{ \begin{array}{c} x_{i,j,N+1}, y_{i,j,N+1}, z_{i,j,N+1}, \\ v_{i,j,N+1}, vx_{i,j,N+1}, vy_{i,j,N+1}, \\ a_{i,j,N+1}, ax_{i,j,N+1}, ay_{i,j,N+1}, \\ p_{i,j,N+1} \end{array} \right\}. \quad (4)$$

In the next section, we describe the assumptions of the simulation and present the results and conclusions obtained from the simulations.

## 3 Simulations

In the simulations, the DeepSignDB distributed by BiDA Lab see [4, 9, 10, 16]) was used to test the proposed method for the prediction of the dynamic signature sample values. The database contains signatures of 1084 users, acquired in 11 sessions. Each session includes 8 to 25 genuine signatures per user and 6 to 25 so-called skilled forgeries (signatures prepared by qualified forgers) per user.

**Table 2**. Structure and parameters of the FFNN used in simulations.

| Layer Type | Output Shape | Details |
|---|---|---|
| Input layer | (100) | — |
| Fully Connected layer (Dense) | (512) | 512 units, ReLU activation function. |
| Fully Connected layer (Dense) | (256) | 256 units, ReLU activation function. |
| Fully Connected layer (Dense) | (128) | 128 units, ReLU activation function. |
| Output layer | (10) | 10 units, linear activation function. |

**Table 3**. Structure and parameters of the GRU neural network used in simulations.

| Layer Type | Output Shape | Details |
|---|---|---|
| Input layer | (100) | — |
| GRU layer | (512) | 512 GRU units, ReLU activation function. |
| Fully Connected layer (Dense) | (256) | 256 units, ReLU activation function. |
| Fully Connected layer (Dense) | (128) | 128 units, ReLU activation function. |
| Output layer | (10) | 10 units, linear activation function. |

In our simulations, we used signatures from 300 randomly selected users. Four randomly selected genuine signatures from each user were used to train the neural network models. We assumed that each signer had their own prediction model. Another set of four randomly selected genuine signatures from each user was used to evaluate the created models. As mentioned earlier, we used three different types of neural networks with varying complexities to predict the values of the dy-

namic signature signals: FFNN, GRU, and Transformer. Our simulations were performed using a test environment implemented in Python. Each neural network model was trained using the Adam optimizer and Mean Squared Error (MSE) as the loss function, with an early stopping criterion. The details of the network parameters used in the simulations can be found in Tables 2-4.

### 3.1 Simulation results

Prediction accuracy in our simulations is evaluated by the Root Mean Square Error (RMSE) between predicted and reference samples. Tables 5-6 contain RMSE values averaged for each test signature of the considered users. The tables show RMSE values determined for each signature signal separately and an average value computed for all signals. As mentioned earlier, the prediction was performed on four randomly selected genuine signatures of the user (see Table 5), which were not involved in the training process, and on four randomly selected skilled forgeries created by a qualified forger (see Table 6). We can see that the best prediction accuracy (the lowest RMSE value) for genuine signatures was achieved by the Transformer neural network, while the worst prediction accuracy was achieved by the feed-forward neural network. The difference between the RMSE values of the best and worst approaches is 0.0118. Considering the data normalization interval $[-1,1]$, this is not a very significant difference, but it may be important in biometric systems requiring high security. We can also see that the GRU neural network achieves slightly worse prediction results than the Transformer.

We can observe that the prediction efficiency for skilled forgeries was significantly lower than for real signatures across all neural network models used. This result is consistent with expectations because the dynamics of each user's signatures are characterized by strong individual expression, making it impossible for a forger to replicate the dynamics of the signature perfectly.

Considering individual signals, we can see that the highest prediction accuracy across all used neural network models was achieved for the $x$, $vy$, and $y$ signals. We can consider these signals the most reliable ones. The lowest prediction accuracy was observed for the $p$, $a$, and $z$ signals.

An interesting subject of research may also be which parts of a given user's signals are most predictable by artificial neural networks. Signals describing the dynamics of individual users' signatures are characterized by different numbers of samples, making it difficult to make a clear comparison. Nevertheless, in Figure 2, we present the values of the differences between the predicted and reference values for individual samples of each signal. The figure concerns the prediction process performed by the Transformer model, which achieved the best results in simulations. We can see that for the most reliable signal, $x$, the prediction error rate is relatively constant across all user samples. The chart describing this signal is characterized by one prominent peak, but it is of little significance. Conversely, for some signals, such as $a$, error peaks are distributed at different times within the signature samples, making it difficult to identify the most stable areas for prediction. However, looking at the $z$ signal, we can see that in the first part of the signature, prediction errors are lower, making this part of the signature more predictable for this signal. Also worth noting is the graph for the $p$ signal, which indicates whether the pen touches the surface of the graphics tablet. Reference signals of this type take two values - zero or one. Therefore, in the event of an incorrect prediction of the signal state, relatively large error values may appear, as seen in the peaks of this graph. The analysis of errors for individual signal samples performed for a selected user shows that this research problem is interesting and warrants further investigation in the context of a larger group of signers.

Summarizing the simulation results, it can be stated that artificial neural networks can predict the values of subsequent signal samples describing the dynamics of signature creation with satisfactory accuracy.

## Conclusion

In this paper, a method for predicting the values of signals describing an individual's dynamic signature is proposed. The method uses a set of samples describing these signals to predict the values of consecutive samples. The proposed algorithm uses an artificial neural network for the prediction process and was tested with three models: feed-forward

**Table 4**. Structure and parameters of the Transformer neural network used in simulations.

| Layer Type | Output shape | Details |
|---|---|---|
| Input layer | (10, 10) | Receives input data formatted as a 10x10 matrix. |
| Transformer Encoder Block (repeated twice) | (10,10) | Multi-Head attention with 2 attention heads, each with a size of 256; layer Normalization to stabilize the learning process; Feed Forward Network with 256 units and ReLU activation function; dropout layer to prevent overfitting, with a dropout rate of 0.1. |
| Normalization layer | (10, 10) | Normalizes the output from the transformer blocks to maintain stable activations. |
| Flatten layer | (100) | Flattens the output into a single dimension of 100 units. |
| Fully Connected layer (Dense) | (128) | 128 units, ReLU activation function. |
| Dropout layer | (128) | Dropout rate value set as 0.1. |
| Output layer | (10) | 10 units, linear activation. |

**Table 5**. RMSE prediction values for the method predicting the dynamics of signature signals obtained for genuine signatures of users (a lower value indicates better prediction accuracy).

| Signal | RMSE Values for FFNN Predictions | RMSE Values for GRU Predictions | RMSE values for Trans-former Predictions |
|---|---|---|---|
| *x* | 0.0279 | 0.0257 | 0.0221 |
| *y* | 0.0378 | 0.0372 | 0.0352 |
| *z* | 0.1053 | 0.0846 | 0.0774 |
| *v* | 0.0521 | 0.0486 | 0.0421 |
| *vx* | 0.0420 | 0.0423 | 0.0413 |
| *vy* | 0.0369 | 0.0316 | 0.0273 |
| *a* | 0.1026 | 0.0780 | 0.0906 |
| *ax* | 0.0737 | 0.0633 | 0.0513 |
| *ay* | 0.0542 | 0.0474 | 0.0431 |
| *p* | 0.1465 | 0.1391 | 0.1308 |
| **Average value** | **0.0679** | **0.0598** | **0.0561** |

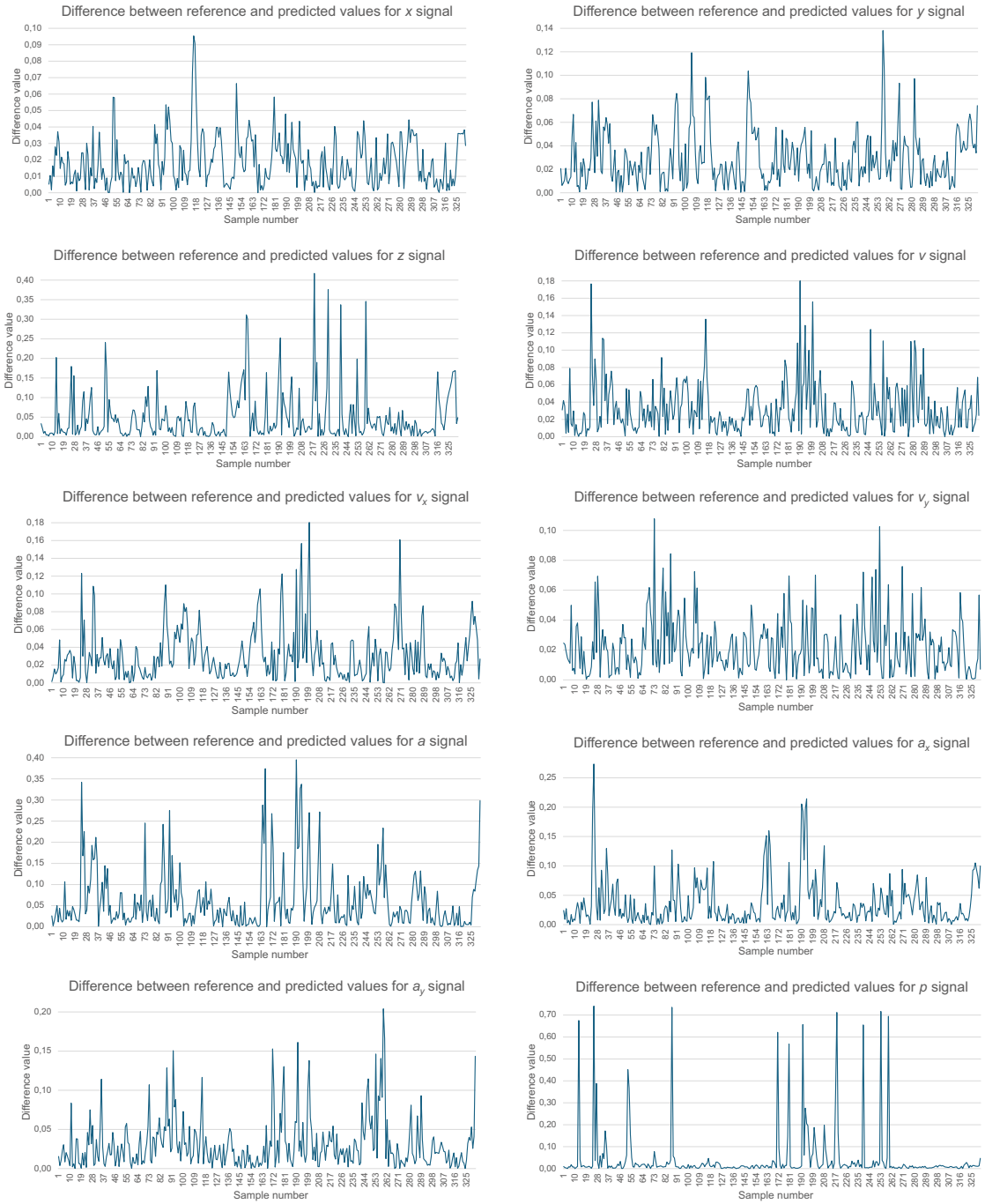


**Figure 2**. Differences between reference signal values and values predicted by the Tranformer neural network for signals describing the dynamics of the signing process (the differences are shown as absolute values).

**Table 6**. RMSE prediction values for the method predicting the dynamics of signature signals obtained for skilled forgeries of users (a lower value indicates better prediction accuracy).

| Signal | RMSE Values for FFNN Predictions | RMSE Values for GRU Predictions | RMSE values for Trans-former Predictions |
|---|---|---|---|
| *x* | 0.2277 | 0.7199 | 0.3265 |
| *y* | 0.3766 | 0.5753 | 0.3546 |
| *z* | 0.5358 | 0.6248 | 0.5032 |
| *v* | 0.3690 | 0.4328 | 0.4099 |
| *vx* | 0.2454 | 0.2797 | 0.3690 |
| *vy* | 0.2872 | 0.5562 | 0.3740 |
| *a* | 0.1365 | 0.7527 | 0.3479 |
| *ax* | 0.5273 | 0.5166 | 0.5049 |
| *ay* | 0.4170 | 0.8346 | 0.3353 |
| *p* | 0.6349 | 0.4718 | 0.6841 |
| **Average value** | **0.3757** | **0.5764** | **0.4209** |

fully connected, GRU, and Transformer neural networks. These models were trained individually for each signer.

The results obtained by the proposed algorithm show that this type of prediction can be performed with satisfactory accuracy. The best prediction accuracy was achieved by the Transformer model, which is equipped with a self-attention mechanism. This mechanism allows the model to weigh the importance of different parts of the input data and effectively capture long-range dependencies and relationships. However, the selection of the neural network model used for prediction should depend on the application. In biometric systems that do not require high security, models with lower computational complexity can be used.

In future works, we plan to investigate how the considered model performs with different numbers of input samples, analyze errors for individual signal samples across a larger group of signers, and determine whether it is possible to predict values of signals describing velocity, pressure, and acceleration based solely on shape signal values. Additionally, we aim to use different artificial intelligence methods for the prediction task, attempt to predict values of signature descriptors based on the signal values, and develop a universal model for predicting signature dynamics for a group of users.

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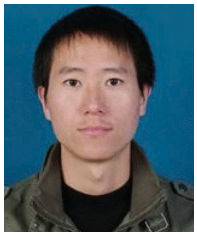

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