This work proposes two statistical approaches for the synthesis of keystroke biometric data based on universal and User-dependent Models. Both approaches are validated on the bot detection task, using the keystroke synthetic data to better train the systems. Our experiments include a dataset with 136 million keystroke events from 168,000 subjects. We have analyzed the performance of the two synthesis approaches through qualitative and quantitative experiments. Different bot detectors are considered based on two supervised classifiers (Support Vector Machine and Long Short-Term Memory network) and a learning framework including human and generated samples. Our results prove that the proposed statistical approaches are able to generate realistic human-like synthetic keystroke samples. Also, the classification results suggest that in scenarios with large labeled data, these synthetic samples can be detected with high accuracy. However, in few-shot learning scenarios it represents an important challenge.

1. Introduction

Biometric recognition is the ability to authenticate a person with the highest possible reliability based on their physical characteristics or behavioral attributes [10]. This technology can be used to uniquely recognize one user among others (e.g., user identification/authentication), to recognize groups of subjects (e.g., soft-biometrics classification), or finally to differentiate real users from non-real users (e.g., bot detection). This work focuses on the topic of bot detection, more precisely in the generation and detection of synthetic keystroke patterns.

Society is becoming more and more digital nowadays. As a result, the security has moved from physical to the digital domain. Along with the massive use of the Internet, the usage of bots to access digital services and platforms has grown, being an open challenge with a high worldwide economical impact [21].

In bot detection, a platform/system must detect bot attacks and differentiate them from legitimate user’s interactions. Traditionally, this detection has been carried out with conventional CAPTCHAS, which ask the user to perform some cognitive challenges. Traditional CAPTCHA methods are becoming less and less effective due to advances in Computer Vision and the image classification approaches based on Deep Learning. As a result, other less intrusive and more effective CAPTCHAS are being developed nowadays based on the interaction information between the human/bot and the platform without actively requesting any information [1,2]. The behavioral biometric characteristics, and specially the so called web-biometrics [8], play an important role in this interaction modelling. These web-biometrics characteristics include keystroke dynamics, mouse dynamics, and mobile interaction, among others.

In this work we propose two synthetic keystroke data generation methods with application to bot detection. The main contributions of this work can be summarized as follow:

- Two approaches for the synthesis of keystroke dynamics data based on Universal and User-dependent Models. The proposed approaches are based on the statistical modelling of the biometric keystroke dynamics features of more than 100,000 subjects, generating realistic human-like synthetic samples.
- A novel bot detection method based on keystroke dynamics using algorithms trained with human and synthetically generated samples.
- A comprehensive performance analysis including: i) amount of data available to train the bot detector; ii) type of synthetic data used to model the human behavior; iii) input text dependencies.

The rest of the work is organized as follows: Section 2 summarizes the related literature. Section 3 presents the proposed synthesis approaches. Section 4 describes the bot detection method. Section 5 presents the experimental results of the bot/human classification methods trained with the synthetic and human samples. Finally, in Section 6 we present the conclusions and limitations.
2. Related Literature

The synthesis of biometric data is a crucial step in the development of a new generation of bot detection approaches. For example, in [1] the authors proposed modelling the mouse interactions for bot detection based on the analysis of the neuromotor features extracted from the human and synthetic mouse trajectories. The same authors proposed in [2] bot detection methods based on human and synthetically generated mobile phone interactions, using sensors such as accelerometer, gyroscope, and touchscreen gestures.

During the last decades, the performance of keystroke biometric recognition approaches has improved to reach the actual state of the art. Some of these approaches include non-elastic sample alignment (e.g., Dynamic Time Warping [19]), scaled Manhattan distances [16], and statistical models (e.g., Hidden Markov Models [5]). The performance of these approaches varies depending on the characteristics of the database and experimental protocol, but in general, Equal Error Rates (EER) over 5% were consistently reported. During those years, the performance of free-text approaches was far from the performance achieved by fixed-text methods [20, 9]. More recently, the release of new large-scale datasets and the use of Deep Neural Networks have boosted the performance of free-text keystroke biometrics with EERs under 5% [3, 18].

The synthesis of keystroke data is not new. One of the first studies was presented in [22] creating a synthetic database with 20 subjects using first-order Markov chains. An improved keystroke biometric attack generator was presented in [17], using a Linguistic Buffer and Motor Control model. The use of synthetic keystroke samples to study the vulnerability of keystroke biometric systems was also studied in [9, 13, 14]. Those studies have proposed methods using higher-order contexts and empirical distributions to generate impersonation attacks (i.e., samples generated to confuse the identity of an specific user). The conclusions from previous studies suggest that it is possible to generate realistic keystroke data. Regarding keystroke bot detection, a pioneer work involving the use of function calls analysis was presented in [4]. The system proposed in [4] was based on communication protocol analysis (frequency of keyboard logs) rather than keystroke dynamics modelling.

3. Keystroke Data Synthesis

3.1. Keystroke Dynamics Dataset

The Dhakal Dataset is considered in this study to obtain the statistical models necessary to synthesize large-scale keystroke biometric data. There are 168,000 subjects and 136 million of keystrokes in the database. Regarding the acquisition procedure, each subject had to learn a sentence and then write it as fast as possible (semi-fixed text scenario) using their own keyboard. Each subject has 15 sentences with a variable with a minimum of 3 words and a maximum of 70 characters.

Following the traditional keystroke dynamics modelling, the dataset is processed to extract 4 time features derived from the two main typing events (key press and key release) and the ASCII code for each key pressed [3]:

1. Hold Latency ($f_1^j$): Time between the key $j$ is pressed and released.
2. Inter-Press Latency ($f_2^j$): Time between two consecutive keys are pressed, $j$ and $j + 1$.
3. Inter-Release Latency ($f_3^j$): Time between two consecutive keys are released, $j$ and $j + 1$.
4. Inter-Key Latency ($f_4^j$): Time between a key $j$ is released and the next key $j + 1$ is pressed.
5. Key Code ($f_5^j$): ASCII code normalized between 0 and 1 for each key $j$.

Figure [1] presents the distribution of these features for the complete dataset. As can be seen, the Hold Time feature follows a normal distribution except for some outlier examples. The rest of the features presents tails related to the characteristics of the typist and the key-pressed (some combinations of keys used to present larger timing than others). Note that the Inter-Key Time feature presents negative times, i.e., the next key is pressed before the currently one is released. This effect is called rollover-typing and it is common in keystroke recognition systems.

3.2. Keystroke Synthesis: General Outlook

We propose two synthesis approaches based on the statistical modelling of the feature distribution of the keystroke time series. As described in the previous section, the keystroke dynamics features model the biometric patterns during a typing task as differences of times (i.e., time gaps between key press and key release events). We propose to model the probability distribution of the keystroke biometric features $F = [f_1, ..., f_5]$ to generate realistic human-like time sequences. We use the Kernel Density Estimator algorithm (KDE) [11]. KDE is a nonparametric algorithm to estimate univariate or multivariate densities. KDE allows to compute the density of keystroke biometrics features as a set of functions $F = [F^1, F^2, F^3, F^4]$, here the KDE approximates each one of the time features at a point $x$ as:

$$F^i(x) = \frac{1}{N} \sum_{j=1}^{N} K(x - f_j^i; \sigma)$$

where $K$ is the kernel function (Gaussian in our experiments) and $\sigma$ is the bandwidth ($\sigma = 1.0$ in our experiments). We used this method to model the probability distributions $F$ of the keystroke biometric features of 100,000 users in the Dhakal Dataset (see Figure [1]). The synthesis of keystroke dynamic samples is divided into: 1) generation of a sequence of $K$ keys representing the typed
Figure 1. Original human data (bars) and Kernel Density Estimator fitting model (continuous line) for all subjects (4 images on the left) and two independent subjects (4 images on the right).

text: $k = [k_0, ..., k_K]$; 2) generation of the corresponding keystroke biometric features $f^i$ as random samples from the learned models $F^i$ (random sampling serves to introduce human-like variability between samples); and 3) the calculation of a sequence of timestamps: $t' = [t'_0, ..., t'_{2K}]$ associated to the key press and key release events. The timestamp vector $t'$ can be easily obtained from the time features $f^1$ and $f^4$. The following equations show the calculation of timestamps for the first two keys:

$$t'_0 = 0, t'_1 = t'_0 + f^1 \to (\text{key 1})$$

$$t'_2 = t'_1 + f^4, t'_3 = t'_2 + f^4 \to (\text{key 2})$$

The values of $f^1$ and $f^4$ are generated using the KDE functions $F^1$ and $F^4$. We propose two synthesis approaches depending on the information used to model the feature distributions of $f^i$: Universal Model or User-dependent Model.

### 3.3. Synthesis Approach 1: Universal Model

The Universal Model is based on the estimation of a unique set of KDE functions $F$ representing the behavior of all subjects in the Dhakal dataset. As a result, only 4 KDEs are necessary to model the human typing behavior distributions. To estimate the KDE, we consider 123,000 samples (0.1% of total data). Figure 1 shows the set of trained functions (blue curves in the four images on the left). In general, this approach could approximate in a good way the human features as a group. However, it could also generate unnatural samples due to the combination of every subjects times. It is important to highlight that this universal synthesis approach is not able to model the intra-user dependencies (i.e., the user behavior changes in different sessions) or the key-dependent features (i.e., each key has a typing pattern depending on itself and also to a certain extent on the previous and following keys). Figure 2 shows the block diagram of the proposed synthesis method. First, the keystroke timestamps $t$ from real human samples is parameterized according to the four time features $f^i$. Second, the probability function $F^i$ of each time feature is independently modeled according to a KDE function (see Eq. 1). The four trained KDE are then used to generate new keystroke dynamic features $f'$ from which the synthetic keystroke timestamps $t'$ are obtained (see Eq. 2 and 3).

### 3.4. Synthesis Approach 2: User-dependent Model

The fundamental principle of keystroke biometric recognition systems is that typing patterns vary from one user to another. The User-dependent generation method tries to incorporate this intra-user characteristics into the synthesis process. However, the data available for each user is limited and therefore, the User-dependent Models could be less accurate than the previous Universal Model. This way, the user-dependent generation approach is aimed to capture the relations between the dynamics features $f^u,i$ along the sentence typed by the user $u$. Figure 2 shows the block diagram of the proposed synthesis method. First, keystroke samples from the Dhakal dataset data are divided by subjects. Second, the keystroke timestamps data $t^u$ from user $u$ is parameterized to obtain the four time feature sequences $f^u,i$. Then, the probability distribution of each time feature from each training user ($F^u,i$) is independently modeled according to a KDE function (i.e., four $F^u,i$ per user). This process is repeated for $M$ different human subjects in the database. Finally, the $M$ models are used to generate synthetic feature vectors $f'^u$ and its corresponding synthetic keystroke timestamps $t'^u$ following the probability distributions of independent human subjects.
4. Keystroke Bot/Human Classification

Most bots are not developed to generate realistic keystroke time series. They are usually developed to interact with a web service/platforms and this interaction usually includes introducing text as input (e.g., searching information) [21]. The code of a traditional bot is exclusively focused on the generation of a sequence of keys \( k \) necessary to produce a desired result. This work explores a more challenging scenario where the bot is developed to spoof a keystroke bot detection system, generating human-like keystroke time sequences \( t' \).

We propose the use of synthetic keystroke samples to train bot detection systems (see Figure 4). First, the synthetic samples are generated using the text (i.e., Key-Codes) from the real ones, i.e., the human and bot key sequences are exactly the same. Note that, the Dhakal Dataset was captured according to a semi-fixed text protocol. This protocol implies that the text varies for each human sample in most of the cases. Second, the human and synthetic keystroke sequences are truncated to \( L \) keys (\( L \) is equal to 30 in our experiments). Third, each keystroke sequence is parameterized according the features presented in Section 3.1. The total number of features per keystroke sequence is calculated as \( N = 1 + (L - 1) \times 4 \). Finally, we evaluate two different classification algorithms: Support Vector Machine (SVM) and Recurrent Neural Network based on Long Short-Term Memory (LSTM). These algorithms are trained using both human and bot feature vectors. We describe in Section 5.2 the experimental protocol details.

5. Experiments and Results

5.1. Analysis of the Synthetic Samples

We first evaluate the quality of the synthetic samples in a qualitative manner. The first step is to use the LSTM model proposed in [3], called TypeNet, to extract embedding representations of human and synthetic keystroke sequences. TypeNet was trained according to a Distance Metric Approach (Triplet Loss) for user authentication/verification. The learning framework of the model was developed to extract distinctive feature vectors related to the user typing patterns. TypeNet is composed of 2 LSTM layers with 32 units, and a final embedding layer with 128 units (i.e., size of the embedding vector). We are using the original model published in [3]. Therefore, no synthetic samples are used in the training process. Only subjects of the Dhakal Dataset are employed during the training process.

We consider TypeNet to extract feature embedding vectors from synthetic and human data. We applied t-SNE to project the resulting 128-embedding representations in a 2-dimensional feature space. Note that t-SNE is an unsupervised learning algorithm. The motivation of this experiment is to analyze how TypeNet represents the synthetic and human samples in this reduced feature space. The hypothesis is that realistic synthetic features will be represented similarly to real human data.
Figure 4. Application of the two proposed keystroke data generation approaches to bot detection.

Figure 5. ROC curves obtained for the SVM (left) and LSTM (center and right) with Key-Codes. Experiments using the same synthesis methods in training/testing (left and center) and using different synthesis methods in training/testing (right).

The t-SNE projections showed in Figure 3 varies depending on the synthesis approach considered. The Universal Model has three clearly differentiated clouds, one for synthetic samples, another for human samples, and a third one where both human and synthetic samples have similar dynamics (top left corner). The representation of the User-dependent Model shows a more uniform distribution between human and synthetic samples in comparison with the Universal Model. In this case, the representation suggests that the User-dependent Model is capable of generating synthetic subjects with different dynamics.

5.2. Bot Detection: Experimental Protocol

The Figure 4 shows the block diagram of the bot detection classification system. Note that the training subjects were different from test subjects, to avoid correlations at user level and ensure this way the generalization of the model. We use the Receiver Operating Characteristic (ROC) curves as performance metric.

Including or not the key-codes in the classifier can have great relevance in the detection of bots as our synthesis approaches do not take into account the key for the creation of times and therefore this information could be an advantage for the classifier. As a result, we consider experiments with and without the key-codes to better understand its impact in the performance.

The scarcity of labeled bot samples is a common challenge in bot detection [21]. For this reason, the experiments are divided into different scenarios depending on the data available to train the bot detector (from 20 bot users to 500). Each bot user comprises 15 synthetic samples and all experiments are designed to include the same number of human and synthetic samples. Therefore, training with 20 bot users result in 300 synthetic samples and 300 human samples. All the models are evaluated using the same 500 bot and 500 human samples (15,000 samples in total).

5.3. Bot Detection: Results

Two main objectives are considered in the analysis. First, the quantitative evaluation of the synthesis methods (O1): during the validation of the synthetic samples, a high classification error will suggest that synthetic data and human data present similar biometric patterns. Second, the evaluation of the keystroke bot detection O2: the analysis is focused on understanding the challenges of bot detection based on keystroke biometric patterns. The performance of the bot detection is analyzed depending on multiple variables: (i) the classification algorithm (LSTM or SVM); (ii) the number of bot samples available to train the classifier; and (iii) the availability of key-codes to train the classifiers.

Figure 5 shows the ROC curves of the SVM (left) and LSTM (center and right) classifiers trained using the Key-Codes ($f_5$) together with the rest of features ($f_i$, $i \in 1, ..., 4$). Analyzing the quality of the synthetic samples (O1), the ROC curves suggest that both synthesis methods are able to generate samples with biometric patterns similar to the hu-
man ones. The classification performance obtained for the User-dependent Model is lower in both classifiers. According to these results, the User-dependent Models seem to be the most effective synthesis approach, even if the subjects were modelled from only 15 human samples.

Analyzing the bot detection performance (O2), the results suggest that it is necessary large number of samples in order to ensure high detection rates. The performance achieved with 20 bot subjects \((20 \times 15 = 300 \text{ synthetic samples})\) is far from the performance achieved with 500 bot subjects \((500 \times 15 = 7500 \text{ synthetic samples})\). The generalization ability of the bot detector is also evaluated. We include experiments performed using the same synthesis methods during train and test (center), and different ones during train and test (right). The results showed in Figure 5 demonstrate that training with samples synthesized with the User-dependent Model allows to better generalize against unseen synthetic samples.

5.4. Input Text Dependency in Bot Detection

Privacy-preserving technologies have a great importance in our society [7, 12]. In order to protect the access to the information typed by the subjects, in this experiment we consider the scenario where the Key-Codes are not available for the classification model.

The LSTM classifier does take into account the temporal correlation between the times in the sequence, for which the Key-Code has an influence (i.e., the features obtained from the sequence of keys A-B are different compared to the features obtained in the sequence B-A). The absence of Key-Codes can potentially affects the performance of the classifier. Figure 6 shows the results for the classification approaches considered, discarding the Key-Code information from the training process of the Human/Bot classifier. The results obtained without the Key-Code are not very far from those obtained in previous experiments with Key-Code (Figure 5). The biggest differences can be observed in the LSTM classifier where the sequence of Key-Codes seems to be relevant during the classification process. We also tested again the generalization ability of the bot detector but this time without the key-codes. Figure 6 (right) shows the cross-synthesis results (different synthesis methods in train and test) for the LSTM network. The graph shows the same trend as in the previous section, the detector trained with the user-dependent samples generalizes better.

6. Conclusions and Limitations

In this work we have proposed two keystroke dynamics generation approaches based on Universal and User-dependent statistical models based on the Kernel Density Estimator algorithm. We analysed the feasibility of using a behavioral trait, which is the dynamic typing, such as passive CAPTCHA where the user has no need to perform any activity in order for the system to determine if this user is a bot or a human. This bot detection task has been treated as a supervised learning problem, specifically a classification problem.

We have evaluated the performance of synthetic samples for bot classification tasks using two classification algorithms based on SVM and LSTM network. The results suggest that synthesized samples present similar biometric keystroke pattern when compared to human samples. The performance depends on the data available, demonstrating that bot detection in scenarios with scarce training data is an open challenge. The experiments also include a comparison between scenarios with Key-Codes and privacy-preserving scenarios where Key-Code is not available.

The main limitation of the proposed generation methods is the absence of key-dependent features during the modelling of the human data. It is well know that keystroke biometrics are text dependent and future works will be focused on introducing text dependencies in the generation approaches.
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