Generation of Enhanced Synthetic Off-line Signatures Based on Real On-line Data

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***Abstract*—One of the main challenges of off-line signature verification is the absence of large databases. A possible alternative to overcome this problem is the generation of fully synthetic signature databases, not subject to legal or privacy concerns. In this paper we propose several approaches to the synthesis of off-line enhanced signatures from real dynamic information. These synthetic samples show a performance very similar to the one offered by real signatures, even increasing their discriminative power under the skilled forgeries scenario, one of the biggest challenges of handwriting recognition. Furthermore, the feasibility of synthetically increasing the enrolment sets is analysed, showing promising results.**

***Keywords*-Signature synthesis; Signature verification; Texture Measurement; Biometric recognition**

I. INTRODUCTION

In this rapidly evolving era, person authentication is becoming a key task for many everyday applications, such as access control or border crossing. Biometrics offer a fast, automatic and reliable solution to this problem, based on personal traits such as the face, the iris or the fingerprint. Among these traits, handwritten signature is widely accepted for identity verification due to being easily acquired in an user-friendly and non-invasive manner [1], [2]. However, off-line signatures present a large intra-user variability (signatures are strongly influenced by human behaviour) and a small inter-user variability (skilled forgeries are neither difficult to obtain nor easy to tell apart from genuine signatures), which leads to lower accuracy with respect to other biometric modalities.

In order to improve the performance of signature verification systems, bigger databases are required. Since the acquisition and distribution of real signatures arises legal and privacy concerns, the use of realistic synthetic signatures could be regarded as a good alternative. As a consequence, over the last years, several works on both on-line [3], [4], [5] and off-line [6], [7] signature synthesis have been carried out. These synthetically generated signatures show a similar behaviour to real ones, thus enabling to enlarge existing databases and offering new possibilities for off-line recognition.

Some efforts have been performed through off-line signature verification using simple methods to create static signatures [8], [9]. In this paper, we propose different approaches to generate synthetic enhanced static data that performs similarly, or even outperforms, real off-line samples, taking into account dynamic features during the synthesis process. Experiments are carried out on a publicly available database comprising both on-line and off-line signatures, so that a comparison between the performance of real and synthetic off-line samples can be fairly established. Among others, the current study presents the following possible practical applications: i) generation of synthetic static samples to be fused with the original on-line signatures in order to improve the performance in an on-line verification scenario; ii) enlarge existing off-line signature databases.

The main contribution of the paper with respect to other related previous works [6], [7], is the integration of different typical on-line features in the generation of synthetic and "dynamically enhanced" off-line signatures, in order to improve their discriminative power (i.e., recognition rates).

The rest of the paper is organized as follows. The proposed approaches to generate enhanced synthetic off-line signatures from dynamic data are described in Sect. II. The experimental protocol for the evaluation of the signatures, including the databases and recognition system used, are summarized in Sect. III. Finally, results are presented in Sect. IV and conclusions drawn in Sect. V.

II. ENHANCED OFF-LINE SIGNATURE GENERATION FROM DYNAMIC SIGNATURE SEQUENCES

Dynamic features based on the trajectory ($\{x_t[m], y_t[m]\}_{m=1}^{M}$) and pressure ($\{p[n]\}_{m=1}^{M}$) signals, as well as their derivatives (i.e., speed, acceleration), contain information not available in static samples. Nevertheless, discriminative information, such as geometric relationships, can also be extracted from off-line signatures. In order to take advantage of both types of features and overcome the on-line vs. off-line dichotomy, several novel approaches for generating "dynamically enhanced" synthetic static signatures from on-line dynamic information are proposed in this paper.

Although a simple static signature can be generated linking the points of the dynamic trajectory ($\{x_t[m], y_t[m]\}_{m=1}^{M}$), additional dynamic information could be used to enrich the static signature. This addition is

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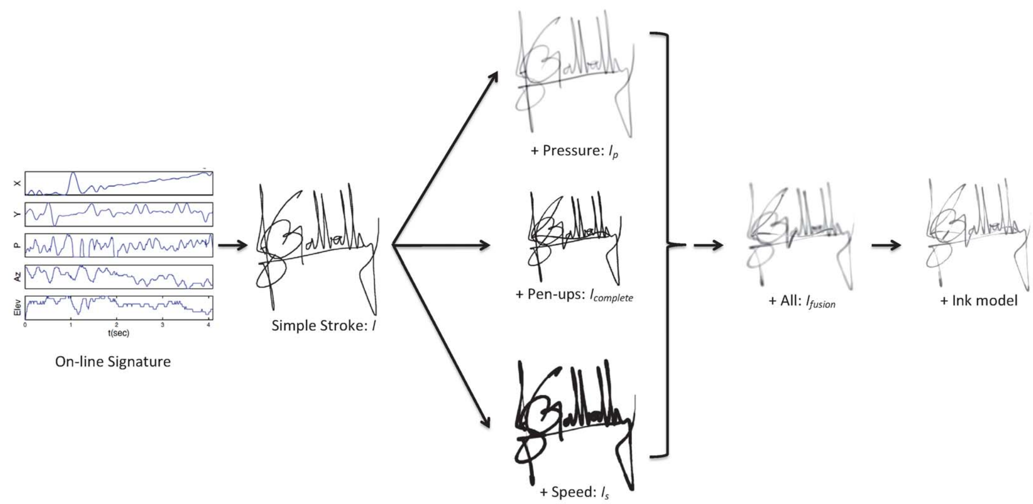

Figure 1: Diagram and examples of the proposed approaches to enhanced synthetic signature generation.

expected to lead to less realistic but more discriminative images. In this section, several approaches to the generation of these dynamically enhanced static signatures are proposed. First, the generation of a simple stroke signature image is described. Afterwards, several procedures to include dynamic information, such as pressure, speed and pen-ups, are presented.

A. Simple Stroke Signature Generation

While dynamic signatures are usually captured with digital devices such as tablets, smart-phones or PDAs, static signatures are acquired with commercial scanners. Therefore, some pre-processing must be carried out in order to obtain compatible images:

- Since the resolutions are usually different ($R_{Tab} \sim 2540$ dpi and $R_{Scan} \sim 600$ dpi), the on-line coordinates should be scaled by a factor $\kappa = R_{Scan}/R_{Tab}$.
- Since static signatures are continuous, the scaled discrete sequence of on-line coordinates and the pressure signal are then linearly interpolated to obtain 8-connected sequences of length L: $\{x_c[n], y_c[n]\}_{n=1}^{L}$, $\{p_c[n]\}_{n=1}^{L}$.

In order to obtain the final signature image, $I(x, y)$, the scaled and interpolated coordinate sequences, $\{x_c[n], y_c[n]\}_{n=1}^{L}$, are plotted on a white background for $p_c[n] > 0$, resulting in a binary black and white image. This signature image is then dilated with a 4×4 square structural element to obtain a stroke width similar to those obtained with real pens (see Fig. 1, left).

B. Enhanced Static Signatures: Pressure Information

The gray level amplitude of the stroke can be modulated with the pressure level. Therefore, the enhanced static signature with pressure information, denoted by $I_p(x, y)$, is defined as a convolution of $I(x, y)$ with a Gaussian function of the pressure signal:

$$I_p(x, y) = \sum_{n=1}^{L} I * G_p(x, y) \tag{1}$$

where $I(x, y)$, $x_c[n]$ and $y_c[n]$ are defined in Sect. II-A, and G_p is a 2D Gaussian function that models the pen dot with an amplitude modulated by the stroke pressure.

The standard deviation of G_p, ϕ, represents the blob spread. It is defined as $\phi = \phi_{pen} \cdot R_{Scan}/\delta$, where δ is the conversion factor from mm to inches and ϕ_{pen} the real stroke width (empirically fixed to 3 mm). On the other hand, the Gaussian amplitude $A[n]$ is defined as a normalization of $p_c[n]$ to the range $[0.2, 2.2]$ (this interval allows a wide range of gray-scale values related to the pressure signal): $A[n] = p_c[n] \cdot \Delta p + p_{min}$. Finally, $I_p(x, y)$ is smoothed with a Gaussian convolution and the image gray values are normalised to $[0, 1]$.

An example is shown in Fig. 1 (center), where it can be observed that the pressure influence is proportional to the stroke gray level.

C. Enhanced Static Signatures: Speed Information

One of the most discriminant on-line features is the time used by the signer, which depends on the speed and the signature length. The speed can be obtained as the first derivative of the original coordinate signals, with $v[1] = [0, 0]$. As described in Sect. II-A, the speed signal is then linearly interpolated to obtain $\{v_c[n]\}_{n=1}^{L} = \{v_{xc}[n], v_{yc}[n]\}_{n=1}^{L}$.

The enhanced static signature image with speed information, $I_s(x, y)$, is defined as:

$$I_s(x, y) = \sum_{n=1}^{L} I * G_s(x, y) \tag{2}$$

where $I(x, y)$, $x_c[n]$ and $y_c[n]$ are defined in Sect. II-A, and G_s is a 2D Gaussian that introduces the speed changing the blob width.

In this case, the Gaussian amplitude is constant. However, the standard deviation (spread of the elliptical blob) is defined as

$$[\phi_x[n], \phi_y[n]] = \frac{\phi_{pen} \cdot R_{Scan}}{\delta} \cdot cos\left([v_{nx}[n], v_{ny}[n]]\right)$$

where

$$[v_{nx}[n], v_{ny}[n]] = \frac{\pi/2}{\max\limits_{n}\left(\{v_{xc}[n], v_{yc}[n]\}\right)} \cdot [v_{xc}[n], v_{yc}[n]]$$

δ and R_{Scan} are defined as in Sect. II-A and Sect. II-B, and ϕ_{pen} is empirically fixed to 7 mm in order to highlight the speed effect in the stroke.

Fig. 1 (center) shows an example of the speed deforming the real stroke appearance.

D. Enhanced Static Signatures: Pen-up Information

On-line devices are usually able to recognize the movement of the pen tip when it is close to the device, even if it is not in contact with the writing surface. This contactless movement is known as pen-up trajectory, and corresponds to the coordinates $\{x_t[m], y_t[m]\}_{m=1}^{M}$ when $p_t[m] = 0$.

Since the pen does not deposit ink during the pen-ups, they are not depicted in the static signature image. These trajectories, however, could be highly discriminative for skilled forgeries: impostors try to imitate the inked image neglecting the unseen pen-up trajectory. Their addition to the basic static signature described in Sect. II-A could therefore improve the discriminative power of the static signatures, at a low computational cost: the enhanced static signature $I_{complete}(x, y)$ is obtained by depicting the entire $\{x_c[n], y_c[n]\}_{n=1}^{L}$ sequence, regardless of the pressure values, and dilating the image with a 4×4 square structural element, as in Sect. II-A. The results can be seen in Fig. 1 (center).

It should be noted that, in order to obtain an image including only the pen-up information, $I_{pen-up}(x, y)$, and not the inked strokes, only the values $\{x_c[n], y_c[n]\}_{n=1}^{L}$ when $p_c[n] = 0$ should be plotted. Then, $I_{complete}(x, y) = I(x, y) + I_{pen-up}(x, y)$.

E. Enhanced Static Signatures: Combination of Dynamic Effects

All the improvements proposed in the previous subsections can be combined into a single enhanced image as follows: the pressure is added as gray level values, the speed as stroke width and the pen-ups as additional strokes. The image is defined as:

$$I_{fusion}(x, y) = \sum_{n=1}^{L} I_{complete} * G_{ps}(x, y) \tag{3}$$

where

$$G_{ps} = A[n] \cdot exp\left(-\left(\frac{(x - x_c[n])^2}{2\phi_x} + \frac{(y - y_c[n])^2}{2\phi_y}\right)\right)$$

$A[n]$ is defined in Sect. II-B, ϕ_x and ϕ_y in Sect. II-C.

In Fig. 1 (right) the appearance of an enhanced static signature image comprising pressure, speed and pen-up information can be observed.

F. Virtual Ink Deposition Model

Finally, an ink deposition model is considered. A method to generate realistic static signature images with a virtual ink model is proposed in [7], which is here applied to the enhanced signature I_{fusion}. It should be noted that this method is aimed at obtaining realistic images in terms of the stroke texture.

III. Experimental Protocol

In order to evaluate the quality of the synthetic signatures, a state-of-the-art off-line verification system was used in the experiments. Two fully compatible real databases, comprising on-line and off-line signatures, were used for the verification system training and the evaluation of the synthetic signatures. Finally, the experimental protocol was designed so that the quality of the signatures was measured in terms of the system performance (is it similar to the real off-line signatures performance?), for several enrolment scenarios (is the performance even if the enrolment protocol changes?). Another experiment was carried out to assess the feasibility of synthetically increasing the number of samples used at the enrolment stage.

A. Off-line Verification System

The system used for the evaluation of the real and synthetic signatures is a fusion of two LS-SVM classifiers [10], based on Local Binary Patterns (LBP) and Local Directional Patterns (LDP), respectively. Signature images are divided into twelve overlapping blocks and the corresponding features are extracted. Dimensionality is then reduced using the Discrete Cosine Transform, and the final score is computed as the sum of the two partial scores.

In the present work, this LS-SVM system is adapted to work with signatures containing pen-up information. In this case, two different feature vectors are obtained for the I and I_{pen-up} images. Then, both vectors are concatenated and used as input to each classifier.

It should be noted that, since the pen-up vectors are considerably shorter than the inked strokes, their addition has a negligible effect on the dimensionality of the templates. Moreover, the noise that could be introduced with the pen-ups (their randomness is higher compared to the inked strokes) is compensated by the higher energy of the original features.

B. Databases

The experiments were carried out on the BiosecurID database [11]. This multimodal database comprises on-line and off-line signatures of 400 users. Signatures were captured using a special digital inking pen on a paper placed over a digitizing tablet. This way, both versions, on-line and off-line, of the exact same real signature were acquired at the same time. The database was captured in 4 sessions distributed over 4 months. Each subject signed 4 times and forged 3 signatures, thus leading to $4 \times 4 = 16$ genuine samples and $3 \times 4 = 12$ skilled forgeries. The performance of the real and synthetic signatures is evaluated on a subset of 132 subjects.

The LS-SVM classifier used in the experiments needs to be trained with positive and negative samples. Positive samples were taken from BiosecurID as described below (see Sect. III-C) while negative samples were taken from the MCYT database [12] in order to ensure totally unbiased results in the recognition experiments. The size of the negative set was empirically fixed to the 25 samples of the first 100 signers in MCYT.

Following the methodology described in Sect. II, six synthetic databases have been generated, replicating the structure of the selected subset of BiosecurID: 132 subjects with 16 genuine samples and 12 skilled forgeries. Each synthetic database consists of one type of synthetic signatures, namely: $i)$ simple strokes, $ii)$ enhanced with pressure information, $iii)$ enhanced with speed information, $iv)$ enhanced with pen-ups, $v)$ enhanced with pressure, speed and pen-ups, and $vi)$ enhanced with pressure, speed, pen-ups and the ink deposition model.

C. Experimental Protocol

In order to answer the questions stated at the beginning of this section, two different experiments are carried out:

- **Experiment 1: Real vs synthetic signatures performance**. The performance of the selected verification system for the real and each of the synthetic databases is evaluated in the first experiment. The BiosecurID database is divided into a an enrolment set of 90 users, from which genuine and skilled impostor scores are computed, and a test set, comprising the remaining 42 subjects used to compute the random impostor scores. Two different protocols have been considered to compute the 90 user enrolled models: $i)$ a *mono-session* approach, using the four samples of the first session, and $ii)$ a *multi-session* approach, using one sample of each session. In both cases, genuine scores are computed matching the non-enrolled genuine samples of the subject (12) to the enrolled model ($90 \times 12 = 1,080$ genuine scores). Random impostor scores are calculated comparing the first sample of the test subjects to the enrolled model, leading to $90 \times 42 = 3,780$ random impostor scores, and skilled impostor scores are calculated with the skilled forgeries samples of the enrolled users (12 per subject) to the enrolled model ($90 \times 12 = 1,080$ skilled impostor scores).
- **Experiment 2: Mixed enrolment set**. Finally, one possible application of the proposed synthetic off-line signatures generation method is to increase the number of samples available in a database. In order to assess whether such increase leads to a better recognition performance, three different enrolment sets are considered in experiment 2: $i)$ 4 real samples belonging to the first acquisition session (as in experiment 1 - mono session), $ii)$ 8 real samples belonging to the first and the second sessions, and $iii)$ 4 real samples belonging to the first session plus 4 synthetic samples belonging to the second session.

IV. RESULTS

As described in Sect. III, two different experiments are carried out in order to analyse the quality of the synthetic signatures and the feasibility of synthetically increasing the enrolment samples. Therefore, the goal of the experiments is threefold, namely: $i)$ measure the similarity between real and synthetic images, $ii)$ assess whether using synthetic signatures affects the recognition performance, and $iii)$ analyse the impact of using real and synthetic signatures for enrolment.

A. Experiment 1: Real vs Synthetic Signatures Performance

In order to evaluate the performance of the different synthetic signature generation techniques described in Sect. II, two different protocols are followed (see Sect. III): the signatures used for enrolling the user models belong to $i)$ the first acquisition session (Experiment 2 - mono-session), or $ii)$ all sessions, one signature per session (Experiment 2 - multi-session).

Table I shows the Equal Error Rate (EER) achieved by the real and each of the six synthetic signatures databases. As it may be observed, under the random forgeries scenario, the EERs achieved by the different types of synthetic signatures are very close. On the other hand, under the skilled forgeries scenario, adding pen-up information significantly increases the discriminative power of the signatures: EERs decrease from about 20% to 17% for the mono-session training, and from 17% to 15% for the multi-session training. Since the average EER for the last three columns under the skilled forgeries scenario is 16.50%, 16.93% and 16.36%, respectively, the enhanced synthetic signatures with the ink deposition model could be considered as the best performing ones.

We may also observe in Table I a difference between real off-line signatures and the synthetic signatures generated as a simple stroke. It could be explained by: $i)$ non-linear deformations introduced during the signing process over a sheet (such deformations are visible with a visual inspection

Table I: Experiment 1: EER for real and enhanced synthetic off-line signatures, for all the approaches considered under the two possible scenarios (i.e., random and skilled forgeries), where fusion denotes the combination of pressure, speed and pen-up information. Ink model denotes signatures enhanced with pressure, speed, pen-ups and the ink deposition model.

Training	Random Forgeries						
	Real	**Simple Stroke**	**Pressure**	**Speed**	**Pen-ups**	**Fusion**	**Ink Model**
mono-session	4.81 %	4.03 %	3.61 %	4.45 %	4.64 %	4.57 %	4.89 %
multi-session	3.15 %	2.37 %	2.57 %	2.24 %	3.18 %	4.01 %	3.78 %
	Skilled Forgeries						
mono-session	20.28 %	21.86 %	20.83 %	20.25 %	17.93 %	17.04 %	17.41 %
multi-session	17.13 %	16.85 %	16.86 %	17.24 %	15.06 %	16.81 %	15.28 %

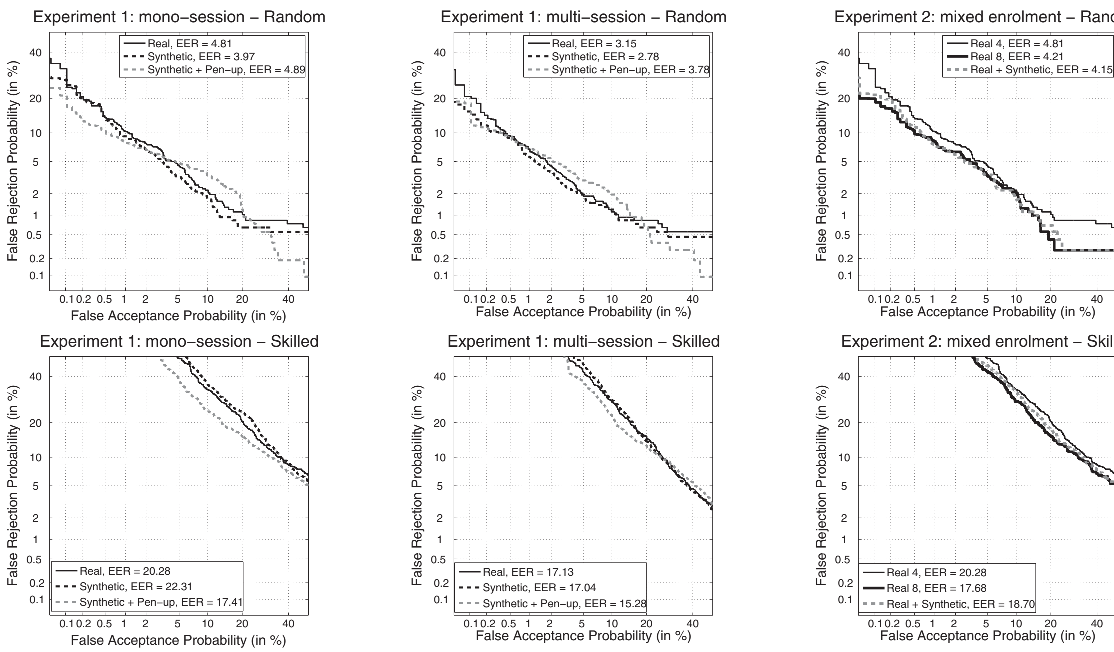

Figure 2: DET curves for real off-line signatures and the best performing synthetic signatures (fusion + ink model, with and without pen-ups), for the three experiments carried out (mono-session and multi-session enrolment, synthetic + real enrolment), for the two scenarios considered (random and skilled impostors).

of both real and synthetic signatures); and ii) human errors introduced during the acquisition and labelling of both on-line and off-line data (misalignment, duplicated strokes,...).

In Fig. 2 (left - mono-session, center - multi-session) we may observe that the behaviour of the system with real (continuous black line) and the best synthetic signatures without pen-ups (dotted black line) is quite similar, regardless of the training protocol or the scenario considered. On the other hand, adding the pen-up information to the synthetic signatures (dotted gray line) leads to some changes in the system behaviour, as it could be expected: this information is not available in the real samples. However, it should be noticed that under the skilled forgeries scenario, the recognition performance significantly improves with this addition: EER decreases over 10%, from 20.28% to 17.41% for the mono-session training, and from 17.13% to 15.28% for the multi-session training. Therefore, these synthetic signatures containing pen-up information show a bigger discriminative power for one of the most challenging problems in signature verification: skilled forgeries.

B. Experiment 2: Mixed Enrolment Set

In the last experiment, the feasibility of synthetically increasing the enrolment set is analysed. As described in Sect. III, three different enrolment sets are considered. As it may be observed in Fig. 2 (right), the DET curves for the mixed enrolment (real + synthetic, grey dotted line), show a better performance compared to the case with only four real enrolled samples (thin black line), regardless of the operating point or the scenario considered. More specifically, the EER decreases in 14% (from 4.81% to 4.15%) and 8% (from 20.28% to 18.70%), respectively. The addition of synthetic samples for training thus leads to better recognition results.

It should also be noted that the behaviour of the mixed enrolment is very similar to the scenario with eight real enrolled samples (i.e., using eight real samples instead of four real and four synthetic, thick black line). We may thus conclude that, when there are not enough off-line signatures available, a good alternative is using both real off-line signatures and enhanced synthetic signatures generated from real on-line samples in order to increase the accuracy of the system.

V. Conclusion

A novel method to synthesize enhanced off-line signatures from dynamic real information has been proposed. Several generation approaches that take advantage of the data present in on-line signatures in order to produce more reliable static samples are described, and their performance studied.

The results suggest that the combination of all features at image level (i.e., modulating the gray level with the pressure information, the stroke width with the speed and considering a second image with the pen-ups) plus the ink deposition model is the most promising strategy. These enhanced synthetic images show a very similar behaviour to the real samples, for all the enrolment protocols considered. Therefore, such synthetically generated databases could potentially be used to estimate the performance of off-line verifiers when not sufficient real static data is available. Furthermore, it is also shown that, in case of having only a limited number of off-line enrolment samples, completing the set with synthetic signatures leads to a better performance. As such, the proposed method could also be used for synthetically improving the enrolment process in off-line signature verification.

The efficiency of signature verification based on the combination of both on-line and off-line features has been shown in [13]. However, these approaches require an unsuitable acquisition scenario, which reduces its applicability to real-world environments. Being able to generate the off-line signatures from their on-line versions could be a good alternative to this acquisition issue.

Finally, we may observe that synthetic images offer a higher discriminative power under the skilled forgeries scenario, one of the biggest challenges in handwriting recognition. Therefore, the combination of real on-line and synthetically generated off-line signatures, when only the on-line information is available, is foreseen to yield improved recognition results and will be addressed as part of future work.

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