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A Noise Robust Gait Representation: Motion Energy Image

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Abstract: Gait-based human identification aims to discriminate individuals by the way they walk. A unique advantage of gait as a biometric is that it requires no subject contact and is easily acquired at a distance, which stands in contrast to other biometric techniques involving face, fingerprints, iris, etc. This paper proposes a new gait representation called motion energy image (MEI). Compared with other gait features, MEI is more robust against noise that can be included in binary gait silhouette images due to various factors. The effectiveness of the proposed method for gait recognition is demonstrated using experiments performed on the NLPR database.

Keywords: Biometrics, gait recognition, MEI, NLPR database, noise.

1. INTRODUCTION

Gait recognition is described as recognizing individual using visual cues that characterize the motion of a walking person [1]. Gait has the advantage of being non-invasive and it can easily be acquired at a distance [2]. Gait is less likely to be obscured as compared to other biometrics such as face, fingerprints, and iris. Hence, using gait as a biometric trait has recently attracted the interest of many biometric researchers.

To date, much research has been conducted regarding gait recognition. Gait recognition can be broadly classified into two categories model-based approach and silhouette-based approach [3]. Model-based approach [4-6] proposes to explicitly model human body or motion and performs matching based on the model in each frame of a walking sequence. Parameters such as trajectories, angles etc. are measured according to the model used in the approach. The effectiveness of the model-based approach is however still limited due to current imperfect vision techniques in body structure/motion modeling and parameter recovery from a walking image sequence. Moreover, the computational cost of model-based approaches is relatively higher than model free approaches.

Silhouette-based approaches [7-10] characterize body movements by using the statistics of walking patterns which capture both the static and dynamic properties of body shape. This approach does not recover a structural model of human motion. Motion silhouette image (MSI) [10] has been considered as an effective gait representation for the silhouette-based approaches. MSI is a gray level image and the intensity at each pixel of a MSI represents the temporal motion history of that pixel. MSI includes spatial and temporal information of the gait sequence, however MSI is sometimes corrupted with noise since the constituent binary silhouette images are also corrupted, so they consequently degrade the recognition performance of the system. To solve the above mentioned predicament we propose a new gait representation called motion energy image (MEI). MEI is motivated by MSI and belongs to silhouette-based approach. Since it adopts time-normalized accumulative energy of human walking which is not much affected by noise, it has the advantage of being less susceptible to noise than MSI. A mathematical proof for the enhanced robustness of MEI over MSI is also presented in this paper.

This paper is organized as follows: Section 2 provides a preliminary review of MSI. Section 3 proposes a new gait representation called MEI. The proposed scheme is applied to the NLPR gait database and its effectiveness is demonstrated by comparing it with other methods in Section 4. Finally, a conclusion is drawn in Section 5.

2. MOTION SILHOUETTE IMAGE (MSI)

The motion silhouette image (MSI) is a gray level image where the intensity at each pixel represents the temporal history of the motion of that pixel. It is defined as

$$M(x,y,t)=\begin{cases}255 & \text{if } S(x,y,t)=1\\ \max\left[0, M(x,y,t-1)-1\right] & \text{if } S(x,y,t)=0,\end{cases} \tag{1}$$

where $S(x,y,t)$ is the silhouette image, t is the frame

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(a) (b) (c)

Fig. 1. Motion silhouette images for (a) lateral view (b) oblique view (c) frontal view.

number in the gait sequence, and (x, y) are the coordinates of the MSI image [10]. Fig. 1 shows examples of MSI for lateral, oblique and frontal views. Since the constituent binary gait silhouette images may be corrupted with noise, the MSI may also be corrupt. Let $\tilde{M}(x, y, t)$ be a noisy MSI represented by

$$\tilde{M}(x,y,t) = \begin{cases} 255 & \text{if } \tilde{S}(x,y,t) = 1 \\ \max[0, \tilde{M}(x,y,t-1) - 1] & \text{if } \tilde{S}(x,y,t) = 0, \end{cases} \tag{2}$$

where $\tilde{S}(x, y, t)$ is a noisy gait silhouette image that is formed by the addition of noise $\mu(x, y, t)$ to an original silhouette image $S(x, y, t)$

$$\tilde{S}(x,y,t) = S(x,y,t) + \mu(x,y,t). \tag{3}$$

The error analysis of the gait representation given below is motivated by [11]. We assume that the noise at different moments t is uncorrelated and identically distributed. Under these constraints, noise $\mu(x, y, t)$ satisfies the following distribution

$$\mu(x,y,t) = \begin{cases} \mu_1(x,y,t) = \begin{cases} P\left[\mu(x,y,t) = -1 \mid S(x,y,t) = 1\right] = p \\ P\left[\mu(x,y,t) = 0 \mid S(x,y,t) = 1\right] = 1 - p \end{cases} \\ \mu_2(x,y,t) = \begin{cases} P\left[\mu(x,y,t) = 1 \mid S(x,y,t) = 0\right] = p \\ P\left[\mu(x,y,t) = 0 \mid S(x,y,t) = 0\right] = 1 - p. \end{cases} \end{cases} \tag{4}$$

Then, we have

$$E\left[\mu(x,y,t)\right] = \begin{cases} E\left[\mu_1(x,y,t)\right] = E\left[\mu(x,y,t) \mid S(x,y,t) = 1\right] = -p \\ E\left[\mu_2(x,y,t)\right] = E\left[\mu(x,y,t) \mid S(x,y,t) = 0\right] = p. \end{cases} \tag{5}$$

Now, let us consider the noisy MSI

$$\tilde{M}(x,y,t) = M(x,y,t) + \eta(x,y,t), \tag{6}$$

where $\eta(x, y, t)$ is the noise in MSI and it satisfies the following distribution

$$\eta(x,y,t) = \begin{cases} \eta_1(x,y,t) = \begin{cases} P[\eta(x,y,t) = (\max[0, \tilde{M}(x,y,t-1) \\ \qquad -1] - 255) \mid S(x,y,t) = 1] \\ = P[\mu(x,y,t) = -1 \mid S(x,y,t) = 1] = p \\ P[\eta(x,y,t) = 0 \mid S(x,y,t) = 1] \\ = P[\mu(x,y,t) = 0 \mid S(x,y,t) = 1] = 1 - p \end{cases} \\ \eta_2(x,y,t) = \begin{cases} P[\eta(x,y,t) = (255 - \max[0, \tilde{M}(x,y,t-1) \\ \qquad -1]) \mid S(x,y,t) = 0] \\ = P[\mu(x,y,t) = 1 \mid S(x,y,t) = 0] = p \\ P[\eta(x,y,t) = 0 \mid S(x,y,t) = 0] \\ = P[\mu(x,y,t) = 0 \mid S(x,y,t) = 0] = 1 - p. \end{cases} \end{cases} \tag{7}$$

Here, under the Markov assumption, the current MSI, $\tilde{M}(x, y, t)$ is influenced only by one frame earlier MSI, $\tilde{M}(x, y, t-1)$. Therefore, we have

$$\begin{aligned} &E[\eta(x,y,t)] \\ &= \begin{cases} E[\eta_1(x,y,t)] = E[\eta(x,y,t) \mid S(x,y,t) = 1] \\ E[\eta_2(x,y,t)] = E[\eta(x,y,t) \mid S(x,y,t) = 0] \end{cases} \\ &= \begin{cases} (\max[0, \tilde{M}(x,y,t-1) - 1] - 255) P[\mu(x,y,t) \\ = -1 \mid S(x,y,t) = 1] \\ (255 - \max[0, \tilde{M}(x,y,t-1) - 1]) P[\mu(x,y,t) \\ = 1 \mid S(x,y,t) = 0] \end{cases} \\ &= (255 - \max[0, \tilde{M}(x,y,t-1) - 1]) E[\mu(x,y,t)] \\ &= \begin{cases} (\max[0, \tilde{M}(x,y,t-1) - 1] - 255) p \\ (255 - \max[0, \tilde{M}(x,y,t-1) - 1]) p. \end{cases} \end{aligned} \tag{8}$$

3. MOTION ENERGY IMAGE (MEI)

This paper proposes a new gait representation called motion energy image (MEI). Unlike MSI, MEI uses the mean of the silhouette images which is time-normalized accumulative energy of human gait within a fixed size window. Therefore, MSI can be considered as a special case of MEI with window size equal to one. MEI is given by

$$ME(x,y,k) = \begin{cases} 255 & \text{if } G(x,y,k) \geq 0.5 \\ \max\left[0, ME(x,y,k-1) - 1\right] & \text{if } G(x,y,k) < 0.5, \end{cases} \tag{9}$$

where k is the window number in the sequence and $G(x, y, k)$ is average of the silhouette images within the k th window and is obtained by

$$G(x,y,k) = \frac{1}{N} \sum_{t=N(k-1)+1}^{Nk} S(x,y,t), \tag{10}$$

where N is the window size. Similarly MEI and $G(x, y, k)$ may be corrupt with noise which can be included in the constituent binary silhouette images. The noisy MEI and noisy $G(x,y,k)$ are defined as follows:

$$\tilde{ME}(x,y,k)= \begin{cases} 255 & if\ \tilde{G}(x,y,k)\geq 0.5 \\ \max\left[0,\tilde{ME}(x,y,k-1)-1\right] & if\ \tilde{G}(x,y,k)<0.5 \end{cases} \quad (11)$$

and

$$\tilde{G}(x,y,k)=G(x,y,k)+\sigma(x,y,k), \quad (12)$$

where $\tilde{ME}(x,y,k)$ is the noisy MEI, $\tilde{G}(x,y,k)$ is the average of noisy gait silhouette images within the k th window and $\sigma(x,y,k)$ is the additive noise in $\tilde{G}(x,y,k)$. Given a k th window $(N(k-1)+1\leq t\leq Nk)$ where $S(x,y,t)=1$ at a pixel (x,y) only in M_k frames, we have

$$\begin{aligned}&\tilde{G}(x,y,k)\\&=\frac{1}{N}\sum_{t=N(k-1)+1}^{Nk}\tilde{S}(x,y,t)\\&=\frac{1}{N}\sum_{t=N(k-1)+1}^{Nk}S(x,y,t)+\frac{1}{N}\sum_{t=N(k-1)+1}^{Nk}\mu(x,y,t)\\&=\frac{M_k}{N}+\frac{1}{N}\sum_{t=N(k-1)+1}^{Nk}\mu(x,y,t).\end{aligned} \quad (13)$$

Therefore, the noise in $\tilde{G}(x,y,k)$ is

$$\begin{aligned}&\sigma(x,y,k)\\&=\frac{1}{N}\sum_{t=N(k-1)+1}^{Nk}\mu(x,y,t)\\&=\frac{1}{N}\left[\sum_{t=N(k-1)+1}^{N(k-1)+M_k}\mu_1(x,y,t)+\sum_{t=N(k-1)+M_k+1}^{Nk}\mu_2(x,y,t)\right]\end{aligned} \quad (14)$$

and the average of $\sigma(x,y,k)$ is

$$\begin{aligned}&E\left[\sigma(x,y,k)\right]\\&=E\left[\frac{1}{N}\sum_{t=N(k-1)+1}^{Nk}\mu(x,y,t)\right]\\&=\frac{1}{N}\left[\sum_{t=N(k-1)+1}^{N(k-1)+M_k}E\left[\mu_1(x,y,t)\right]\right.\\&\qquad\left.+\sum_{t=N(k-1)+M_k+1}^{Nk}E\left[\mu_2(x,y,t)\right]\right]\\&=\frac{1}{N}\left(M_k(-p)+(N-M_k)p\right)=\frac{N-2M_k}{N}p.\end{aligned} \quad (15)$$

On the other hand, if $\sigma(x,y,k)$ satisfies the following distribution

$$\begin{aligned}&\sigma(x,y,k)\\&=\begin{cases}\sigma_1(x,y,k)= \\ \begin{cases}P[\sigma(x,y,k)=-1\mid G(x,y,k)\geq 0.5]=q\\P[\sigma(x,y,k)=0\mid G(x,y,k)\geq 0.5]=1-q\end{cases}\\ \sigma_2(x,y,k)= \\ \begin{cases}P[\sigma(x,y,k)=1\mid G(x,y,k)<0.5]=q\\P[\sigma(x,y,k)=0\mid G(x,y,k)<0.5]=1-q,\end{cases}\end{cases}\end{aligned} \quad (16)$$

the average of $\sigma(x,y,k)$ is

$$\begin{aligned}&E[\sigma(x,y,k)]\\&=\begin{cases}E[\sigma_1(x,y,k)]\\=E[\sigma(x,y,k)\mid G(x,y,k)\geq 0.5]=-q\\E[\sigma_2(x,y,k)]\\=E[\sigma(x,y,k)\mid G(x,y,k)<0.5]=q.\end{cases}\end{aligned} \quad (17)$$

Now, let us consider the noisy MEI

$$\tilde{ME}(x,y,k)=ME(x,y,k)+\nu(x,y,k), \quad (18)$$

where $\nu(x, y, k)$ is the noise and it satisfies the following distribution

$$\begin{aligned}&\nu(x,y,k)\\&=\begin{cases}\nu_1(x,y,k)\\ \begin{cases}P[\nu(x,y,k)=(\max[0,\tilde{ME}(x,y,k-1)-1]\\ \qquad -255)\mid G(x,y,k)\geq 0.5]\\=P[\sigma(x,y,k)=-1\mid G(x,y,k)\geq 0.5]=q\\P[\nu(x,y,k)=0\mid G(x,y,k)\geq 0.5]\\=P[\sigma(x,y,k)=0\mid G(x,y,k)\geq 0.5]=1-q\end{cases}\\ \nu_2(x,y,k)\\ \begin{cases}P[\nu(x,y,k)=(255-\max[0,\tilde{ME}(x,y,k-1)\\ \qquad -1])\mid G(x,y,k)<0.5]\\=P[\sigma(x,y,k)=1\mid G(x,y,k)<0.5]=q\\P[\nu(x,y,k)=0\mid G(x,y,k)<0.5]\\=P[\sigma(x,y,k)=0\mid G(x,y,k)<0.5]=1-q.\end{cases}\end{cases}\end{aligned} \quad (19)$$

Then, we have

$$\begin{aligned}&E[\nu(x,y,k)]\\&=\begin{cases}E[\nu_1(x,y,k)]=E[\nu(x,y,k)\mid G(x,y,k)\geq 0.5]\\E[\nu_2(x,y,k)]=E[\nu(x,y,k)\mid G(x,y,k)<0.5]\end{cases}\\&=\begin{cases}(\max[0,\tilde{ME}(x,y,k-1)-1]-255)P[\sigma(x,y,k)\\=-1\mid G(x,y,k)\geq 0.5]\\(255-\max[0,\tilde{ME}(x,y,k-1)-1])P[\sigma(x,y,k)\\=1\mid G(x,y,k)<0.5]\end{cases}\\&=\begin{cases}(\max[0,\tilde{ME}(x,y,k-1)-1]-255)q\\(255-\max[0,\tilde{ME}(x,y,k-1)-1])q\end{cases}\\&=(255-\max[0,\tilde{ME}(x,y,k-1)-1])E[\sigma(x,y,k)]\\&=(255-\max[0,\tilde{ME}(x,y,k-1)-1])\frac{N-2M_k}{N}p.\end{aligned} \quad (20)$$

For the sake of simplicity, we assume that $\tilde{ME}(x,y,k-1)=\tilde{M}(x,y,t-1)$ and compare the magnitude of (8) and (20). In (20), $\frac{N-2M_k}{N}$ varies from -1 to 1 as M_k varies from N to 0. That is, when $M_k=0$, $\frac{N-2M_k}{N}=1$ and when $M_k=N$, $\frac{N-2M_k}{N}=-1$. For the intermediate values between N and 0, $\frac{N-2M_k}{N}$ has a value between -1 and 1. Thus,

$$-1\le\frac{N-2M_k}{N}\le 1\; for\;\; 0\le M_k\le N. \tag{21}$$

In view of (8), (20) and (21), $|E[\nu]|$ is less than $|E[\eta]|$. To show the effectiveness of the proposed algorithm, the proposed MEI and the MSI are applied to a single pixel problem $S(t)$ in which the value of a single pixel changes over time as shown in Fig. 2. Noise $\mu(t)$ is added to the single pixel with the probability p. The probability changes from 0.01 to 0.1 and the noisy MSI and MEI are evaluated. Fig. 3 compares the expected noise of MEI and MSI as p varies. It can be seen that $|E[\nu]|$ is much less than $|E[\eta]|$, as expected.

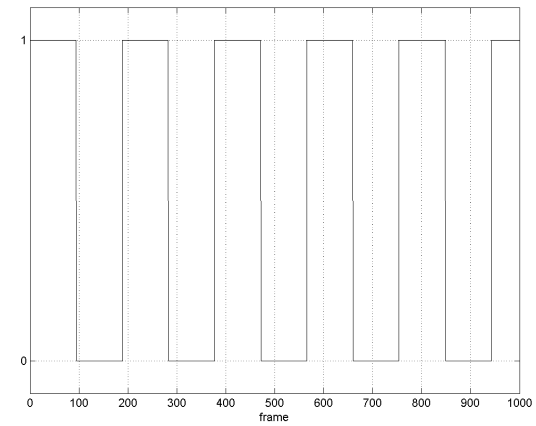

Fig. 2. Single pixel's true state.

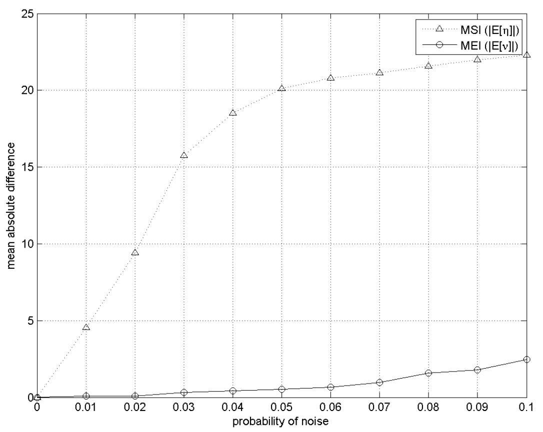

Fig. 3. Comparison of noises of MEI and MSI in single pixel.

Thus, the proposed method is less sensitive to noise in individual silhouette images as compared to MSI and is expected to make gait recognition a more reliable biometric. The reason might be that the proposed method employs the time-normalized accumulative energy of human walking which is not much affected by noise. Further, in comparison with gait representation using a binary silhouette sequence, MEI saves both storage space and computation time for recognition.

4. EXPERIMENTAL RESULT

4.1. Database

In this section, we apply the proposed MEI to the gait recognition problem and show its effectiveness and applicability to gait recognition. We carry out three experiments on the NLPR database [9]. This database is widely used to benchmark algorithms in gait recognition. NLPR database is also known as the CASIA gait database. All subjects in the database walked along a straight-line path at free cadences in three different views with respect to the image plane i.e. lateral (0°), oblique (45°) and frontal (90°). Fig. 4 shows the example images in three different views. A digital camera fixed on a tripod captured gait sequences on two different days in an outdoor environment to compile the NLPR database. The database includes twenty subjects. Each subject has four sequences for each viewing angle: two sequences in one walking direction and two in the reverse walking direction.

4.2. Results

Leave-one-out cross-validation rule is used to evaluate the general performance of the algorithm on the NLPR database. The silhouette images are obtained by background subtraction [12]. Subsequently, to eliminate the scaling effect, a bounding box is constructed around the contour of the silhouette and the contour is resized to a fixed size. In the experiments, MSI and MEI are first projected to the eigenspace using principal component analysis (PCA) and K-nearest neighbors (K-NN) [13] classifier is applied on the projected features for classification. The experiments are repeated for three different angles and the experimental results are shown in Tables 1, 2 and 3. Tables 1, 2 and 3 compare MSI and MEI in terms of correct classification rate (CCR). It can be seen that, in all the three views, the proposed methods show better performance than the previous methods. The

(a) (b) (c)

Fig. 4. Examples for (a) lateral view (b) oblique view (c) frontal view.

Table 1. Gait correct classification rate for the lateral view.

Features	Number of features	Methods		
		1-NN	3-NN	5-NN
MSI	50	76.25	62.50	66.25
	60	73.75	62.50	65.00
	70	77.50	67.50	67.50
MEI	50	78.75	71.25	76.25
	60	83.70	71.25	73.15
	70	88.75	72.50	76.25

Table 2. Gait correct classification rate for the oblique view.

Features	Number of features	Methods		
		1-NN	3-NN	5-NN
MSI	50	80.00	52.50	72.50
	60	80.00	58.75	72.50
	70	83.75	60.00	76.25
MEI	50	81.25	71.25	80.00
	60	82.50	71.25	82.50
	70	86.25	87.50	86.25

Table 3. Gait correct classification rate for the frontal view.

Features	Number of features	Methods		
		1-NN	3-NN	5-NN
MSI	50	73.75	50.00	67.50
	60	72.50	53.75	67.50
	70	76.25	53.75	68.75
MEI	50	83.75	56.25	68.75
	60	85.00	60.00	75.00
	70	85.00	60.00	75.00

basis for the better performance of MEI over MSI could be due to the fact that MEI is more robust against noise in individual silhouette images as compared to MSI.

We repeat the same experiments with synthesized gait database to emphasize the robustness of MEI against noise. The synthesized gait database includes individual silhouette images that have been purposely corrupted with noise. We observe the CCR while varying the probability of noise in silhouette images from 0.001 to 0.025. 1-NN classifier and NLPR gait database in lateral view are used for the experiments. The experiment results are reported in Table 4. It is obvious from the experimental results that MEI shows more robust and better performance than MSI. Thus, we can conclude from the experimental results that the proposed MEI is less sensitive to noise, and the reason might be that it adopts time-normalized accumulative energy of human gait which is not much affected by noise. Fig. 5 compares the CCRs of MEI and MSI with noise corruption. While the CCR of MSI drops almost exponentially with the increase of noise probability, the CCR of MEI nearly maintains a constant value with increasing additive noise.

Table 4. Comparison of MSI and MEI when the silhouette images are corrupted by noise.

Probability of noise	MSI + 1-NN	MEI + 1-NN
0.001	70.00	82.50
0.005	51.25	81.25
0.010	35.00	80.00
0.015	20.00	78.75
0.020	11.25	78.75
0.025	6.25	77.50

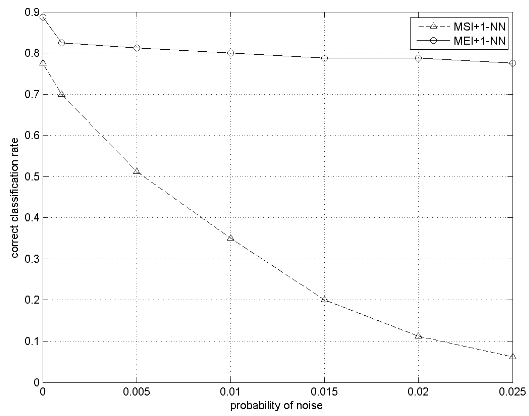

Fig. 5. Comparison of correct classification rates for MEI and MSI with noise corruption.

Table 5. Comparison of several algorithms of the NLPR database in the lateral view.

Methods	CCR
BenAbdelkader *et al.* [6]	72.50
Collins *et al.* [8]	71.25
Lee *et al.* [14]	87.50
Phillips *et al.* [15]	78.75
Wang *et al.* [9] (w/o validation)	75.00
Wang *et al.* [9] (with validation)	82.50
Kale *et al.* [16]	82.50
Proposed method	88.75

In addition, the performance of the proposed scheme is compared with those of the previous gait recognition methods [6,8,9,14-16] for NLPR database with a lateral viewing angle shown in Table 5. The performances of the previous methods are directly cited from [9] and we reimplemeted the width vector profile and DTW matching in [16] using the NLPR database. It is evident from Table 5 that MEI is an effective and robust representation method for gait recognition and it can help make gait a more reliable biometric.

5. CONCLUSIONS

This paper presents, a new gait representation called MEI and the mathematical proof of its robustness against noise. MSI has been considered as an effective gait representation. However, MSI is sometimes corrupted with noise. Since the constituent binary silhouette images are also corrupted, thereby degrading the recognition performance. Therefore, we propose MEI, which has the advantage of being less susceptible to noise as compared to MSI. The experimental results on three different views of the NLPR database show that the proposed method clearly outperforms the classical classification methods.

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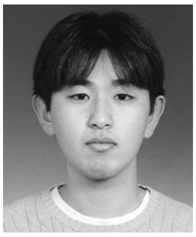

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