Jurnal Teknologi

Full Paper

Gait Analysis and Classification on Subjects with Parkinson's Disease

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Article history
Received
15 May 2015
Received in revised form
1 July 2015
Accepted
11 August 2015

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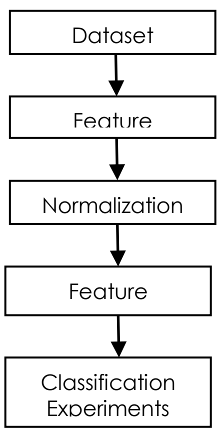
Graphical abstract



Abstract

The objective of this paper is to analyse the gait of subjects with suffering Parkinson's Disease (PD), plus to differentiate their gait from those of normal people. The data is obtained from a medical gait database known as Gaitpdb [1]. In the data set, there are 73 control subjects and 93 subjects with PD. In our study, we first obtained the gait features using statistical analysis, which include minimum, maximum, median, kurtosis, mean, skewness, standard deviation and average absolute deviation of the gait signal. Next, selection of the extracted features is performed using PSO search, Tabu search and Ranker. Finally the selected features will undergo classification using BFT, BPANN, k-NN, SVM with Ln kernel, SVM with Poly kernel and SVM with Rbf kernel. From the experimental results, the proposed model achieved average of 66.43%, 89.97%, 87.00%, 88.47%, 86.80% and 87.53% correct classification rates respectively.

Keywords: Parkinson disease, gait, classification

1.0 INTRODUCTION

The Global Declaration for Parkinson's disease [2] 2004 estimated that there are 6.3 million people who are diagnosed with the Parkinson's disease. Parkinson's disease (PD) is an illness that affects the motion of a human body. The affected symptoms including tremors, speech disorders, rigidity, slowness and postural instability [3]. Genetic and environment factors cause PD, where the symptom affects the production of dopamine from neurons which is important for movement coordination.

PD is a disease which is linked to the movement of the human being, in another word, it is affecting the gait. Gait is the pattern of how a person walks. It is associated with simultaneous performance of locomotion while maintaining balance in a complete set of behaviours. Human gait is said to be the basic of locomotion where the most comfortable and economical way of a movement at short distances take place [3]. Pietraszewski *et al*. characterized gait by the smooth and repeatable movements that take place in human joints [4].

There is a great risk of fall with the PD patient while walking, especially if they are changing direction. PD patients need to take larger number of steps because of their smaller stride. Thus, their balance will be affected if they quickly change their direction and this may result in a fall. It is important to detect this in PD patients, so that falls can be prevented and symptoms can be diagnosed earlier.

In this work, we propose a model to extract gait features from a medical database using statistical analysis, which includes the minimum, maximum, median, kurtosis, mean, skewness, standard deviation and average absolute deviation of the gait signal. Feature selection is performed using three features selection techniques, namely Particle Swarm Optimization (PSO) search, Tabu search and Ranker. The selection results will then be analyzed to find the differences between subjects with PD and control subjects. Finally the selected features will be used for classification to demonstrate the performance of the proposed model to identify subjects with PD using four classifiers, such as Best First Tree (BFT), Backpropagation Artificial Neural Network (BPANN), Support Vector Machine (SVM) and k-Nearest Neighbors (k-NN).

2.0 LITERATURE REVIEW

Parkinson's disease (PD) is an illness, which causes gradual loss of dopaminergic and other sub-cortial neurons, also known as substantia nigra, in the brain which lead to the deterioration of mobility [5]. One of the symptoms of PD is the Parkinsonian gait. As gait is associated with simultaneous performance of locomotion while maintaining the balance in a complete set of behaviours [6]. Parkinsonian gait is the term which refers to the gait portrayed by the PD patients. Festinating gait happened due to the low production of the dopamine in the basal ganglia. The characteristic of this type of gait is that the small shuffling steps displayed by the Parkinson disease patient due to reduced stride size and length when the patients are walking [7].

PD patients also have the characteristic in slowness to start walking, and they have a reduced arm swing when running [3]. PD patient also experience the freezing of gait whereby they have difficulty in walking such as moving one's feet. Freezing of gait occurred mostly in a confined area such as doorways and it can be related to the turning motion. Start hesitation which is also a part of the freezing of gait refers to the momentary difficulty in starting a movement such as starting a walk once risen up from the sitting position [8].

The Oxford Dictionary defines gait as "a person's manner of walking" that is associated to the pattern of how a human uses his or her limbs to walk. Aristotle was the first person to start gait analysis and wrote a book entitled "On the Gait of Animals" in 350 B.C. Then Giovanni Alfonso Borelli (1608 – 1679) was the first person to start studying the biomechanics of human locomotion. After that, Muybridge (1830 – 1894) was the pioneer to apply the technique of photography to comprehensively capture leg movement activity [9].

In 1964, using the markers that are attached to human's legs, Murray *et al*. [10] managed to develop orthodox locomotion gait patterns from fifty clinically ordinary individuals and extended the work to sixty pathologically malformed individuals in 1967 [11].

In addition, gait can be quantified by using a series of parameters which measure the average timing, linear displacement and velocity. These parameters are listed as follows:

i. Step - the movement of consecutive heel strikes of both feet.

ii. Gait cycle - a full gait cycle is made up of double steps.

iii. Cadence - the total number of complete gait cycles within a minute.

iv. Stride - the duration of a complete gait cycle.

v. Step length - the length between consecutive heel strikes of differing feet.

vi. Stride length - the length travelled for two repeated heel strikes of the identical foot in a gait cycle. It is calculated by first tracking the subject and calculating their space journeyed over a period of time.

Whittle [7] has defined gait analysis as the systematic way of study to understand of the locomotion of walking process. Gait analysis comprises the observation of body movements, mechanics and muscle activities. In general, gait analysis is carried out for three purposes:

i. Medical diagnosis on pathologically abnormal patients: doctors perform gait analysis of patients suffering stroke, cerebral palsy pervasive or motor disease likes Parkinson's disease, so that proper medical therapies and intervention strategies can be made during the rehabilitation treatment.

ii. Sport development of athletes: coaches and scientists analyze athletes' gait during training, so that they can help to optimize and improve athletics performance.

iii. Biometrics and forensic: airport security officers and police apply gait analysis in capturing suspected criminals.

There are many medical studies on gait analysis of subjects that suffering PD. Hausdorff *et al*. [12] measured and evaluated the gait rhythm of subjects with stroke or cerebral palsy with normal people. They constructed a Neuro-Degenerative Disease Database of 15 subjects with PD, 20 subjects with Huntington's disease (HD), 13 subjects with amyotrophic lateral sclerosis (ALS) and 16 healthy control subjects. They discovered a matrix of measures based on gait rhythm dynamics that can trace disease evolution and also computing subtle effects of prospective therapeutic interventions.

Arora *et al*. [13] employed statistical analysis of PD patient's walking task recorded using the smartphone accurately differentiate 10 individuals with PD from 10 control subjects. They applied the three dimensional accelerometry time traces on gait motion to calculate the measures such as mean, standard deviation, median acceleration, Teager–Kaiser energy operator and detrended fluctuation analysis. Sophisticated measures, such as the Teager–Kaiser energy operator and detrended fluctuation analysis, indicated disease progression.

Leddy *et al*. [14] conducted various walking-based balance tests on 80 individuals with PD to determine their fall risk. They examined the gait motion of PD patients while walking forward with normal condition, backward with eyes blinded, walking over obstacles, varying gait speeds with different head rotations and with a restricted base.

Sejdic *et al*. [15] employed tri-axial gait accelerometry signals from 35 subjects to differentiate between healthy subjects and PD patients. The data were collected during the subjects walked on a treadmill at a designated walking speed. They extracted time, frequency and time-frequency domains from the accelerometer signal features.

In this research, standard statistical analysis is applied to extract gait features from the Gaitpdb, similar to those performed by Arora *et al*. [13], with additional measures, extra kurtosis and skewness.

3.0 METHODOLOGY

This section details the methodology of this research. Gait data preparation, features extraction, features selection and classification techniques are elaborated in the following Sub-Sections.

3.1 Gait Dataset

The gait dataset, namely Gaitpdb used in this work was contributed by Hausdorff *et al*. [1]. This database comprises of gait data from 93 subjects suffering PD (mean age: 66.3 years; 37% female), and 73 healthy control subjects (mean age: 66.3 years; 45% female). The subjects with PD were engaged from an outpatient clinic of the Movement Disorders Unit which is located at the Tel-Aviv Sourasky Medical Center. Meanwhile, the healthy control subjects were engaged from the nearby neighborhood, with the purpose of comparison can be made on both of these two group's data. During the recruitment, there were some criterions set on both of these two groups of people beforehand, whereby if these people are clinically diagnosed with illness such as musculoskeletal disease, cardiovascular disease, respiratory disease, dementia and others neurological disease, they will be excluded from the study.

The population of the study was then characterized based on the age, sex, tallness, body mass, Mini-Mental State Exam where this exam is employed for dementia inspection and also the Timed Up and Go test where it is used to measure the balance and the smaller extremity function. The subjects were also cross-examined beforehand concerning their history of falling. In order to quantity the disease severity and extrapyramidal signs of the PD subjects, Unified Parkinson's Disease Rating Scale is used [16].

Every subject was provided time to walk on the hallway and on the treadmill. They were examined for three type of walking circumstances which were:

a. Walk with the usual and unassisted on the level ground at their comfortable speed.

b. Walk with their comfortable speed with the aid of wheeled walker. Wheeled walker is a four rolling wheels rotator.

c. Walk on a medical treadmill which was motorized.

The duration for each of these three circumstances is two minutes. Other than that, for the safety purpose when walking on the treadmill, the subjects were attached with the safety harness around their waist. The treadmill speed was regulated to coordinate with the gait speed for the walking with condition b. For the condition a and b, the gait speed was recorded by referring to the stopwatch where it is used to measure the average time of the subject walked on the 10 meters distance of the 35 meter walk for the 2 minutes of testing.

As for the walking condition b and c, the subjects walked while using the treadmill's handrail as the support. Prior to the testing on conditions a and b, subjects were given time to get themselves familiarized on walking up and down a 35 meter hallway.

As for condition c, the subjects get themselves familiarized with walking on the treadmill before undergo the testing. Once the subjects get comfortable with walking on the treadmill using their usual gait speed, the familiarization period was completed. The subjects were then given 5 minutes rest to decrease their fatigue. The treadmill measurements were taken after 30 seconds after the treadmill speed was increased to match the desired speed which was the usual gait speed that was set during condition b [1].

The computerized force-sensitive system is being used during the data gathering [1]. The force-sensitive system is used to measure the forces underneath the foot against the function of time. A pair of shoes and a recording unit is the component that made up this system. Eight loads of sensors covered the surface of the sole on each shoe and it measures the vertical forces underneath the foot. The recording unit with the weight of 1.5kg was carried by the subjects on the waist.

Each foot's plantar pressure was recorded at a rate of 100 Hz. During the walk, the measurements were stored in the memory card and were transferred to the personal computer after the walk for further analysis purposes. The average stride time, swing time, swing time variability and stride time variability were the gait parameters determined [1]. The value of average stride time was obtained by multiplying the average gait speed with the average stride time.

3.2 Features Extraction

In total, 17 data points were considered, which consist of the value of average stride time in seconds, eight vertical ground reaction force values from left foot sensors in Newton and eight vertical ground reaction force values from right foot sensors also in Newton.

For each data point, features describing the major statistical parameters of its sample distribution were extracted to form nine new features. The nine statistical parameters are listed in Table 1. Therefore, 153 extracted features in total were generated for each subject.

Before the extracted features are utilized in classification, feature normalization is required to be carrying out. It normalizes each extracted feature in numerous dimensions, in order to ensure the features are regulated and not biased. If not the distance measures like Euclidean distance would implicitly allocate more weight to feature with larger values than those with smaller values. Therefore, it can prevent the case of biasing towards a specific feature can be prevented. For this research work, linear scaling is applied to scale the values of the features to fall within the range of 0 and 1.

Table 1 List of statistical characteristics

Statistical parameters	Description
Minimum	return smallest number in a data set
Maximum	return largest number in a data set
Standard deviation	measurement of the variation of a set of data from its mean
Median	returns the number in the middle of the set of the data
Average	returns the average (arithmetic mean) of its arguments
Skewness	characterization of the degree of asymmetry of the data set around its mean
Kurtosis	return the kurtosis (peak value of the data according to the normal distribution) of the data set
Absolute Skewness	absolute value of the skewness
Absolute Kurtosis	absolute value of the kurtosis

3.3 Features Selection Techniques

In order to reduce the dimensionality of extracted gait features in the dataset, features selection was carried out before the dataset was passed on to a classifier. In this research work, PSO search, Tabu search and Ranker were used to find the extracted features that provided constructive contribution in the classification progression. These feature selectors are utilized as they have not been applied to classify the subject with PD, although they have been used successfully applied to pattern recognition systems.

PSO search [17] explores the attribute space by means of the PSO algorithm. It is primed with a population of random potential solutions, specifically termed as particles, are flown through the problem space. PSO search seeks for optima satisfying performance or the best recognition rate in the search algorithm.

Tabu search [18] conducts a search through the space of extracted gait features subsets. Tabu search is evading local maximums by accepting bad and diverse solutions and make further search in the best solutions. It search process stops when there is not more improvement in the iterations.

Ranker [19] ranks extracted gait features in conjunction with correlation attribute evaluator. It evaluates the worth of an attribute by measuring the correlation between it and the subject. It treats each nominal extracted gait feature as the individual significance indicator on a merit basic. The overall correlation for a nominal extracted gait features is established by a weighted average.

3.4 Classification Techniques

Those normalized features that are descriptive of walking pattern of subject will be transformed into a feature vector. Then, the classifier will make decisions of which class (PD or Control) an incoming set of feature vector belongs to. In order to assess the implementation of our approach, four classification techniques were employed. Best First Decision Tree (BFT), Back-Propagation Artificial Neural Network (BPANN), k-Nearest Neighbor (k-NN) with Euclidean distance metrics and Support Vector Machine (SVM) were employed. These classification techniques are employed as they have been found successfully applied to various classification works.

BFT is one of the branches under decision tree learners. Standard decision tree learners is a tree consists of internal node and terminal node [20]. Every internal node represents a selection from a set of substitutes and the terminal node is demonstrated by a classification. In BFT, the best node is extended first. The best node is the node whose parted leads to maximum decrease of impurity among all existing nodes for splitting. The resulting tree is being the same when fully grown, only difference by the sequence of the order. In fact, some branches of a fully-expanded tree do not actually reflect the underlying data in the domain [20]. For this work, the parameters that were used are minimal number of instances at the terminal nodes (*M*) and Number of folds in internal cross-validation (*N*). The number seed to be used (seed) is constantly set to one.

BPANN is often used due to its nature of having high learning capacity and simple algorithm. It strides to minimize the error backwards from input to output [21]. The parameters such as momentum (*MO*), learning rate (*L*) and hidden layer (*HL*) were used in this work.

k-Nearest Neighbors (k-NN) [22] is a non-parametric classifier that is used to distinguish different subjects established on the training data in the feature space. This algorithm exploits the entire accumulated data to substantiate its memory. k-NN algorithm classified an unknown class based on the information of its *k* nearest neighbors stored in the memory In other words; subjects are classified according to the majority vote of nearest neighbors in the training data. The number of neighbor, *k* is used to assign a class or calculate a relative measurement for the test vector during classification.

SVM introduced by Cortes and Vapnik [23] It is a learning machine for two-group classification problem. The concept of SVM is where a very high dimension feature space is non-linearly mapped with the input vectors. Based on the feature space, a linear decision surface is structured collectively with the special properties that construct the capability of the high generation of a network. There were three kernels that were used, which were Linear (Ln), Polynomial (Poly) and Radial basis function (Rbf) kernel. The parameters that were trained for these three kernels are as below:

- Ln kernel: cost (*C*)
- Poly kernel: cost (*C*), gamma(*G*), degree(*D*) and coefficient(*Coef)*
- Rbf kernel: cost (*C*) and gamma(*G*)

This study employed ten folds cross validation for the classification process, where the gait data from the dataset were randomly divided into ten disjoint subsections, nine subsections are employed for training and one subsection is employed for validation. The cross-validation process was repeated for ten turns, where the features vectors of each disjointed subsection will be channeled into classifiers as the validation test. Then, the single mean correct classification rate can be obtained by averaging the cross validation results.

3.5 Performance Evaluation

Four quality measures were used in the experiment namely the correct classification rate (CCR), true positive rate (TPR), false positive rate (FPR) and the area under Receiver operating characteristics (ROC). CCR is denoted as the percentage of the number of subjects correctly classified divided by the total number of subjects in the dataset. TPR is denoted as the percentage of the number of subject correctly classified divided by the total number of the subject in a class. FPR is denoted as the percentage of the subjects wrongly labeled belonging to class *i*, but belong to a different class, among all the subjects which are not of class *i*. ROC is a employed to visualizing the classifier's performance. ROC graph is a two-dimensional graph whereby FPR is plotted on x-axis and TPR is plotted on the y-axis.

4.0 ARCHITECTURE OF EXPERIMENTS

The experiments are performed in two phases: training and testing. All the gait data provided in Gaitpdb [1] were used during the training and testing phases. Figure 1 illustrates the flow of the processes that involved during the experiments.

The training involves obtaining the models for classification, by optimizing parameters for each classifier. Based on the heuristic results obtained during the training, the parameter values were set as the models for testing are shown in Table 2. In the testing phase, the models obtained from the previous phase are utilized for class classification for the Gaitpdb database.

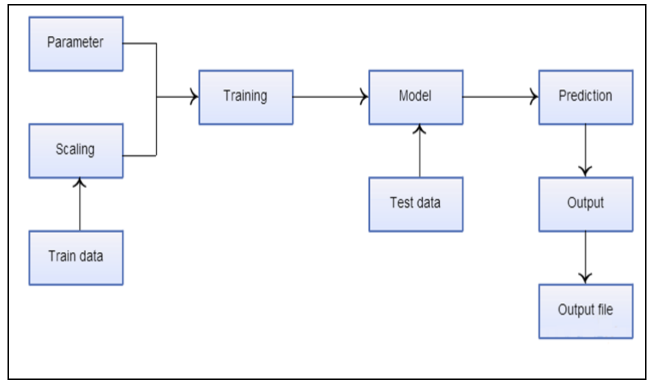


Figure 1 The flow of the processes

Table 2 The parameter values for each classifier

Classifiers	Parameters
BFT	*M* = 5, N = 4
BPANN	*MO* = 0, *L* = 0.1, *HL* = 20
k-NN	*k* = 7
SVM with Ln kernel	*C* =2
SVM with Poly kernel	*C* = 4 , *G* = 0, *D* = , *Coef* = 0
SVM with Rbf kernel	*C* = 7, *G* = 0

5.0 EXPERIMENT RESULTS AND DISCUSSION

5.1 Analysis of Extracted Features

From the values of the normalized extracted features, certain features are found to be distinct and distinguishable. These features include the statistical parameters for average stride time, vertical ground reaction force (VGRF) for left foot sensor and right foot sensor. Their range of values is shown in Table 3. (Only a few of the features are shown due to space constraints). The distinct features discussed in this Section are a result of the average stride time and leg motion differences in subjects with PD.

Table 3 The ranges of values of selected extracted features for the two classes

Features	Subjects with PD	Control subjects
Average stride time	0.1 to1.0	0 to 0.5
Maximum of average stride time	0.1 to 1.0	0 to 0.5
Median for VGRF for left foot sensor 1	0 to 1	0 to 0.5
Median for VGRF for right foot sensor 7	0.3 to 1	0 to 0.5
Median for VGRF for left foot sensor 2	0 to 1.0	0 to 0.3
Average for VGRF for right foot sensor 8	0.1 to 1.0	0 to 0.6
Kurtosis for VGRF for left foot sensor 4	0 to 1.0	- 0.3 to 0.2
Skewness for VGRF for left foot sensor 4	0 to 0.8	0.2 to 1

From Table 3, it can be observed that the range of average stride time for subjects with PD is longer than control subjects. In addition, the ranges of kurtosis and VGRF for sensors are found to be longer for subject with PD, usually due to the freezing of gait, an interruption of walking caused by debilitating muscle control. This was also discovered by many researchers in the medical field [24][25].

Generally, subjects with PD have higher stride time but lower in gait speed and stride length as compare to healthy elderly subjects [26]. PD patients are affected by gait disturbances and often found to exhibit slackens and unstable gait, even during straight line walking and gait initiation. Compared to healthy elderly subjects, they normally encounter abnormal force regulation and excessive variability during locomotion [26]. Therefore, their stride time and cadence rate are found higher than others.

5.2 Performance Classifiers and Feature Selectors

In order to evaluate the performance of the proposed model on the Gaitpdb database, numerous experiments have been conducted. This section presents and discusses the results of these experiments which were aimed to assess the classification results of the proposed model. Three features selectors; PSO search, Tabu search and Ranker were used to select the positive extracted features. Four classifiers; BFT, BPANN, k-NN and SVM were applied to find CCR, TPR, FPR, ROC and to verify the consistency of the results. Tables 4 to 9 summarized the overall classification results. Table 10 shows the average of CCR obtained for each feature selector.

Table 4 Classification results of BFT

Feature selection method	CCR (%)	TPR (%)	FPR (%)	ROC (%)
Ranker	67.60	84.10	54.70	67.60
PSO Search	65.80	83.30	51.70	68.50
Tabu Search	65.90	83.30	54.90	65.90
Average	66.43	83.57	53.77	67.33

Table 5 Classification results of BPANN

Feature selection method	CCR (%)	TPR (%)	FPR (%)	ROC (%)
Ranker	92.20	89.70	24.70	92.20
PSO Search	91.10	88.10	34.70	91.10
Tabu Search	86.60	85.70	32.00	86.60
Average	89.97	87.83	30.47	89.97

Table 6 Classification results of k-NN

Feature selector method	CCR (%)	TPR (%)	FPR (%)	ROC (%)
Ranker	88.90	86.50	41.40	88.90
PSO Search	89.50	87.30	44.40	89.50
Tabu Search	82.60	84.90	54.50	84.00
Average	87.00	86.23	46.77	87.47

Table 7 Classification results of SVM with Ln kernel

Feature selection method	CCR (%)	TPR (%)	FPR (%)	ROC (%)
Ranker	89.90	88.90	34.50	89.90
PSO Search	89.30	88.90	34.50	89.30
Tabu Search	86.20	86.50	41.40	86.20
Average	88.47	88.10	36.80	88.47

Table 8 Classification results of SVM with Poly kernel

Feature selection method	CCR (%)	TPR (%)	FPR (%)	ROC (%)
Ranker	89.50	90.50	27.70	89.50
PSO Search	87.70	89.70	34.30	87.70
Tabu Search	83.20	88.90	37.70	83.20
Average	86.80	89.70	33.23	86.80

Table 9 Classification results of SVM with Rbf kernel

Feature selection method	CCR (%)	TPR (%)	FPR (%)	ROC (%)
Ranker	90.40	89.70	31.10	90.40
PSO Search	87.60	89.70	34.30	87.60
Tabu Search	84.60	88.10	37.90	84.60
Average	87.53	89.17	34.43	87.53

Based on the result in Tables 4 to 9, the classifier that gave the highest accuracy is BPANN where the average CCR is 89.97%, slightly higher than the SVM with LN kernel whose accuracy is 88.47%. As BPANN has high tolerance against noisy data, ability in decision making and it also used in the complex data [21].

From Table 10, it can be observed that the best performances are produced by Ranker, where all the 153 extracted features were selected for classification, with comparing to 45 (PSO Search) and 48 (Tabu Search). This is because Ranker only ranked list of features without eliminating any important features that contribute positively to the classification process.

Table 10 Average of CCR (%) obtained for each feature selector

Classifier	Ranker	PSO Search	Tabu Search
BFT	67.60	65.80	65.90
BPANN	92.20	91.10	86.60
k-NN	88.90	89.50	82.60
SVM with Ln kernel	89.90	89.30	86.20
SVM with Poly kernel	89.50	87.70	83.20
SVM with Rbf kernel	90.40	87.60	84.60
Average	86.42	85.17	81.52

6.0 CONCLUSIONS

We presented a statistical model to extract gait features from a medical database (Gaitpdb) using statistical analysis. Various experiments have been performed to show the performance of the proposed model by employing three feature selectors and four classifiers. The proposed model is found able to differentiate subjects with PD from the control subjects. It can potentially predict disease severity, which could be used to monitor disease progression based on walking pattern.

Acknowledgement

The authors would also like to thank Prof. Jeffrey M. Hausdorff, Tel Aviv University, Ramat Aviv, Israel, for offering the database in this research work.

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