Design and validation of automated femoral bone morphology measurements in cerebral palsy

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Abstract

Accurate quantification of bone morphology is important for monitoring the progress of bony deformation in patients with cerebral palsy. The purpose of the study was to develop an automatic bone morphology measurement method using one or two radiographs. The study focused on 4 morphologic measurements — femoral neck shaft angle, femoral anteversion, shaft bowing angle and neck length. Fifty-four three-dimensional (3D) geometrical femur models were generated from the computed tomography (CT) of cerebral patients. Principal component analysis was performed on the combined data of geometrical femur models and manual measurements of the four morphologic measurements to generate a statistical femur model. The 3D-2D registration of the statistical femur model to radiographs computes four morphological measurements of the femur in the radiographs automatically. The prediction performance was tested by leave-one-out cross validation and was quantified by intraclass correlation coefficient (ICC) and by measuring absolute differences between automatic prediction from two radiographs and manual measurements using original CT images. For the neck-shaft angle, femoral anteversion, shaft bowing angle and neck-length, the ICCs were 0.812, 0.960, 0.834 and 0.750, respectively, and the mean absolute differences were 2.52°, 2.85°, 0.92° and 1.88 mm, respectively. The four important dimensions on the femur could be predicted from two views with high agreement with manual measurements from CT and hip radiographs. The proposed method can help young patients avoid large radiation exposure from CT and their femoral deformities can be quantified robustly and effectively from one or two radiograph(s).

Keywords : femoral morphology, cerebral palsy, automatic morphology quantification, statistical shape model

1. Introduction

Cerebral palsy is a disorder in the development of movement and posture from a brain injury during the fetal or infant period and display functional limitations of varying severity according to the extent and area of the central nervous system dysfunction [1]. The most common musculoskeletal manifestation is motor spasticity causing joint deformities. Abnormal growth of the femur is the primary cause for the significant hip problems and gait disturbance in cerebral palsy [2-7]. Increased femoral anteversion and coxa valga are common proximal femoral conditions in patients with cerebral palsy; these conditions cause an intoeing gait and hip instability, respectively [2-7]. Femoral osteotomy is commonly performed to treat this problem. Therefore, an accurate assessment of abnormal femoral morphology would provide useful information in determining the treatment options available for children with cerebral palsy. Femoral neck shaft angle and femoral anteversion are important morphological markers of abnormal femur morphology in cerebral palsy patients. Also, femoral bowing angle and neck length are additional potential markers of cerebral palsy.

The morphology of the femur can be obtained from a computed tomography (CT) scan. Important clinical dimensions of the femur such as the neck-shaft angle, femoral anteversion, shaft bowing angle and neck length can be measured from a CT scan [8-11]. Although CT scans expose children to relatively high doses of radiation [12], they provide data on the morphological dimensions of the femur from a projective view of the bone. Routine clinical measurements of the morphology of the femur are obtained from a few views at different angles, but these measurements can be inaccurate if the radiograph is taken from wrong angles [13].

The abnormal morphology of the femur in cerebral palsy patients is predicted from physical examinations [14], whose accuracy have been assessed using image based methods [8-11].

In this study, we hypothesized that the morphological dimensions of the femur in cerebral palsy patients can be predicted as accurately as manual measurements in CT using a novel statistical shape modeling approach. The specific aims include developing processes for reconstructing the 3D shape of a femur from one or two radiographs, and for automatically calculating the femoral morphological dimensions from a reconstructed femur model in cerebral palsy.

The proposed method was tested using clinical CT data and artificially reconstructed radiographs from the CT data. The accuracy in predicting the dimensions of the four morphological markers mentioned above was validated against the measurements obtained from the standard manual method using CT data.

2. Materials and Methods

2.1 Data acquisition

This study was approved by the institutional review board at Seoul National University Bundang Hospital (SNUBH IRB, B-1202/145-108). Fifty-four cerebral palsy patients who were examined by CT for torsional bony deformities and who had a hip anteroposterior (AP) and frog-leg lateral radiograph, between May 2004 and January 2010, were included. Patients with a concurrent neuromuscular disease, other than cerebral palsy, or with a history of gait correcting surgery were excluded.

To build a shape database of femurs, 3D geometric shapes were created from the CT data using medical image processing software (Mimics, Materialise N.V., Belgium, version 14.1).

2.2 Standard measurements of dimensions of the femur

Standard clinical measurements of femoral dimensions were carried out from the CT images and from radiographs by one of the authors (KHS) with 8 years of orthopaedic experience. The dimensions include neck-shaft angle, femoral anteversion, shaft bowing angle and neck length as illustrated in Figure 1. Neck-shaft angle, shaft bowing angle and neck length were measured on the hip radiographs and femoral anteversion was measured on the 3D CT image. All measurement were taken using a picture archiving and communication system software (PACS) (IMPAX; Agfa HealthCare, Mortsel, Belgium).

For their measurements, we defined the distal femoral posterior line, the center of the femoral head, and the femoral neck point on the geometry of the femur. The distal femoral posterior line connects the most posterior points in the medial and lateral condyles on the 3D CT image. The center of the femoral head was defined as the center of the circle of best fit for the femoral head on the hip AP radiographs. The femoral neck point is the intersection between the line connecting the center of the femoral head and the mid-point of the femoral neck, and the line passing through the mid-portion of the proximal femoral shaft.

The femoral anteversion was measured on the 3D CT image as the angle between the distal femoral posterior line and the line connecting the center of the femoral head and the femoral neck point. The neck shaft angle was measured with the line connecting the center of the femoral head and femoral neck point and the line passing through the upper half of the femoral shaft. The shaft bowing angle was measured with the two lines passing through the upper half and lower half of the femoral shaft. The neck length was the length between the center of the femoral head and the femoral neck point.

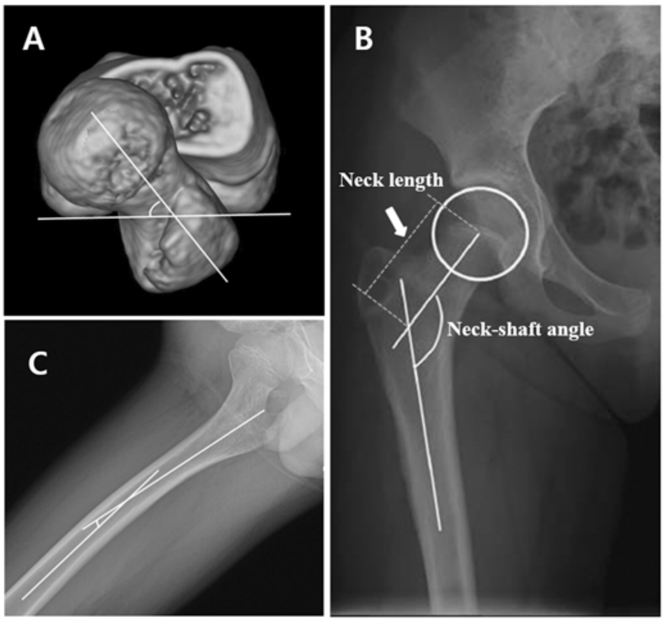

Figure 1. Clinical dimensions of the femur – (A) femoral anteversion in CT, (B) neck-shaft angle and neck length in hip radiograph, and (C) shaft bowing angle in hip radiograph

2.3 Statistical shape model and principal component analysis

For the automatic measurements of femoral dimensions, a statistical shape model based on principal component analysis was adapted in this study. The geometric locations of points on the surface of the reconstructed femur model were extracted and used to make a point distribution model [15]. Before performing principal component analysis, the 3D femur shape was aligned using the long shaft axis and the shape of the distal femoral condyles so that the analysis could focus on characteristic shape features affected by cerebral palsy. That is, the femoral shapes of cerebral palsy patients have abnormal bony deformations more in the superior part than in the inferior part; thus, the pre-alignment of the femur models with the inferior part made the statistical shape model more sensitive to the shapes in the superior part of the femur.

The numbers of feature points from the reconstructed geometric models may vary between models. To perform principal component analysis on these point data, a mesh decimation algorithm was employed to re-tessellate all geometric shapes to have an identical structure and the same number of vertices [16]. In previous studies on statistical shape modeling, the principal component analysis of 3D shape was applied only to vertex coordinates [17-19]. In this study, pre-computed clinical measurements were included in statistical shape modeling and equally treated as vertex coordinate information. Thus, a model vector consists of the XYZ coordinates of all vertices and four clinical shape measurements.

Principal component analysis of model vectors in the database produces an average model vector and model variation vectors with the same number of components as the model vector.

From the result of principal component analysis shown in Figure 2, A represents the eigenvectors for femoral shapes. Thus, a 3D femur shape (vertices of the shape) is represented as

$$v = v_{average} + Ax \tag{1}$$

where $v_{average}$ is the average shape vector and A is the shape matrix of eigenvectors. Then, a new 3D femur shape v can be made by adding the multiplication of the shape matrix of eigenvectors and weight vector x, which is called shape variation, to the average shape vector.

Once x is determined for a new femur shape, we can also determine clinical measurements, vector y, such that

$$y = y_{average} + Bx \tag{2}$$

where $y_{average}$ in equation (2) is the average clinical measurements and matrix B is the matrix of eigenvectors for the clinical measurements in Figure 2.

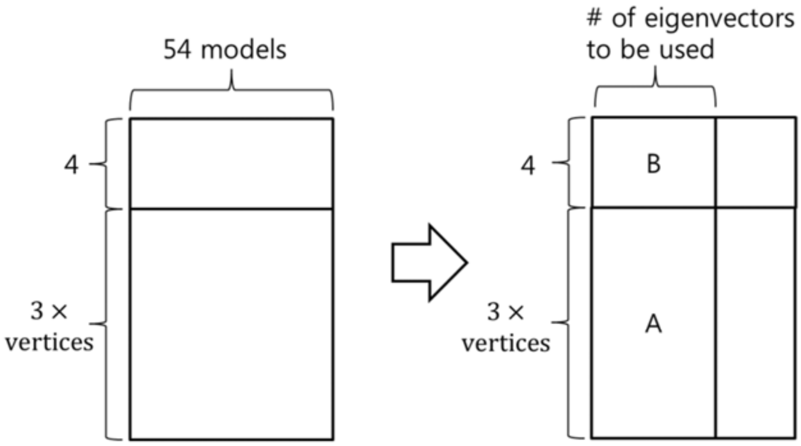

Figure 2. Principal component analysis was applied to the 54 model vectors from femur data to compute eigenvectors. The eigenvectors with higher eigenvalues were weighted and added to the average model vector to build a new model vector. A and B represent eigenvectors for the shape and 4 clinical measurements, respectively.

2.4 3D-2D Reconstruction

To reconstruct the shape of a target 3D femur in cerebral palsy patients from one or two radiographs as shown in Figure 3, a new 3D femur shape was constructed by adjusting the weight vector x in equation (1). The silhouette landmark points of the average 3D femur shape were projected to the target radiograph image(s) of a patient with cerebral palsy. Each projected landmark point was matched with the nearest femur edge point on the radiograph image(s). The three-dimensional distance between the landmark point and the nearest point on the ray connecting the corresponding femur edge point and the x-ray source were calculated and used as a matching score. Then, using the conjugate gradient descent method, variation x was adjusted to minimize 3D distance. Generally, the gradient descent method converges to a local minimum. In order to find the global optimum after it reaches a local minimum, we applied a perturbation by adding small random values to the weight vector x. This optimization process terminated when the 3D distance was less than the threshold or when it reached repeatedly at the same local point.

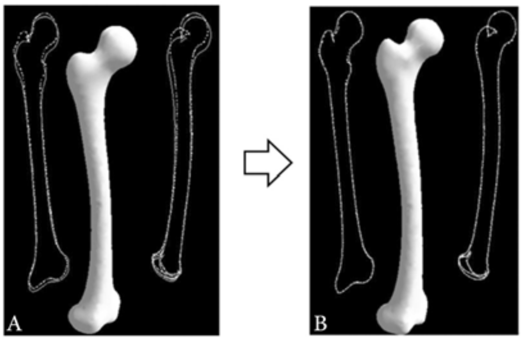

Figure 3. (A) 2D-3D reconstruction process starting from an average shape and through matching for the artificially created radiograph with bone boundaries and (B) the final predicted shape

The 3D-2D reconstruction for the femur was tested using a single image and two images from two different views –AP view only, lateral view only, and AP and lateral views together - for comparison. Also the target femur model was positioned in nine different poses for combinations of three different internal-external rotations and three different angles in the sagittal plane as shown in Figure 4 to investigate the effect of femur pose on the reconstruction results.

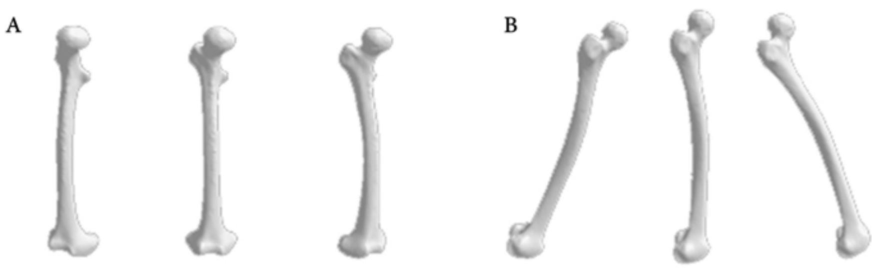

Figure 4. (A) Three different internal-external rotation angles and (B) three different flexion

angles in the sagittal plane

2.5 Statistical method

For statistical independence, only the data from a single femur of each patient were included in the statistical analysis [20]. The leave-one-out cross validation was used to understand the accuracy of the predictions of clinical measurements. Thus, a femur model out of 54 models was selected as a test model and the remaining 53 models were used as training models to create a statistical shape model for 3D-2D model reconstruction.

The four morphological measurements were estimated from the reconstructed femur models with a single image (AP or lateral) and two images (AP and lateral) each for nine different poses.

To evaluate the effect of viewing directions, each of the four clinical measurements were averaged for the nine poses and compared with the measurements from the manual standard method. The intraclass correlation coefficients (ICC) and their 95% confidence intervals were calculated by using a two-way mixed model.

The effect of a specific femur pose was also tested for two views (AP and lateral) using the ICC. An ICC of 1 indicates perfect reliability, and an ICC of > 0.8 indicates excellent reliability [21].

3. Results

The right femur models from the 54 patients (36 males and 18 females) were included in this study. The mean age of the patients was 9.9±6.5years. Neck-shaft angle, femoral anteversion, shaft bowing angle, neck length and age were selected as clinical measurements (Table 1).

Table 1. Patient demographics and manual measurements of the morphological dimensions (the gold standard in this study) from hip radiographs and 3D CT. Reported values are mean ± standard deviation.

Gender (male / female)	36 / 18
Age (years)	9.9±6.5
Types of limb involvement (hemiplegia/ diplegia/ triplegia)	16/ 36/ 2
Neck-shaft angle (˚)	133.7±5.4
Femoral anteversion (˚)	35.1±12.1
Shaft bowing angle(˚)	7.6±2.2
Neck length (mm)	41.4±3.8

First, the automatic predictions of the morphological measurements were estimated using both the AP and lateral view images and averaged for nine different poses of the femur. This was repeated with all models for leave-one-out cross validation. The result of the ICC analysis between the predictions and the primary manual measurements from the standard method is shown in Table 2. The ICC is larger than 0.8 for the neck-shaft angle, femoral anteversion and shaft bowing angle. This means that the automatic predictions agree with the primary manual measurements. The neck lengths show the lowest agreement between the predictions and the measurements with an ICC of 0.750.

Table 2. Agreement between automatic measurements using both anteroposterior and lateral views, and the primary manual measurements using standard method

Clinical measurements	ICC	95% Confidence Interval
Neck-shaft angle	0.812	0.697 - 0.886
Femoral anteversion	0.960	0.932 - 0.977
Shaft bowing angle	0.834	0.730 - 0.900
Neck length	0.750	0.604 - 0.847

ICC, Intraclass Correlation Coefficient

The ICC was calculated for the nine different poses to understand the similarity in the four predicted measurements between the poses. The predictions were made using both anteroposterior and lateral views. The ICC values for the four measurements ranged from 0.893 to 0.950, as shown in Table 3.

Table 3. Reliability of automatic measurement for 9 different poses of the femur using both anteroposterior and lateral views.

Clinical measurements	ICC	95%Confidence Interval
Neck-shaft angle	0.950	0.929 - 0.968
Femoral anteversion	0.983	0.975 - 0.989
Shaft bowing angle	0.971	0.959 - 0.981
Neck length	0.893	0.851 - 0.929

ICC, Intraclass Correlation Coefficient

The demographic statistics for the differences between the automatic measurements with two views and manual measurements showed that the femoral anteversion had the highest mean difference with 2.85 degrees, while the shaft bowing angle had the lowest mean difference with 0.92 degrees as in Table 4. The maximum differences were noticeable with 7.64 degrees (2.7 times the mean) for the femoral anteversion and 3.79 degrees (4.1 times the mean) for the shaft bowing angle.

Table 4. Difference between the automatic measurements using both anteroposterior and lateral views and the primary manual measurements using standard method

Clinical measurements	Mean	Standard deviation	Maximum	Minimum
Neck-shaft angle (˚)	2.52	1.97	7.31	0.01
Femoral anteversion (˚)	2.85	1.8	7.64	0.2
Shaft bowing angle (˚)	0.92	0.73	3.79	0.01
Neck length (mm)	1.88	1.57	7.92	0.06

To test the effect of using a single image in the evaluation of accuracy of the automatic prediction method, the statistical shape model was registered to either the AP view image or the lateral view image, and the demographic statistics on the differences between the automatic prediction method and the standard method are shown in Tables 5 and 6, respectively. In the case of using only the AP view image, all mean differences in the predictions were slightly greater than those in the predictions with two views (Table 4) with angles of about 0.5 degree and length of 0.35 mm. The prediction errors from only a lateral view image were slightly larger than those from only an AP view image, except for the prediction errors related to the shaft bowing angle.

Table 5. Difference between the automatic measurements using AP view image and the primary manual measurements using standard method

Clinical measurements	Mean	Standard deviation	Maximum	Minimum
Neck-shaft angle (˚)	2.87	2.18	8.05	0.12
Femoral anteversion (˚)	3.38	2.48	9.55	0.04
Shaft bowing angle (˚)	1.21	0.93	4.77	0.05
Neck length (mm)	2.23	1.62	7.1	0.08

Table 6. Difference between the automatic measurements using lateral view image and the primary manual measurements using standard method

Clinical measurements	Mean	Standard deviation	Maximum	Minimum
Neck-shaft angle (˚)	3.04	2.7	16.35	0.04
Femoral anteversion (˚)	3.54	3.19	16.57	0.01
Shaft bowing angle (˚)	0.88	0.69	3.16	0
Neck length (mm)	2.37	2.22	11.17	0.02

4. Discussion and conclusions

The four important morphological dimensions of the femur could be automatically determined by performing the 3D-2D registration of a three-dimensional statistical shape model to single plane or bi-plane artificially reconstructed radiographs [15, 22-24]. The statistical shape model of the femur was generated using the femur models of 54 young cerebral palsy patients; thus, the statistical femur model could encompass the variations of femoral deformity incurred by cerebral palsy and predicts the morphological measurements of the femur. The analyses in this study focused on the agreement between the automatic measurements from the statistical femur model and the manual measurements from the clinical standard method, and the level of agreement is shown as ICCs.

Advances in the field of computer vision have allowed the prediction of three-dimensional (3D) shapes and poses of geometric models from multiple-view projective images [25]. Thelen et al. could predict lower limb alignment using radiographs from two different views [26]. Advanced methodologies have been adopted for skeletal shape reconstruction from stereo radiography of a bone [15, 22-24]. Chaibi et al. presented a fast 3D bone geometry reconstruction method for lower limb and calculated clinical measurements using a parametric model and statistical inferences [23]. Heimann et al. reviewed several techniques of creating a statistical shape model based on landmarks for 3D medical image segmentation [24]. Zheng et al presented a method of 2D-3D reconstruction for the surface of proximal femur using a statistical model and a shape deformation technique from fluoroscopic images [15]. However, these studies targeted normal bones. The previous studies did not consider abnormal deformation of bones beyond the general scope of normal bones and immature bones in children.

In the shape model registration process previous studies included the angle between the gradient vector in a radiograph and the edge normal vector for each of the projected landmark points, and the Mahalanobis distance on every landmark point in the calculation of the matching score [22]. But the morphological variation of the femur in patients with cerebral palsy was larger than that of the normal femur; thus, its rate of convergence was slow and sometimes it would not converge to the global optimum when the Mahalanobis distance and the angle between gradient and normal were included. So, in this study, the angle and Mahalanobis distance scores were not used.

The limitation of this study is the relatively small sample size. The sample size of 54 may be enough for predicting femur shapes with relatively mild cerebral palsy but not enough for predicting the femur shape of those with severe cerebral palsy, which has a larger shape variation. Thus, the sample size should be further increased to increase the shape prediction accuracy. The statistical shape model generated in this study may not be applicable for predicting the femur shape associated with other diseases.

The results from registering the statistical femur model to the radiographs from two views, AP and lateral, showed high ICCs for neck-shaft angle, femoral anteversion and shaft bowing angle. The femoral anteversion had the highest ICC of 0.960, suggesting this morphological measurement would be very accurately predicted using the automatic measurement scheme.

The neck length showed a relatively lower ICC of 0.750. The automatic measurement for the neck length depends on the accuracy of determining the femoral head. The femoral head of the original femur models from cerebral palsy patients did not have a good spherical shape, as shown in Figure 5. Thus the statistical shape model had relatively higher shape registration errors in this region, which caused differences in predicting the neck length.

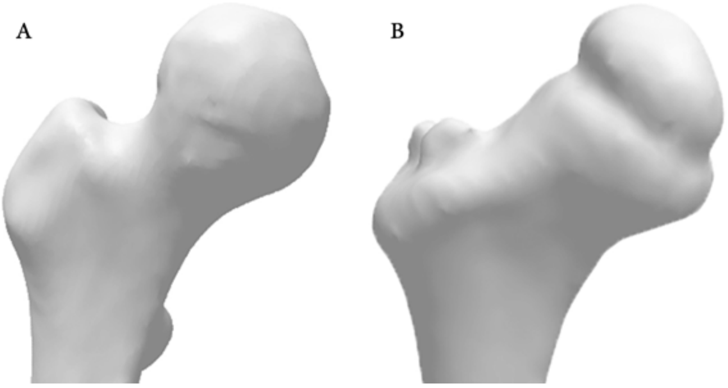

Figure 5. (A) Head of the femur in an adult with cerebral palsy (a 19-year-old female with spastic diplegia), and (B) head of the femur in a child with cerebral palsy (a 5-year-old male with spastic diplegia and increased femoral anteversion)

The absolute differences between automatic measurements and manual measurements are shown in table 4. While the variation of the femoral anteversion in the population shown as a standard deviation in Table 1 was 12.1 degrees around the mean angle, the mean difference in the automatic measurement was 2.85 degrees, which would be a very small difference in a clinical setting. Although the mean differences for neck-shaft angle, shaft bowing angle and neck length were also low compared to the population variations, the maximum differences were slightly high as 7.31˚, 3.79˚ and 7.92 mm, respectively (Table 4). This was caused by a few severely distorted femur models in our cerebral palsy patients. The majority of the original femur models had mild deformities; thus, the statistical shape model did not have a good power span over the femur models with large deformities. This weak point of the method could be improved by adding more irregular models to the database and regenerating the statistical femur model.

The results from registering the statistical femur model to the radiograph from a single view, either AP or lateral, showed absolute mean difference to the results from the two-view case (Table 5 and 6). The maximum differences were about twice larger in the lateral view, suggesting that AP view of the femur may have more features for accurate 3D-2D registration and that when using a single radiograph, AP view has higher prediction power in our method. Interestingly, the mean and maximum differences for shaft bowing angle were lowest with a single lateral view radiograph (Table 6). This may be because the femur has anterior bowing in the sagittal plane, and which is observed on the hip lateral radiographs. The effect of the rotation angle of the femur in AP and lateral views were investigated. The reliability of automatic prediction using the two views were as good as ICC > 0.950 for the measurements of neck-shaft angle, femoral anteversion, shaft bowing angle and were moderate for the measurement of neck length with ICC = 0.893, as shown in Table 3. Thus the proposed method using two views showed reliable prediction accuracies for the four morphological measurements.

In conclusion, we proposed a statistical shape model based on an automatic bone morphology measurement method of the femur of cerebral palsy patients using principal component analysis. The four important dimensions on the femur could be predicted from two views with high agreement with manual measurements from CT and hip radiographs. The proposed method can help young patients avoid large radiation exposure from CT and their femoral deformities can be quantified robustly and effectively from one or two radiograph(s).

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