Fuzzy Logic-Based Gait Phase Detection Using Passive Markers

Chandra Prakash, Kanika Gupta, Rajesh Kumar and Namita Mittal

Abstract With the advancement in technology, gait analysis plays a vital role in sports, science, rehabilitation, geriatric care, and medical diagnostics. Identification of accurate gait phase is of paramount importance. The objective of this paper is to put forward a novel approach via passive marker-based optical approach that automatically recognizes gait subphases using fuzzy logic approach from hip and knee angle parameters extracted at RAMAN lab at MNIT, Jaipur. In addition to stance phase and swing phase, the approach is capable of detecting all the subphases such as initial swing, mid swing, and terminal swing, loading response, mid stance, terminal stance and preswing. The prototype of the system provides an effective and accurate gait phase that could be used for understanding patients' gait pathology and in control strategies for active lower extremity prosthetics and orthotics. It is an automated, easy to use, and very cost-efficient yet reliable model.

Keywords Gait phase detection · Fuzzy logic · Optical based approach · Human gait analysis

1 Introduction

Over the past six decades, the quantification of gait assists health professionals to explore clinical use of gait analysis is done not only in India but worldwide. This is possible because of clinically befitting software and hardware with faster computing

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capability for collection and analysis of data for gait analysis. By definition, *Gait* is termed as manner of walking. Human gait is also known as bipedal and it is a method of locomotion achieved through two legs alternately to offer both support and propulsion with the condition that at least one foot should be in contact with the ground at all times [1]. While in case of running it is not necessary that at least one foot should be in contact with the ground.

The average adult takes 5000–8000 steps a day. The research associated with mechanics of human body while walking on stairs in an ascending/descending order to recognize explicit deviations in the gait pattern and determining their reasons and effects is known as gait analysis. Pathological gait identification is the most unswerving application of gait analysis [2]. It has other numerous applications, such as physical therapy, biometrics, rehabilitation, sports, science, and geriatric care [3–5]. Identification of gait phases is of vital importance in all these applications. Clinicians are able to utilize gait segmentation concept in their routine clinical practice to evaluate a patient's status, treatment, and rehabilitation for complex musculoskeletal and neurological disorders using the spatiotemporal and kinematics parameters.

Gait analysis is not a new research area. Systematic study of gait started with the description of walking principle by Leonardo da Vinci, Galileo, and Newton. In 1682 a student of Galileo, Borelli, described how balanced walking can be achieved using the concept of center of gravity of body in De Motu Animalium. Gait cycle was clearly described by Weber brothers in 1836 at Germany. Since 1960 clinical gait analysis has gained momentum. Contemporary work on clinical gait analysis has been discussed by Perry and Sutherland [2, 6].

Recognition of gait cycle phases is extensively useful to spot the time instance at which feedback should be applied for safety and effective response by the patient undergoing rehabilitation or physical therapy.

This paper implements a fuzzy-based approach for automatic detection of gait phase from hip and knee angle extracted using passive marker. This system is cheaper but efficient with respect to the other system. By comparing the normal and current gait cycle phase pattern, healthcare professionals can suggest an effective treatment. Details of the proposed system are described in the later section of this paper. The paper is planned and structured as follows: Sect. 2 covers the basics about the human gait cycle and the angle patterns followed by literature survey; Sect. 3 presents the implementation of fuzzy inference system for automatic gait phase detection; Sect. 4 discusses the results. Conclusions and future scope are discussed in Sect. 5.

2 Human Gait Cycle

Walking is a series of gait cycles. For understanding pathology, normal gait pattern is essential to detect alteration in gait. Gait is considered as stereotyped activity in both young and old healthy people.

2.1 Gait Cycle

The gait cycle is measured as the time period between two successive incidences of the recurring phenomena of walking. Gait cycle is a combined function of the lower extremity, pelvis, and spinal column.

Gait cycle begins with heel contact of either of the foot and ends with the heel contact of the same foot. Therefore, one complete gait cycle consists of two steps one of either right foot and then left, or vice versa. By convention, normal gait cycle is the time period in which heel of one foot contacts the ground when the heel contact of same foot takes place and forward propulsion of the center of gravity is involved.

A single gait cycle consists primarily of two phases: a swing phase and a stance phase [2]. In general, stance phase begins with the heel contact and ends with the toe of the same foot. The duration when the foot remains in contact with the ground is known as stance phase and accounts for approximately 60 % of the normal gait cycle. The duration when the foot is off the ground is known as swing phase and accounts for 40 % of the gait cycle. Swing phase begins with the toe off of the delete foot and ends with the heel contact of that same foot.

Stance phase and swing phase could be further segmented into eight segments and are referred as critical incidents that enable the examiners to further specify the abnormal aspects of gait. Classical gait model by Perry divides gait cycle into eight subphases (5 stance and 3 swing) [2].

Further, stance phase is divided among five subphases: initial contact, loading response, mid stance, terminal stance, and preswing whereas swing phase has three subphases: initial swing, mid swing, and terminal swing. Figure 1 shows the fundamentals of gait phases and expected interval of phases and subphases in total gait cycle.

For this study, initial contact and loading response are considered as same phase as former is an instance of loading response only. It is seen that different pathologies affect different segments of either swing or stance phase. Any abnormality suggests that there is pathology which should be identified by the examiner.

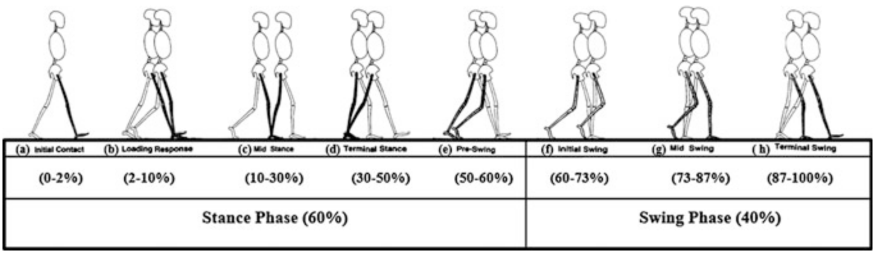

Fig. 1 Fundamental gait phases and expected interval of gait cycle [2]

2.2 Literature Survey

For quantitative gait analysis researchers have used numerous wearable sensors like gyroscopes, accelerometers, EMG sensors, force sensitive resistors (FSRs), inertial sensors, force contact sensors, foot switches, load cells, etc. [7–11]. Alternative approaches such as force plate and vision-based methods can be used to compute quantitative parameters of interest [12, 13]. All these methods have been used in gait segmentation.

Wang et al. were able to identify only initial contact, stance phase, and swing phase by using 3-axis accelerometer fixed on ankle [14]. Pappas et al. used a gyroscope attached to rear end of the shoe along with force sensitive resistors to detect heel strike (Initial Contact), stance phase, heel-off and swing phase. Only four phases were identified by this approach [7].

Computational-based techniques have also been proposed for real and precise gait phase recognition. Researchers have explored fuzzy inference system (FIS) to segment gait phase. Liu et al. used gyroscope and accelerometers to detect four gait phases using fuzzy logic due to its robustness to noise [15]. Kyoungchul et al. implemented fuzzy-based approach to detect gait phases from foot pressure patterns [16]. DeRossi, et al. have used hidden markov model for identification of six gait phases [17].

But in all these techniques, one or more sensors need to be attached to one or both legs which is not an appropriate approach as the presence of sensors, cables, or other components hinder the subject's natural motion. In contrary, vision-based analysis systems can be used to obtain gait kinematics smoothly and continuously without affecting the natural motion. The technology associated with this measurement approach has continued to change over the past decade.

A new approach using red color reflective marker is used to obtain the gait cycle and spatiotemporal and kinematic parameters [18]. This paper is the extension to this work and uses fuzzy logic for gait phase identification technique using two joint angles obtained from 2D optical system proposed at RAMAN lab, MNIT Jaipur. Other than these, time and stage variables are also considered.

Similar kind of work is reported in [19], in which author deployed hip, ankle, and knee angle to segment gait cycle. Another work in [20] relies on 3D information. MarioI et al. used a noninvasive vision system to identify the phases [21]. The system proposed in this paper is inexpensive but accurate as compared to previous approaches. A system has been fabricated to detect the phases for a normal gait in aforestated sequence. The algorithm employed in this system can identify the abnormality or missing gait phases, thus it could be incorporated in obtaining the timing of feedback in control strategies for active prosthetics.

This automated segmentation method based on the analysis of knee and hip data obtained from 2D optical system has been put to test on six healthy subjects.

3 System Architecture and Joint Angles

The proposed system consists of a digital video camera for recording and a computer for data acquisition and processing. Figure 2a illustrates the marker position. Figure 2b shows an optical motion capture system developed to detect and track the markers fastened to the subject's body at anatomical points of concern [18].

An algorithm has been developed to process video frames and knee and hip angles are obtained as shown in Fig. 2c. The fuzzy inference system (FIS) shown in Fig. 2d maps inputs (hip and knee angles) to outputs (gait phases) using a predefined set of fuzzy rules. These rules will be touched upon in the later section. Finally, the output of this system is segmented as gait cycle. MATLAB has been used to develop FIS.

In [13, 18] Prakash et al. discussed a method of obtaining joint kinematics and Spatio-temporal parameters using passive markers. An optical motion capture system is developed to detect and track the subject's joint movements in 2D space.

The data obtained from the experiment is processed using a simulation framework, which assists in kinematic and dynamic analyses of human gait. The joint coordinates obtained by tracking the five reflective markers are then used for 2D gait analysis. The data are then filtered using average filtering techniques to remove irregularity. Figure 3 shows the average knee and hip joint angle patterns for normal walking.

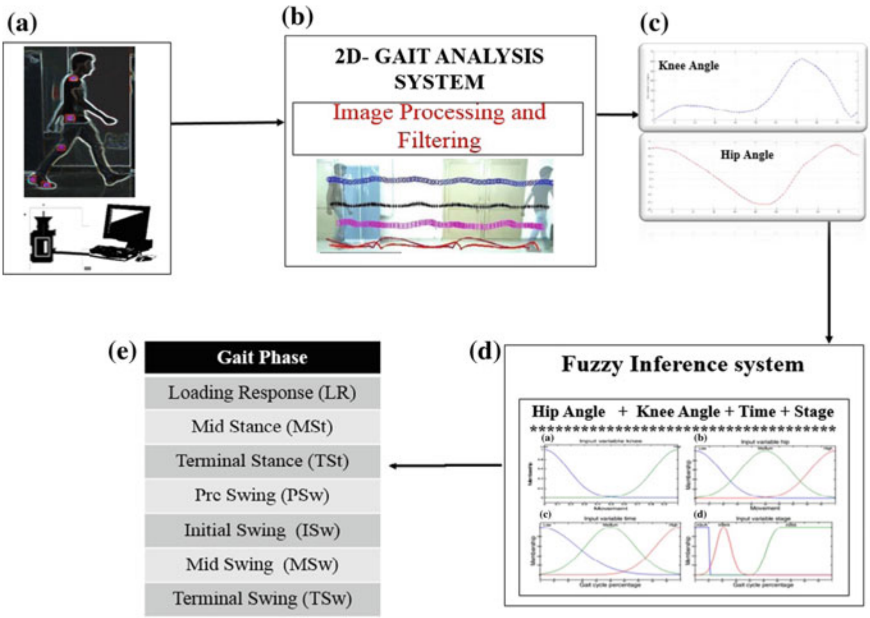

Fig. 2 Gait phase detection system methodology; **a** Marker setup and data acquisition; **b** Gait analysis system; **c** Gait kinematics extraction; **d** Fuzzy inference system for gait phase identification; **e** Phase detection

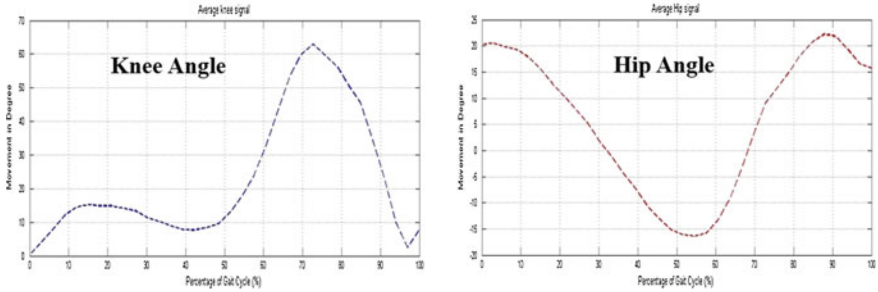

Fig. 3 Average knee and hip joint angle for one gait cycle

4 Fuzzy Inference System

At a given stance of time, kinematic parameters such as hip, ankle, and knee angle can be put to use to detect the gait phase [22]. One possible approach for gait segmentation is by setting threshold for discrete event analysis. But it has a limitation in implementation, for this change the signal should be clearly visible. Change in phases is not visible in knee and hip angle parameter as gait is not a set of isolated actions, although phases keep changing continuously and smoothly. Thus, there is need for a new approach to efficiently detect the gait phase.

Fuzzy logic is best suited for representation of information extracted from inherently imprecise data. Fuzzy logic handles imprecision, vagueness, and insufficient knowledge. Gait phase identification activities are often vague or based on intuition, as one cannot clearly differentiate all phases. Fuzzy logic can work in this scenario with reasoning algorithms to simulate human reasoning and judgment making capability in machines. These procedures let researchers to build intelligent system in the areas where data cannot be represented in binary form. Fuzzy logic lets intelligent systems to perform optimally with uncertain or ambiguous data and knowledge.

Zadeh proposed this concept of fuzzy logic in 1965 [23]. In contrast to conventional, Boolean logic has either ON (1) or OFF (0) value, fuzzy system can have membership value between zero and one. In binary logic, if membership value is zero, phase is not detected; if one, phase is fully detected. It is used in modeling imprecise concepts and dependences (set of rules). Thus, it can be stated that fuzzy logic has an advantage over binary logic in some applications.

A fuzzy expert system involves four modules that are fuzzification, inference, knowledge base, and defuzzification are of expert system. Fuzzification converts crisp number input to fuzzy set by using membership function. In order to draw the inference, fuzzy logic necessitates knowledge which is stored in the fuzzy system and provided by an expert who have experience or who knows the process of that specific domain. If-then rules suggested by expert are stored in knowledge base. Using these rules, inference engine simulates reasoning process similar to humans but output is in fuzzy form. So, there is need of conversion of fuzzy set to crisp value, i.e., defuzzification.

4.1 Input Parameter of the Fuzzy Membership Function

In this research, only two joint angles; knee and hip along with time and stage (function of time) variables have been considered. As discussed earlier hip and knee angle used has been taken from our previous work [18]. Time and stage variables have been considered along with hip and knee angles as input [21]. The membership function (MF) values for hip, knee, time, and stage input are defined based on the normative data presented in [2, 21] and is shown in Table 1.

Hip angle can be divided into three intervals (Extension, Low Flexion, and high Flexion). Knee angle movement is also divided into three intervals (Low, Medium, and High). Similarly, input variable, time is divided into low, medium, and high intervals. Stage variable is similar to time variable but not determined function of interval. Instead it has loading response (SLR), Mid stance (SMS) and swing stance (SSS) as its membership functions. In this stage input variable is employed to differentiate between the phases, mid stance and terminal swing and between loading response and initial swing. Gaussian function is used for hip, knee, and time. For stage variable, SLR uses polynomial-based Z-function, Gaussian function is used for SMS membership and S-function is used for SSS. The membership function for phase is used as triangular as shown in Fig. 4.

4.2 Fuzzy Rule Classification

Gait phase detection's If-Then rules recommended by an expert are stored in knowledge base. For defining fuzzy rules, books on gait analysis and biomechanics have been referred [1, 2, 24] but all variables are not considered in this research and shown in Table 2.

Table 1 Fuzzy membership function for inputs parameters

Input	Quantity
Hip	Extension (0 to −30), low flexion (0–15), high flexion (15–30)
Knee	Low (0–20), medium (20–40), high (40–70)
Time interval (% of gait)	Low (0–25), medium (25–75), high (75–100)
Stage	Loading response (SLR) (0–10 %), mid stance (SMS) (10–40 %), and swing stance (SSS) (40–100 %)

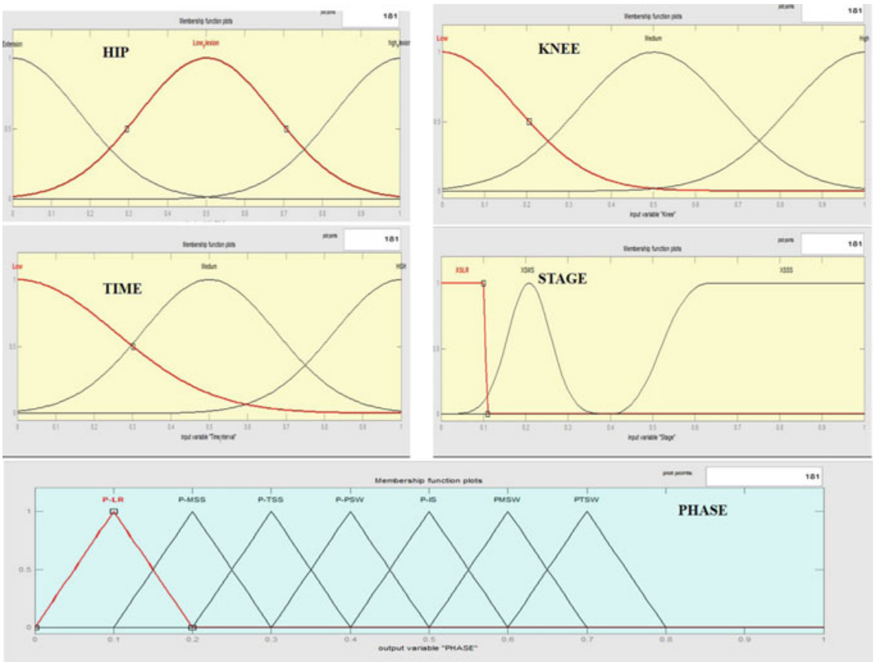

Fig. 4 Membership function for input variable: hip, knee, time and stage, and output variable phase

Table 2 Set of fuzzy rules [1, 2, 24]

	Hip	Knee	Time	Stage	Gait phase
1	High flexion	Low	Low	SLR	Loading response (LR)
2	Not high flexion	Low	Low	SMS	Mid stance (MSt)
3	Low flexion	Low	Low	SMS	Mid stance (MSt)
4	Extension	Medium	Medium	–	Terminal stance (TSt)
5	Extension	Not low	Medium	SSS	Preswing (PSw)
6	Low flexion	Not low	Medium	SSS	Initial swing (ISw)
7	High flexion	High	High	SSS	Mid swing (MSw)
8	High flexion	Low	High	SSS	Terminal swing (TSw)

The fuzzy system designed for this work is a Mamdani system. The defuzzification scheme used is centroid-based. That is, the output is just the consequence of a specific condition of the lower body section.

For example, a condition for the loading response phase in Table 2 suggests that as "If hip angle is of 20° while Knee is 18 and Time period are 18 % and Stage is also 18 % of total time, then the human motion is in the LR phase".

Fuzzy logic expresses the statement as "Hip angle is of High Flexion nature AND Knee angle has Low MF AND Time interval is also Low AND Stage is SLR then PHASE is Loading Response". Value of Membership function of the Loading Response phase is approximately equal to one. Based on these rules, gait phase can be determined at any given instance of time.

5 Experimental Result

5.1 Data Set

Five healthy young subjects were chosen for conducting the experiment. Each subject walked on a starting line six times. Before the actual trial, subject was asked to walk for three trials so that they feel comfortable with the setup. This is very important for normal data collection and subjects confirmed this in feedback. Gait data of five subjects comprising of both male and female subjects with the age group between 18 and 30 years was recorded. Markers were fastened to the clothes of the targeted subject at anatomical points of concern, i.e., shoulder, hip, knee, ankle, and toe. The Kinematics parameters of the subjects were visualized using MATLAB.

5.2 Gait Phase Identification

The result of one of the healthy subjects (age 20, weight 54) corresponding to the knee and hip is shown in Table 3 and Fig. 5. The first phase, loading response is found in the interval 0–10 %, which indicates a normal behavior occurrence of this phase.

Mid stance is detected in 10–32 %. The terminal stance phase is detected in the percentage 33–50 % and preswing is found in the range of 50–64 %. The initial swing is detected in the percentage of 64–75, mid swing is located in 75–87 %. The terminal swing phase is correctly detected in the percentage 87–100 %.

Cross validation of these results with Fig. 1 as shown in Table 3 indicates that this system reports very similar outcome with few differences but these differences are not significant. Detection of gait phase is in natural order, i.e., LR, MSt, TSt, PSw, ISw, MSw, and TSw. This shows that that subject gait pattern is free from gait

Table 3 Extracted gait phases using proposed system for a subject

Gait phase	Our result (%)	Actual values (%) [2]
Loading response (LR)	0–10	0–10
Mid stance (MSt)	10–32	10–30
Terminal stance (TSt)	33–50	30–50
Pre-Swing (PSw)	50–64	50–60
Initial swing (ISw)	64–75	60–73
Mid swing (MSw)	75–87	73–87
Terminal swing (TSw)	87–100	87–100

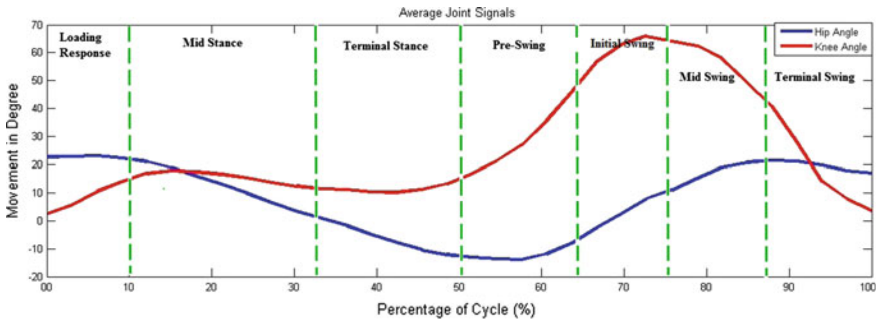

Fig. 5 Kinematics signal and phase detection

abnormalities in the subject gait pattern. The result of the fuzzy system is illustrated in Fig. 6. Based on fuzzy rules, the result follows the natural order of phase sequence and at a time only one gait phase has been detected.

Normal gait phase plots for two strides are clearly shown in Fig. 6. It can be clearly seen that the sequence of gait phases obtained is in natural order. Detected

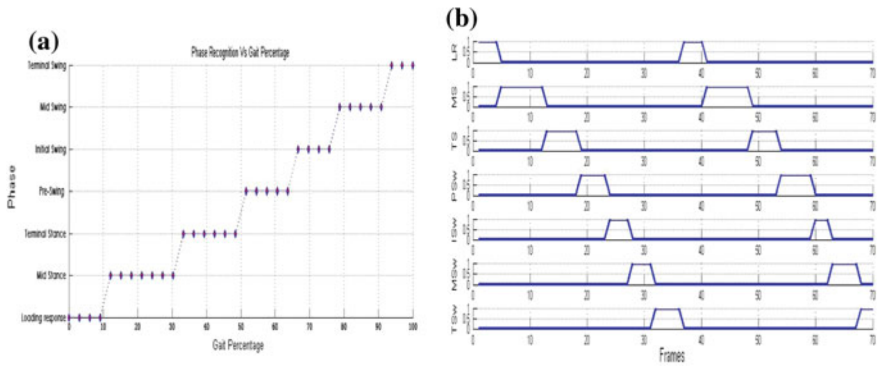

Fig. 6 **a** Gait phase and cycle percentage. **b** Normal gait phase plots for two strides

gait phases in each gait cycle had a maximum membership value of 1, stipulating that within a gait cycle, all phases were fully identified. It also indicates that a maximum mean deviation of 1.04 % with reference to normative data is spent in transition from one phase to another phase.

6 Conclusions and Future Scope

The work discussed in this paper is initial study of implementing fuzzy based techniques for gait segmentation for 2D optical-based system using passive marker. The main benefit is that these markers do not need high cost and excessive time in placing. The effect of passive makers on normal gait pattern is also very less as compared to other makers. The subjects' opinion on these marker enactments further simplified that the setup did not affect the gait performance. Findings of the experiments indicate that this technique was able to correctly segment the gait phases at very low cost using fuzzy based approach. For all the healthy subjects considered in this research identification rate in natural sequence is 100 %. This approach of gait phase detection has the potential to use in rehabilitation activities and gait analysis.

Though the method presented in the paper is cost-effective, reliability can be improved using sensors such as accelerometer, goniometer, and EMG are used. With the use of hybrid computational techniques, such as neuro-fuzzy approach, could further improve accuracy and robustness of system for the gait phase detection algorithm.

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