Phase Learning to Extract Phase from Forelimb(s) and Hindlimb(s) Movement in Real Time

Dollaporn Anopas, Junquan Lin, Seng Kwee Wee, Peh Er Tow, Sing Yian Chew, and Wei Tech Ang

***Abstract*—Interlimb coordination is important for the enhancement of walking gait in spinal cord injured patients and many studies have recently attempted to dynamically map these movements for use in assistive devices. Nevertheless, there are many difficulties such as high variation of signal and lack of precise algorithms to extract continuous phases in real time. An improved phase learning to extract forelimb(s) and hindlimb phases from movements in real time is proposed. To quantify the performance of our proposed phase learning method, this phase learning is compared to Hilbert transform, a commonly used analytical method for offline process, with principal component analysis (PCA). The comparison between two methods demonstrated that a percentage of root mean square (RMS) time error between goal phase and output phase from our phase learning method is 7.94% as compared to that of Hilbert transform (7.44%). This phase learning that can extract phase in real time improves the analysis of interlimb coordination in robotic application.**

***Index Terms*—phase learning, Hilbert transform, neural network architecture, standardized relative position**

I. Introduction

As the interlimb coordination is crucial for dynamic stability [1], maximization of residual function [2], and stimulation of signal exchange between cervical and lumbar enlargement [3], many studies have attempted to develop an algorithm that can provide interlimb coordination for human spinal cord injured patients [4], [5]. Given that rodents are usually utilized in a spinal cord injury model [6], [7], there are some difficulties to develop the algorithm for interlimb coordination in rat locomotion such as inconsistent walking pattern, signals from unpredictable behavior, and lack of an accurate algorithm to extract a continuous phase in real time.

The existing method to extract a stepping phase is composed of two main methods which are using a motion capture system and attached sensors. The information from each method can be used to extract a discrete phase or a continuous phase. The extraction of a continuous phase using sensors is frequently used in signal processing such as the extraction of electrocardiogram [8] and electroencephalogram [9], [10] phase through electrodes. The advantages of using the motion capture system include no disruption of walking gait, convenient setup on a human body or an animal body, and an ability to capture details of body parts during walking. The disadvantages are a high cost system and an occlusion problem. Alternatively, the advantages of using sensors are a cheaper system and no occlusion problem. The drawbacks of using sensors are disruption of walking gait, inconvenience for setup on a human body or an animal body, and inability to capture the walking motion. Hence, this study aims to develop the algorithm to extract continuous phase from movement signal in real time using two cameras.

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II. Methods

A. Phase Extraction

Based on a previous study, phase learning can extract continuous stepping phases even with speed variation [11]. However, the phase learning method is done offline using the past, current, and future samples which are not suitable for our application. Therefore, this work modifies the above method [11], [12] and uses only the past and current samples to extract a phase from six movement types (forelimbs of injured and healthy rats, individual left and right forelimbs, and individual left and right hindlimbs). Our proposed phase learning method to extract a phase consists of two main steps: a training step and an inferencing step. After the training step is done, the inferencing step is carried out to ensure that the training step is learned correctly.

To prove that this phase learning method has the potential to extract a phase, the percentages of RMS time errors between the goal phase and the output phase from our phase learning are verified. Furthermore, the percentages of RMS time errors of our phase extraction method are compared to those of the phase extraction from an analytical method which is Hilbert transform with PCA. The Hilbert transform is used as a benchmark. Since the Hilbert transform cannot accurately extract a phase in real time, the phase learning method is developed to extract a phase in real time.

1) Data Collection: Fourteen healthy rats were trained on the treadmill at a speed of 3cm/s until they are familiarized with walking on the treadmill. The number of record data is three sessions per rat. However, some rats were recorded for only two sessions because they showed signs of fatigue. One rat was recorded four sessions since it did not get used to the training to observe the performance of the phase learning method. The data from 12 healthy rats were used in the training step and the rest of the data from two healthy rats were used in the inferencing step. Likewise, 14 rats with SCI treated with fiber scaffold were trained on the treadmill at a speed

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of 3 cm/s. The collection was done when the rats adapted well to the training. Walking data from 12 rats with SCI were used in the training step and walking data from other two rats were used in the inferencing step. The rats' locomotion were recorded using two high-speed cameras at 100 fps and the left and right frames are synchronized. The bony landmarks of the rat's hindlimbs and forelimbs were painted and tracked using the mean-shift algorithm. These markers were tracked to study the relationship between the movement of the limbs.

2) Data Preparation: For forelimbs phase extraction in injured and healthy rats, the movement of the forelimbs contains left and right forelimb gait cycles; therefore, the input data are the standardized relative left and right wrist positions (Fig. 1), the state of the last forelimb that lifts above the treadmill's belt, and the heading directions of all these signals. The state of the last forelimb that lifts above the treadmill's belt is to differentiate between the end of the left forelimb swing phase and the end of the right forelimb swing phase. For individual left forelimb phase extraction, the signals are from left wrist position in x- and y-axes and the heading directions of their signals. Similarly, the signals and heading directions for individual right forelimb phase extraction are from the right side. The state of the last forelimb that lifts above the treadmill's belt and its heading direction are excluded as they are not required to extract the individual forelimb phase. For individual left hindlimb phase extraction, the input data of the left hindlimb phase extraction are the standardized relative left ankle position, the state whether the left hindlimb is on the treadmill, the state whether the left ankle is in front of the left iliac crest, and their heading directions. Likewise, the signals to input the individual right hindlimb phase extraction are obtained from the right side. The hindlimb phase extraction is more complex; therefore, it requires a greater number of input signals as compared to the forelimb phase extraction. All input signals are standardized to a mean of zero and a standard deviation of one.

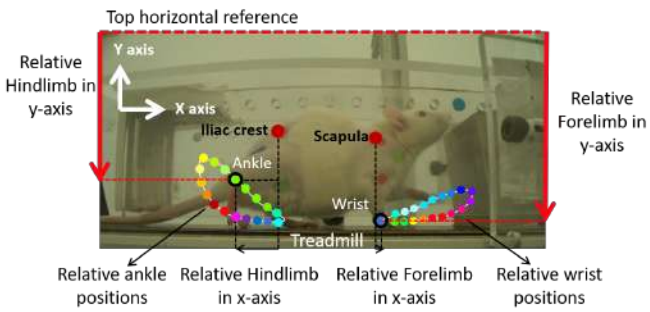

Fig. 1. Diagram of relative wrist and ankle positions

3) Data Training: The six movement types, which are forelimbs phase extraction in injured rats, forelimbs phase extraction in healthy rats, individual left and right forelimb phase extractions in healthy rats, and individual left and right hindlimb phase extractions in healthy rats, share the same neural network architecture as shown in Fig. 2. Only input data are different as mentioned in Section II-A2. It contains four main layers which are input layer, hidden layers, pre-phase layer, and output layer. The input layer contains signal windows and heading direction windows. Each window contains eleven and seven samples for forelimbs phase extraction in injured rats and all types of phase extraction in healthy rats, respectively. The preparation data are fed feed-forwarded to a neural network to extract a phase value. There are five fully connected hidden layers. The first four hidden layers are fully connected with a hyperbolic tangent activation function. In the last hidden layer, all nodes are fully connected to two nodes in the pre-phase layer using a linear activation function. Each layer is composed of 25 nodes. A normalization of two nodes in the pre-phase layer is represented on a 2D unit vector in the output layer. From Jatesiktat's study [13], we use the first three penalty terms: phase progression, distribution, and singularity for phase learning and extraction of limb(s) movement in healthy rats. The marginal singularity penalty is added for phase learning and extraction of forelimbs movement in injured rat since this penalty is to improve a generalization of neural network model. The weights for phase progression penalty term, distribution term (α), singularity term (γ), and marginal singularity term (λ) are 1.00, 0.45, 0.55, 0.55 respectively. The phase progression penalty parameters are a; b; and c according to Jatesiktat's study [13]. These parameters are summarized in Table I.

TABLE I
SUMMARY OF PHASE PROGRESSION PENALTY PARAMETERS

Types of movement	a	b	c
Forelimbs in injured rats	-0.017	0.052	-2.355
Forelimbs in healthy rats	-0.040	0.070	-2.355
Left forelimb and right forelimb in healthy rats	-0.040	0.070	-2.355
Left hindlimb and right hindlimb in healthy rats	-0.040	0.087	-2.355

Another phase extraction method as mentioned above is the Hilbert transform with PCA [8]. Since the Hilbert transform can extract only one-dimensional data, the dimension of input is reduced using PCA. An imaginary part of the complex signal from a real part can be recovered by the Hilbert transform [8]. An instantaneous phase can be calculated by an angle in a complex coordinate [14]. Different types of movement have different input signals. For forelimbs phase extraction in injured and healthy rats, the input signals consist of standardized relative positions of left and right wrists in x- and y-axes. For the individual left phase extraction, input signals are standardized relative positions of left wrist position in x- and y-axes. Similarly, input signals for the individual right phase extraction are obtained from the right side. For the individual left hindlimb phase extraction, input signals are standardized relative positions of left ankle position in x- and y-axes. Likewise, the input signals for individual right hindlimb phase extraction are obtained from the right side.

B. Verification of Phase Extraction Methods

The percentage of RMS time error between goal phase and output phase from both phase extraction methods is quantified

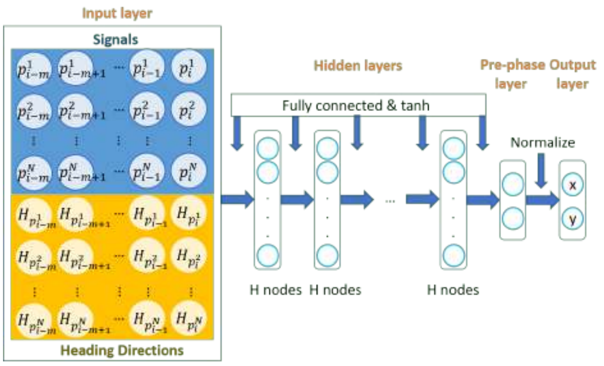

Fig. 2. Neural network architecture for phase learning and extraction. $p^j_{i-m}, p^j_{i-m+1}, ..., p^j_i$ are the signals at past and current samples $i-m, i-m+1, ..., i$. $H_{p^j_{i-m}}, H_{p^j_{i-m+1}}, ..., H_{p^j_i}$ are the heading directions of the signals at past and current samples $i-m, i-m+1, ..., i$. j is the j-th dimension of input signals. N is the dimension of input signals.

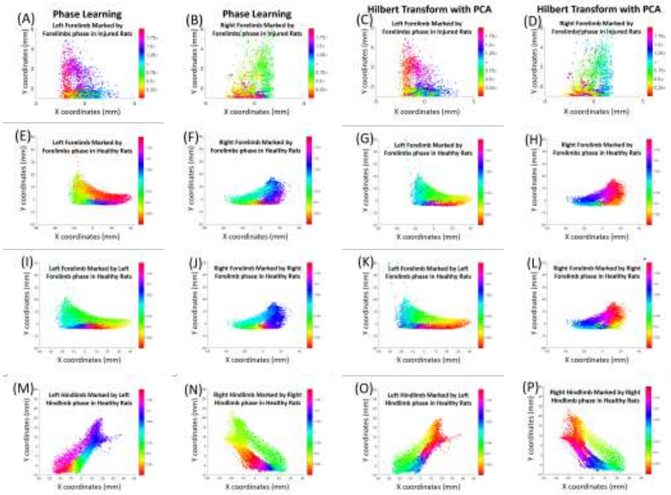

Fig. 3. Standardized relative positions of the wrists (A-L) and ankles (M-P) painted with its (Column 1 and 2) phase learning and (Column 3 and 4) Hilbert transform with PCA using testing data set of (A-D) one injured rat and (E-P) one healthy rat

to evaluate the performance of two phase extraction methods and to compare our phase learning method with the Hilbert transform with PCA, which is our benchmark.

To compare the performance of phase extraction methods, the goal phase at two distinct states which are touch-down and lift-off phases of left and right forelimb phase and heel strike and toe-off phases of left and right hindlimb phase are automatically detected by a change of slope of relative wrist/ankle position in x-axis. Phases are assigned by interpolation. Unpredictable behavior data are manually removed by a researcher. Only normal continuous walking gait data are quantified.

III. Results and Discussions

A. Phase Extraction

1) Phase Learning: From the testing data set, color patterns in each row of Fig. 3 (Column 1-2) are similar to those of Fig. 4 (Column 1-2). The color in those figures represents the phase. For example, while a right forelimb is in a mid-swing phase or a green area, a left forelimb is in a mid-stance phase or a green area as shown in Fig. 4 (Row 1, Column 1-2). Interestingly, relative wrist positions painted with its forelimbs phase learning in injured rats (Fig. 4 (Row 1, Column 1-2)) are more consistent than those of healthy rats (Fig. 4 (Row 2, Column 1-2)) because training data of forelimbs phase learning in injured rats are selected only walking scenario data while training data of forelimbs phase learnings in healthy rats are mostly from walking data and have some unpredictable behaviors of healthy rats. If the abnormal walking patterns in injured rats are not filtered out, it is almost impossible to obtain neural network model of walking data in injured rats because of high adaptation and variation of their movement patterns. For the forelimbs phase learning in injured and healthy rats (Fig. 4 (Row 1 and Row 2, Column 1-2)), the phase difference between left and right forelimbs obtained from forelimbs phase learning is approximately π which conforms with the study by Danner [15]. Mixtures of color in Fig. 4 (Row 2, Column 1-2) appear because of the variation of walking data and the unpredictable behaviors of rats. Since Fig. 4 (Row 1 and Row 2, Column 1-2) show more mixtures of color than Fig. 4 (Row 3, Column 1-2), the forelimbs phase at one timestamp needs to have the same phase in both left and right forelimbs. Therefore, these color mixtures normally appear when a rat pushes an acrylic enclosure. The color trends in Fig. 4 (Row 4, Column 1-2) are also clearer than those of Fig. 4 (Row 1 and Row 2, Column 1-2) because it has no time limitation. Interestingly, the ratios between the step cycle percentage of stance and swing phase from the average left and right hindlimb trajectory are equal to 75:25 and 76:24, respectively. These ratios were in close agreement with Alluin's study which found that the stance phase and swing phase ratio is 78:22 [16].

2) Hilbert Transform with PCA: Relative left and right wrist and ankle positions in x- and y-axes painted with the phase of each type of movement using the Hilbert transform with PCA calculated from training data (Fig. 4 (Column 3-4)) show similar color trends with standardized relative left and right wrist and ankle positions in x- and y-axes painted with the phase of each type of movement using the Hilbert transform with PCA calculated from testing data (Fig. 3 (Column 3-4)). For the forelimbs phase extraction in injured and healthy rats, the phase difference between left and right forelimb phase is approximately π which conforms with the study of Danner [15]. Some color mixtures that appear in Fig. 4 (Column 3-4) might occur from a high variation of walking data of rats and the Hilbert transform cannot accurately extract the signal that rises and falls many times in one period. Hence, the color mixture appears when a signal moves up and moves down multiple times in one period. Interestingly, the color trends in Fig. 4 (Row 3 and Row 4, Column 3-4) are more consistent than those of Fig. 4 (Row 1 and Row 2, Column

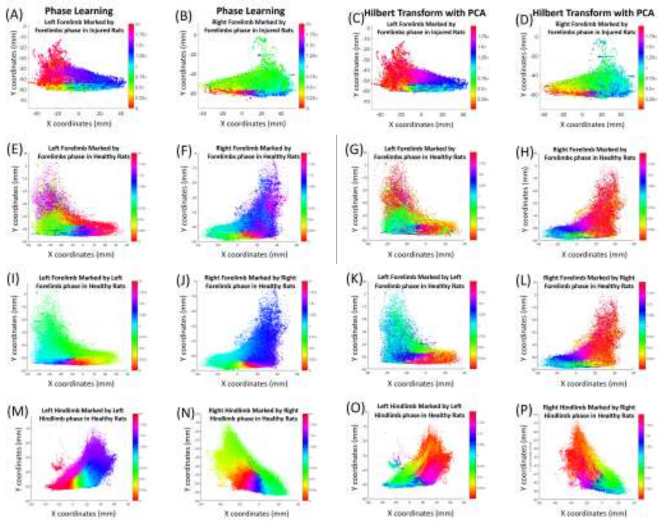

Fig. 4. Relative positions of the wrists (A-L) and ankles (M-P) painted with its (Column 1 and 2) phase learning and (Column 3 and 4) Hilbert transform with PCA using training data set

3-4). This is because the relative positions of the left and right wrists painted with forelimbs phase from the Hilbert transform with PCA which are obtained from left and right forelimb signals at the same timestamp are forced to be the same forelimbs phase while an approach to extract individual forelimb phase and individual hindlimb phase does not have this enforcement. For the individual left and right hindlimb phase extractions (Fig. 4 (Row 4, Column 3-4)), the ratios between the step cycle percentage of stance and swing phase from the average left and right hindlimb trajectory are 52:48. These ratios are far from Alluin's study [16] that shows the ratio of stance and swing phase is approximately 78:22.

B. Verification of Phase Extraction Methods

The mean of all percentages of RMS time error from the Hilbert transform with the PCA method is 7.44% and that of the phase learning method is 7.94%. The average percentages of RMS time error of phase extraction from some types (forelimbs and left hindlimb phase extractions in healthy rats) of phase learning method is less than those of the Hilbert transform with PCA. Nonetheless, the average percentages of RMS time error of phase extraction from the rest types (forelimbs phase extraction in injured rats, left forelimb, right forelimb, and right hindlimb phase extractions in healthy rats) of phase learning method is more than those of the Hilbert transform with PCA. Of note, the difference in the average percentages of RMS time error of phase extraction between these two methods is less than 3.5%. These results prove that our phase learning method can extract an accurate phase as compared to the Hilbert transform with PCA.

IV. CONCLUSION

Even though the mean percentage of RMS time error between goal phase and output phase from our phase learning method is slightly higher than that of Hilbert transform with PCA, our phase learning can accurately extract forelimbs phase in real time while Hilbert transform with PCA cannot extract an accurate phase in real time. We found that the accuracy of phase extraction from our learning method (92.06%) is comparable to the accuracy of phase extraction from the Hilbert transform with PCA (92.56%) which is used as a benchmark. This proves that our phase learning method has the potential to extract phase of the rat's limb movement in real-time application.

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As our study involved animal subjects, the animal-related experiment has been approved by Institutional Animal Care and Use Committee (IACUC-A0309).

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