Detection of lameness and determination of the affected forelimb in lame horses by use of continuous wavelet transformation and neural network classification of kinematic data

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Objective—To investigate wavelet transformation and neural network classification of gait data for detecting forelimb lameness in horses.

Animals—12 adult horses with mild lameness in the forelimbs.

Procedure—Position of the head and foot, metacarpophalangeal (ie, fetlock) joint, carpus, and elbow joint of the right forelimb were determined by use of kinematic analysis before and after palmar digital nerve blocks. We obtained 8 recordings without lameness, 8 recordings of horses with mild lameness of the right forelimb, and 8 recordings of horses with mild lameness of the left forelimb. Vertical and horizontal position of the head and vertical position of the foot, fetlock joint, carpus, and elbow joint were processed by continuous wavelet transformation. A time-sequence composition process was used to create feature vectors that captured the pattern for the transformed signal. A neural network was then trained with the feature vectors extracted from 6 horses and tested with data for the remaining 2 horses for each category. The study continued until each horse was used twice for training and testing. Mean correct classification percentage (CCP) was calculated for each combination of gait signals tested.

Results—By use of wavelet-transformed data for vertical position of the head and right forelimb foot, the CCP (85%) was greater than the CCP determined by use of untransformed data (21%). Adding data from the fetlock joint, carpus, or elbow joint did not improve CCP over that obtained for the head and foot alone.

Conclusions and Clinical Relevance—Wavelet transformation of gait data extracts information that is important in the detection and differentiation of lameness in the forelimbs of horses. All of the necessary information to detect lameness and differentiate the affected forelimb in lame horses can be obtained by observation of vertical head movement in concert with movement of a foot of 1 forelimb. (*Am J Vet Res* 2003;64:1376-1381)

Equine practitioners detect and evaluate lameness by observing movements of the horses. This skill can be difficult to develop, because practitioners need to consider rapidly changing body movements.[1,2] In limited studies[3,4] that have compared scores for visual evaluation between observers or results for visual with results for an objective gait-analysis technique, substantial variability and error has been documented. This variability and error emphasize the need to develop and use more objective methods to identify and quantify lameness in horses.

Kinematic gait-analysis techniques permit objective measurement of movements in horses. Computer-assisted motion-analysis systems use the latest video-based animation technology, and such analysis can be sensitive and accurate with regard to the detection of lameness in horses.[1,2,4,5] A voluminous quantity of data can be collected in a short period by use of these systems. Processing and analysis of such a large volume of data is difficult and time-consuming. Because of the daunting task of analyzing the entire quantity of data, investigators of most kinematic studies have selected only a few, specific variables for measurement. A standard and simple approach is to measure the amplitudes of local events occurring within the collected time-series data. However, this approach leaves much of the potentially useful data recorded but unanalyzed.

Processing of raw displacement data to obtain general movement characteristics is used in an attempt to extract more information for analysis. Fourier analysis, which transforms the signal into its frequency components, is commonly used.[6] **Continuous wavelet transformation (CWT)** is another mathematic technique that transforms a signal into component waveforms. Continuous wavelet transformation captures global frequency and local time-based information about a signal and has been useful in evaluation in many areas of biomedical signals.[7,8]

After extraction of relevant information from the kinematic data, there must be some technique that reliably classifies this information and makes it clinically useful. Numerous mathematic and statistical techniques have been investigated.[9] Standard statistical techniques are widely applied but must be performed in deductive fashion with knowledge of independent variables a priori, which may not be possible in initial gait-analysis evaluations. Standard statistical techniques also are not efficient at handling the multiple-dimensional data sets common in kinematic gait analysis.

Neural network (NN) classification is an inductive computational technique modeled on known physiologic functions of the brain. Input data is processed by multiple neurons interconnected with axons to result in a specific output. Learning is accomplished by iterative modulation of reinforcement or inhibition of neuronal pathways given known input and expected output. Once learning has reached an adequate level, the established distributed knowledge within the NN can be used to classify unknown situations. Neural networks can easily handle large sets of high-dimensional data and are highly tolerant to errors in measurement. Also, because NNs have inherent ability to perform nonlinear mapping, any relationship between variables can be modeled. Gait abnormalities in humans have been classified with NNs by use of input from measurements of ground-reaction forces,[10] patterns of foot pressure,[11] kinematic measurements of joint angles,[12] electromyographic recordings of limb musculature,[13] and various other kinetically and kinematically attained gait variables.[14]

We are searching for a more robust approach to classification in the kinematic investigation of lameness in horses. Specifically, the study reported here investigated objective computational methods that can use collected data on body position as an input and then classify whether the horse is lame or not lame. In another study[15] conducted by our laboratory group, we describe an objective method that uses a curve-fitting technique for quantification of lameness; the technique calculates the amount of perturbation in the normal, biphasic, vertical movement of the head of horses. Although this method adequately quantifies lameness, it is not successful in determining the side of lameness without simultaneous inspection of the gait data from the head and 1 forelimb foot evaluated on a stride-by-stride basis. A computational approach that would be capable of simultaneously analyzing kinematic data from the head, foot, and multiple other body parts could be easier and more effective at detecting and differentiating lameness.

Materials and Methods

Animals—Twelve adult horses with mild lameness attributable to navicular disease were used in the study. Lameness of each horse was scored as 1 or 2 by use of established crriteria.[16] The diagnosis in each horse was confirmed on the basis of a combination of a subjective examination for lameness performed by an experienced equine clinician, results of a palmar digital nerve block, and evaluation of radiographs and bone scans of the feet of the forelimbs. Reduction of lameness after the palmar digital nerve block and increased radionuclide uptake in the navicular area were both required for a definitive diagnosis of navicular disease.

Data collection—Each horse used in the study was trained to trot comfortably on a treadmill at a speed that was selected as most suitable for each particular horse. The most suitable speed was that at which the horse trotted but maintained its position on the treadmill without handler interference.

Motion of the horses while trotting on the treadmill was captured by use of computer-assisted kinematic equipment.[a] Reflective spheres (2.5 cm in diameter) were placed on each horse. Spheres were placed on the head at the zygomatic protuberance of the temporal bone (head), center of the lateral aspect of the hoof wall of the right forelimb (foot), approximate center of rotation of the right metacarpophalangeal joint (fetlock), lateral aspect of the radiocarpal bone (carpus), and lateral epicondyle of the proximal portion of the radius (elbow). Five high-speed (120 frames/s) cameras were used to capture the motion. All cameras were situated on the right side of the treadmill **(Fig 1)**.

The 3-dimensional position of each marker was recorded and tracked for 30 seconds (approx 30 to 40 strides, depending on the horse's speed). All 12 horses were evaluated before application of nerve blocks, after biaxial palmar digital nerve block of the forelimb with the most substantial lameness, and after biaxial palmar digital block of both forelimbs; thus, there were 36 separate horse-nerve block sequences for evaluation. Horse-nerve block sequences were repeated 3 times in each horse (total of 108 recorded sessions).

Each horse-nerve block sequence was then categorized (not lame, lame on right forelimb, or lame on left forelimb) by use of a method described elsewhere.[15] This method corrects for random head movement of the horse and then quantifies lameness on the basis of temporal asymmetry of vertical head movement. Lameness severity is quantified by measuring the ratio of the amplitude of the first 2 harmonic components of the signal for corrected vertical head movement. **Amplitude of the first harmonic (A_1)** is the vertical head movement attributable to lameness, and **amplitude of the second harmonic (A_2)** is the natural vertical head movement. Vertical head movement is then correlated temporally with vertical movement of right forelimb foot. Sequences with asymmetric vertical head movement (ie, A_1/A_2) above a certain threshold value and that consistently had less downward movement of the head during the stance phase of the right forelimb were categorized as lameness of the right forelimb. Sequences with asymmetric vertical head above a certain threshold value and that consistently had less downward movement of the head during the stance phase of the left forelimb (swing phase of the right forelimb) were categorized as lameness of the left forelimb. Sequences with asymmetric vertical head movement below a certain threshold value were categorized as not lame. The threshold for asymmetric vertical head movement was set at $A_1/A_2 = 0.5$ and was determined in a preliminary study by measuring values in 10 horses categorized as not lame on the basis of a lameness evaluation performed by an experienced equine clinician.

Analysis of results for this method of lameness quantification revealed that 12 horse-nerve block sequences did not have unanimous classification agreement between all 3 repeated sessions; these sequences were not used for further analyses. Of the remaining 24 horse-nerve block sequences, 8 were categorized as lameness of the right forelimb, 8 were categorized as lameness of the left forelimb, and 8 were categorized as not lame.

Data analysis

Analysis procedures—Our first objective was to find a set of features that best represented each of the gait signals (ie, head, foot, fetlock, carpus, and elbow) and any important relationship between them that might be unique for differentiating horses that were lame from those that were not lame. We started with the CWT of the kinematic signals **(Fig 2)**. Next, we captured each signal's pattern by use of a **time-sequence (TS)** composition process that built feature combinations for each transformed signal. These feature combinations or vectors were then used as the input to train a NN to distinguish between lameness of the left forelimb, lameness of the right forelimb, and not lame. Each of these 3 steps (wavelet transformation, TS composition to build feature vectors, and NN classification) are explained in detail elsewhere.[17,18]

Application of CWT—A wave is an oscillating function in time or space. Wavelets are waves of limited duration. Continuous wavelet transformation can be considered as a calculation of a series of pattern correlations between a selected wavelet of specific size or scale and segments of the original signal **(Fig 3)**. The more closely the shape of the scaled wavelet is to that of the segment of the signal, the higher the correlation and the larger the CWT coefficients for that signal segment. The wavelet is then shifted along the signal to the next segment, and determination of pattern correlation is repeated. This process continues throughout the entire duration of the signal. Wavelets of small scale extract information from short-duration events within the signal. Wavelets of large scale extract more global features of the signal. Thus, when CWT is used for pattern recognition, 2 important user selections are required: the specific wavelet (ie, shape of the wavelet) and the scale of the selected wavelet.

One way to select a wavelet is to simply choose a wavelet that looks similar to a segment of the signal, perform wavelet transformation, and then inspect the CWT coefficients. However, this method is tedious. Instead, we opted to use a more objective method that is based on information theory.[19] In information theory, signal entropy, which is often calculated as probabilistic entropy, is the average total amount of information output by that signal. We selected the best representative wavelet and scale for each of the gait signals (ie, head, foot, fetlock, carpus, elbow) by calculating the maximum fuzzy entropy values for the transformed signal at a set of preselected scales for each horse-nerve block sequence.[20] The wavelet-scale combination that resulted in the largest entropy for the greatest number of horse-nerve block sequences was selected as the best wavelet-scale pair for that gait signal. All wavelet transformations and entropy calculations were performed by use of commercially available software.[b]

Use of TS composition to build feature vectors—A sliding-window process was used to combine 3, 5, or 7 adjacent points of the transformed signal into 1 feature vector. In this way, each feature vector represented the pattern in the transformed signals over a small window of time. Because the feature vectors were then used as separate inputs into the NN, this also provided a representation of the temporal correlation between the various signals used in the analysis.

Training of the NN and NN classification of data—A commercially available software package[c] was used to construct and train the NN. The NN architecture contained 3 output nodes (representing lameness of the right forelimb, not lame, and lameness of the left forelimb). The number of input nodes was equal to the number of TS composition points (3, 5 or 7) used to build the feature vectors multiplied by the number of kinematic signals or feature vectors used. Number of hidden nodes was 3 times the number of input nodes. Training of the NN was stopped when the output root mean-squared error reached a value of 0.01 or after 4,000 training epochs, whichever came first.

A NN was trained with feature vectors extracted from 6 horses/category and then tested with the remaining 2 horses in that category. At the next training-testing cycle, another set of 6 and 2 horses was randomly selected and used for training and testing, respectively. The method continued until each horse-nerve block sequence was used once for training and testing. A correct classification was made when the output node with the largest value corresponded to the known category for the horse-nerve block sequence. Neural network classification for all possible training and testing sets was performed in triplicate, and the mean **correct classification percentage (CCP)** was calculated.

Testing the best algorithm for wavelet selection—In experiment 1, the vertical positions of the head and foot markers were used as the input. Our best algorithm for wavelet selection was compared to selection of the wavelet on the basis of visual inspection and to no processing of the wavelet prior to wavelet analysis. The number of TS points in the feature vectors was varied (1, 3, 5, and 7; TS point of 1 meant no TS composition). The 3 methods were compared on the basis of the CCP.

Testing the importance of gait signals for the identification and differentiation of lameness—Training of a NN was accomplished by use of various combinations of vertical or horizontal position data for the head and vertical position data for the foot, fetlock, carpus, and elbow. The vertical head and foot position signals were subjected to processing that used the best wavelet-scale pairs determined for the best algorithm for wavelet selection. Horizontal head and vertical fetlock, carpal, and elbow position signals were subjected to processing with 1, 2, and 3 of the best wavelet-scale pairs selected by the best algorithm for wavelet selection by use of 3, 5, and 7 TS composition points to build input feature vectors. We also tested vertical head position subjected to processing with 1, 2, and 3 best wavelet-scale pair combinations as the sole input signal. The NN CCP was calculated and descriptively compared between all combinations of position signals used as the input.

Results

The best wavelet-scale pairs selected by our best algorithm for wavelet selection were the Morlet wavelet (scale, 64) for the head signal and the Mexican Hat wavelet (scale, 32) for the foot signal. Wavelet-scale pairs selected on the basis of visual inspection of the display of the CWT coefficients in the commercially available software package[b] were the Biorthogonal 1.3 wavelet (scale, 40) for the head signal and the Symlet 7 wavelet (scale, 43) for the foot signal.

Results comparing processing of the head and foot points were plotted for the cumulative CCP over the complete training and testing process **(Fig 4)**. The highest CCP (85.4%) was detected by use of the entropy maximization algorithm and 5 or 7 TS composition points. Processing of visually selected wavelets resulted in a maximum CCP of 75%. Use of a signal not subjected to processing before wavelet analysis resulted in a low CCP (21%). A relatively low CCP was obtained for all techniques that did not use the TS composition process (ie, TS composition point of 1). The CCP increased for all techniques concurrent with an increase in the number of TS composition points. The CCP for the entropy maximization algorithm peaked at a TS composition point of 5, whereas the same value that was not processed before wavelet analysis peaked at a TS composition point of 3. The use of larger numbers of TS points (> 7; data not shown) caused a slight decrease in CCP for all processing methods.

The most important results were summarized **(Table 1)**. Training with only 1 (ie, the best) wavelet-scale pair transformation of the vertical head movement signal resulted in a CCP of only 50%. Using the best 3 wavelet-scale pairs for the vertical head signal increased the CCP to 77%. Training with multiple best wavelet-scale pair transformations of the vertical head movement signal in combination with the vertical foot signal did not improve CCP over that of the combination of vertical head and foot signals determined by use of their single-best wavelet-scale pairs. Training with the vertical head movement signal in combination with the fetlock, carpus, or elbow signals by use of the best wavelet-scale pair transformation for each signal resulted in a relatively poor CCP (68 to 77%), compared with the CCP for the combination of the vertical movements of the head and foot. However, training with the vertical head movement signal in combination with the fetlock, carpus, or elbow signals by use of the best 2 or 3 wavelet-scale pair transformations resulted in an improvement in CCP (83% for each of the 3 combinations). Adding the fetlock, carpus, or elbow signals to the combination of the vertical movements of the head and foot did not improve CCP over that for the combination of the vertical movements of the head and foot alone. Training with horizontal (side-to-side) movement of the head in combination with the vertical movement of the right foot resulted in a low CCP (56%) with 1 or a combination of wavelet-scale pair transformations.

Discussion

In the study reported here, we described a method that extracts important features from kinematically collected position signals and identifies and classifies lameness in the forelimbs of horses. Analysis of the results indicates that CWT can be used to effectively capture the unique temporal patterns in kinematic signals that indicate lameness. The combination of the processing algorithm and NN classification was able to correctly detect lameness of mild intensity and to correctly identify the affected forelimb in 85% of recordings when using only vertical movement of the head and the foot of the right forelimb as the input. Wavelet processing of the vertical head and right foot signals were consistently better at classification of lameness compared with results for signals not subjected to processing. This indicates that wavelength processing isolated characteristics of the gait signal that were important when determining the affected forelimb of lame horses. When the vertical movement head signal was used alone, or when the vertical movement head signal was analyzed in combination with the right fetlock, carpus, or elbow, processing with > 1 best wavelet-scale pair increased the CCP. However, whenever movement of the right foot signal was used as an input, CCP was not better than when only the best wavelet-scale pair was processed.

From these results, it seems that vertical movement of the head and the foot of 1 forelimb may be sufficient to differentiate horses that are not lame from horses with forelimb lameness and to distinguish lameness between the left and right forelimbs in affected horses. This supports the clinical knowledge of experienced equine practitioners. However, it is instructive to mention that fetlock, carpal, and elbow signals did not provide additional information for classification of forelimb lameness in this study. Thus, for the purposes of classifying lameness in a forelimb by use of kinematic gait analysis, body marking schemes limited to the head and 1 forelimb foot may be all that is required. This greatly simplifies experimental protocols in kinematic gait-analysis experiments designed to detect and quantify forelimb lameness in horses. In addition, horizontal (side-to-side) movement of the head can be neglected in kinematic gait-analysis experiments designed to detect and differentiate lameness between the forelimbs of affected horses. This information also has practical implications for practitioners performing field-setting lameness examinations. The results of the study reported here support the notion that concentrating observations on vertical head movement (ie, the head nod) correlated to stance and swing phases of 1 of the forelimbs is an accurate method to detect and differentiate lameness in the forelimbs of horses. However, until a wider range of lameness problems are tested, particularly those located in the proximal portion of the forelimb, it may be premature to discard fetlock, carpal and elbow movement when subjectively analyzing lameness.

Attempts to capture more information content in kinematic signals have focused on extracting the dominant patterns. Fourier analysis, a mathematic convolution technique that breaks a signal into component sine waves of various frequencies, is a favorite method that has been used to characterize and differentiate kinematic signals obtained from humans and other animals with normal and pathologic gaits.[21] Fourier analysis isolates the frequency content from periodic signals, which can then be used as an overall characteristic of the signal. However, Fourier analysis of kinematic data loses information about localized time-dependent events. Often, the most important information within the kinematic signal (ie, drift, patterns, stride-to-stride variation, and abrupt changes at the beginning and end of specific events) is lost. Compared to frequency-based techniques, wavelet transformation, because of its ability to capture localized time-dependent events as well as global signal characteristics, is a better choice for processing kinematic data prior to wavelet analysis. Wavelet-based techniques for measurements of joint angles are useful in differentiating between dogs with normal gaits and dogs with pathologic gaits after induced paralysis of the tibial nerve.[22] Similarly, wavelet-based techniques that use ground-reaction forces can be used to differentiate pathologic and normal gaits in humans after total knee displacement.[23] To our knowledge, the study reported here is the first attempt to use wavelet-based processing of kinematic signals to detect lameness in horses or to determine the affected forelimb in lame horses.

In another report,[24] artificial NN classification of kinematic data was successfully used to detect forelimb lameness in 175 horses. In that study, motion of the head and 1 forelimb foot throughout a period of 12 strides was collected at 312.5 Hz, and the vertical components of that motion were transformed by Fourier analysis. The Fourier coefficients were then used as the input into a NN. Output was classified into 6 categories ranging from not lame to moderate lameness. Correct classification was made in 78.6% of the horses. The authors of that study concluded that artificial NNs were potentially capable of making an objective diagnosis of lameness in horses by use of kinematic data as the input. In the study reported here, correct classification for the NN was slightly higher; however differences in experimental protocol are too numerous to make reasonable comparisons between the studies, the most significant being the different output classification categories used. However, results of our study were similar to results of that other study,[24] which supports the conclusion made by the other authors that the difficult decision process of identifying mild lameness in horses can be assisted by NN classification. Also, we believe that a combination of CWT and the best wavelet-scale pair selection method more fully characterizes the differences in input signals between the various groups (not lame, lameness in right forelimb, and lameness in the left forelimb). This may provide for better NN classification.

The cause of lameness in the horses that we used was not the best for initial testing of this classification algorithm. Navicular disease is usually a bilateral condition. Palmar digital nerve blocks sometimes substantially alleviate and sometimes only partially alleviate the lameness attributable to navicular disease. Some of the horse-nerve block sequences could have had left and right forelimb strides that caused pain during the 30-second recording periods. Thus, in these experiments, the reported CCP for our processing and classification schemes are conservative estimates. A better method for initial testing would have been to induce unilateral lameness. It would also be interesting and instructive to test this technique for detection of lameness against another unrelated technique that does not rely on kinematic analysis of head movements, such as force-plate analysis,

Nevertheless, because of the relatively high CCP (85%), we believe this method should be further investigated for use in differentiating more difficult lameness conditions, such as differentiating the site of lameness within an affected limb by use of data from multiple gait signals. The method should also be investigated for detection of lameness in the hind limbs (by use of gait signals from the pelvis and hind limbs) and to differentiate mild lameness fromm early neurologic dysfunction. Also, we believe that this method may be generalized to other kinematic signals, particularly kinematic evaluation of gait and performance in humans.

Footnotes

[a]Vicon 250, Vicon Motion Systems Inc, Lake Forest, Calif.

[b]MATLAB Wavelet Toolbox 2, The Mathworks Inc, Natick, Mass.

[c]MATLAB Neural Networks Toolbox 4, The Mathworks Inc, Natick, Mass.

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Figure legends

Figure 1—Photograph of a horse with attached reflective markers (A) and a 3-dimensional drawing depicting the caudodorsal view of the experimental arrangement for recording of data. The 2.5-cm-diameter reflective spheres (arrows) are attached to the head and right forelimb (elbow joint, carpus, metacarpophalangeal joint [ie, fetlock], and foot). Notice that all camera positions (numbers 1 through 5) are on the right side of the treadmill.

Figure 2—Method used to process and classify data obtained from horses on the treadmill. The raw gait signal (A) is transformed by use of continuous wavelet transformation (CWT) to yield the transformed signal (B). 1 frame = 0.008 seconds. A time-sequence (TS) composition process (C) is performed on the transformed signal to create feature vectors (D) that are used as the input to a neural network (NN; E). Output of the NN is categorized lameness of the left forelimb (LF), not lame (Sound), or lameness of the right forelimb (RF).

Figure 3—Representative wavelets commonly used in biomedical signal processing.

Figure 4—Graph of correct classification percentage (CCP) plotted against the number of TS composition points for 3 processing methods (no wavelet processing [triangles]; entropy maximization [diamonds], which represents wavelet processing by use a wavelet selected by the best wavelet selection method; and visual inspection [squares], which represents wavelet processing by use of a wavelet selected by visual inspection of CWT coefficients.

Table 1—Mean correct classification percentage for all combinations of gait signals as determined by use of a single best wavelet-scale pair or a combination of the best 2 or 3 wavelet-scale pairs

Gait signals*	**1 wavelet-scale pair**	**2 or 3 wavelet-scale pairs**
Head alone	50	77†
Head + foot	85	85‡
Head + fetlock	68	83
Head + carpus	73	83
Head + elbow	77	83
Head + foot + fetlock	85	85
Head + foot + carpus	83	83
Head + foot + elbow	83	83
Head + foot + carpus + elbow	81	ND
Head (lateral movement) + foot	56	56

*Represents vertical motion, unless indicated otherwise. Foot, metacarpophalangeal joint (ie, fetlock), carpus, and elbow joint were all on the right forelimb. †Used a combination of 3 wavelet-scale pairs (Morlet, scale = 64; Biorthogonal 3, scale = 48; and Gaussian 6, scale = 16) for head movement. ‡Used a combination of 3 wavelet-scale pairs (Morlet, scale = 64, Biorthogonal 3, scale = 48; and Gaussian 6, scale = 16) for head movement and 1 wavelet-scale pair (Mexican Hat, scale = 32) for foot movement.

ND = Not determined.

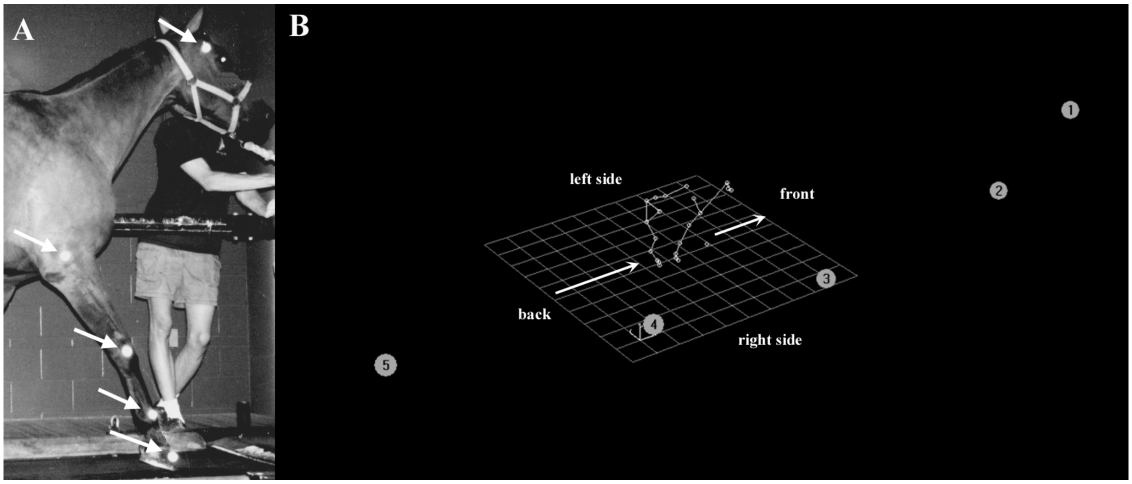
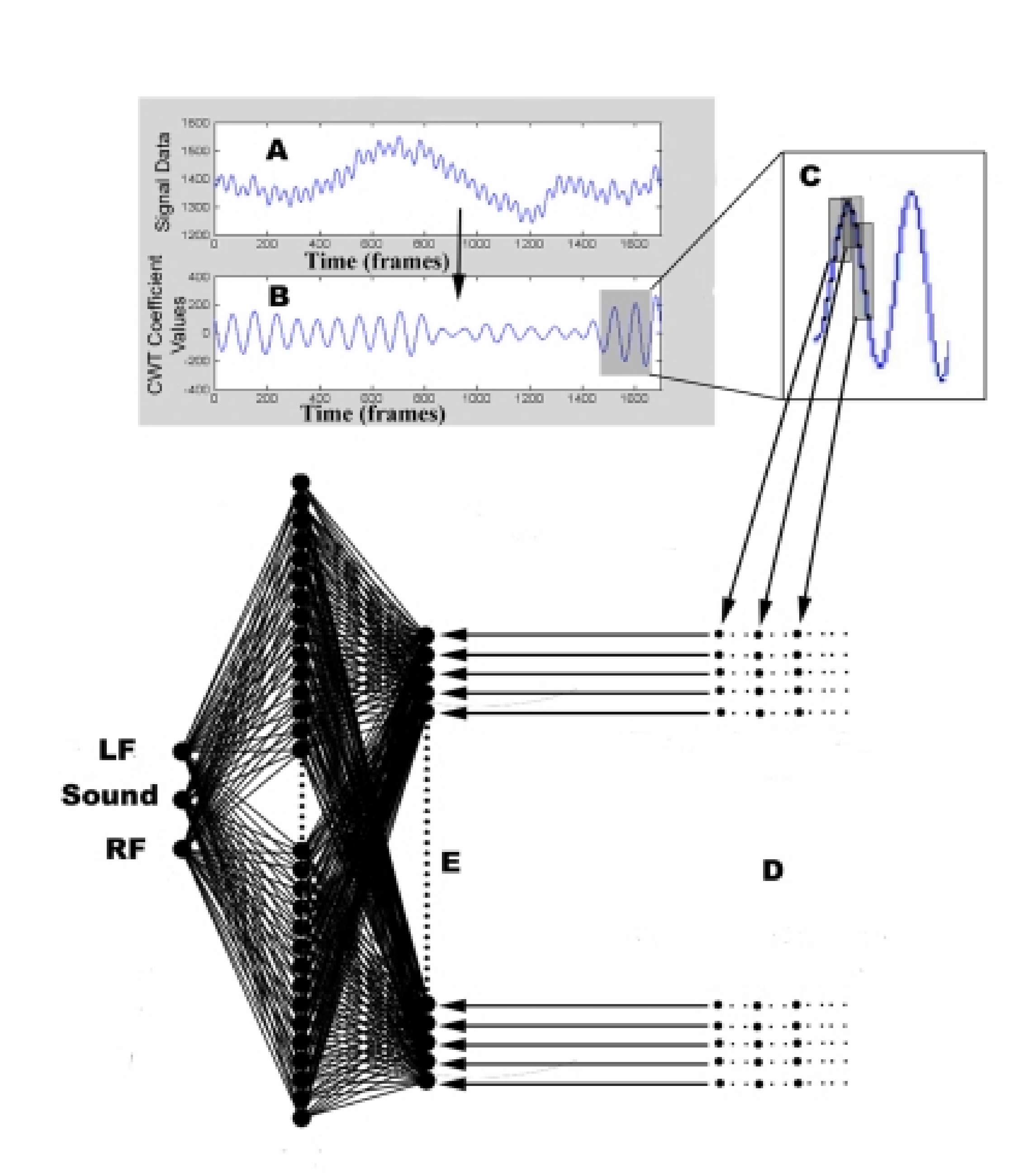


Figure 1.



Signal Data
A
Time (frames)
CWT Coefficient Values
B
Time (frames)
C
LF
Sound
RF
E
D

Figure 2.

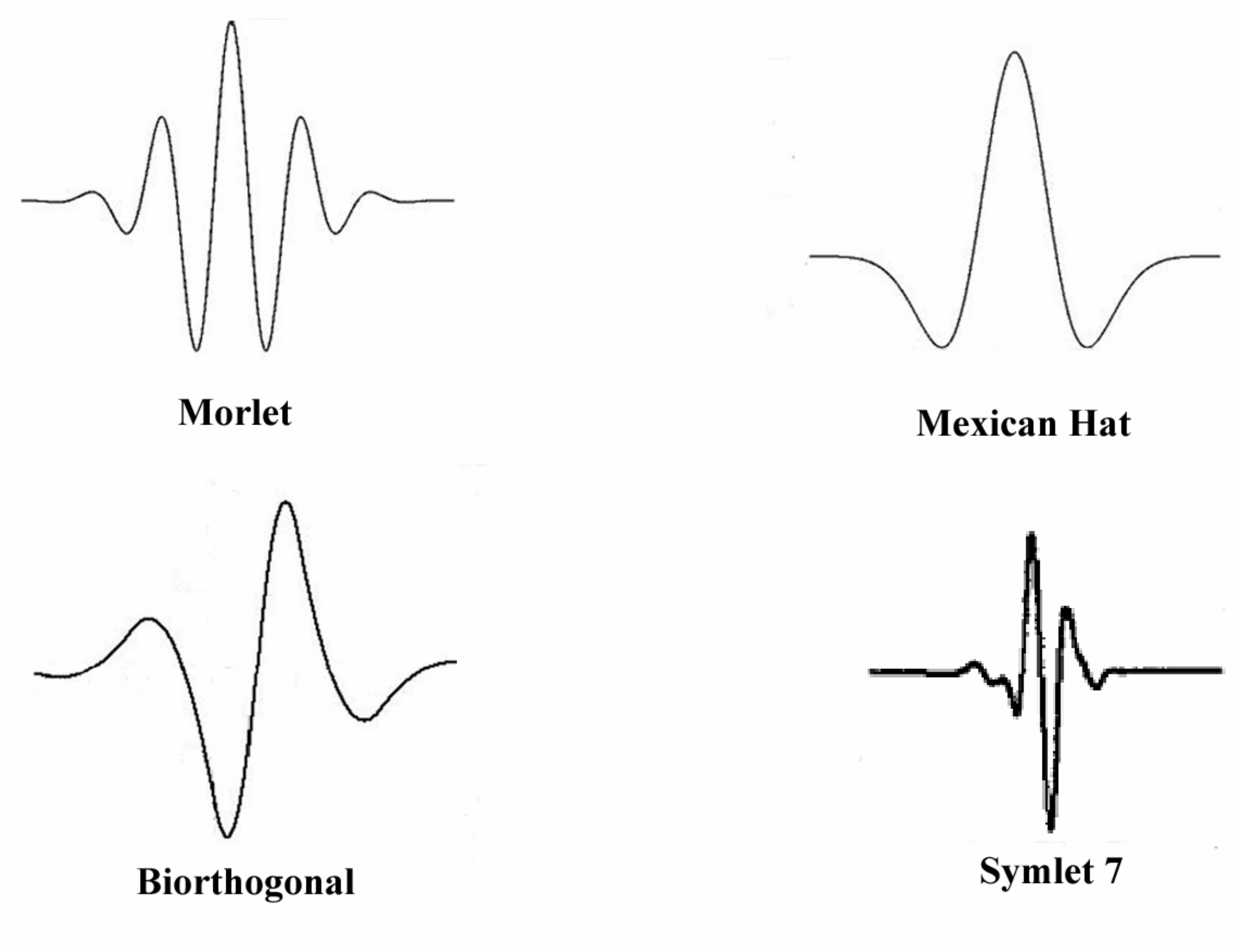
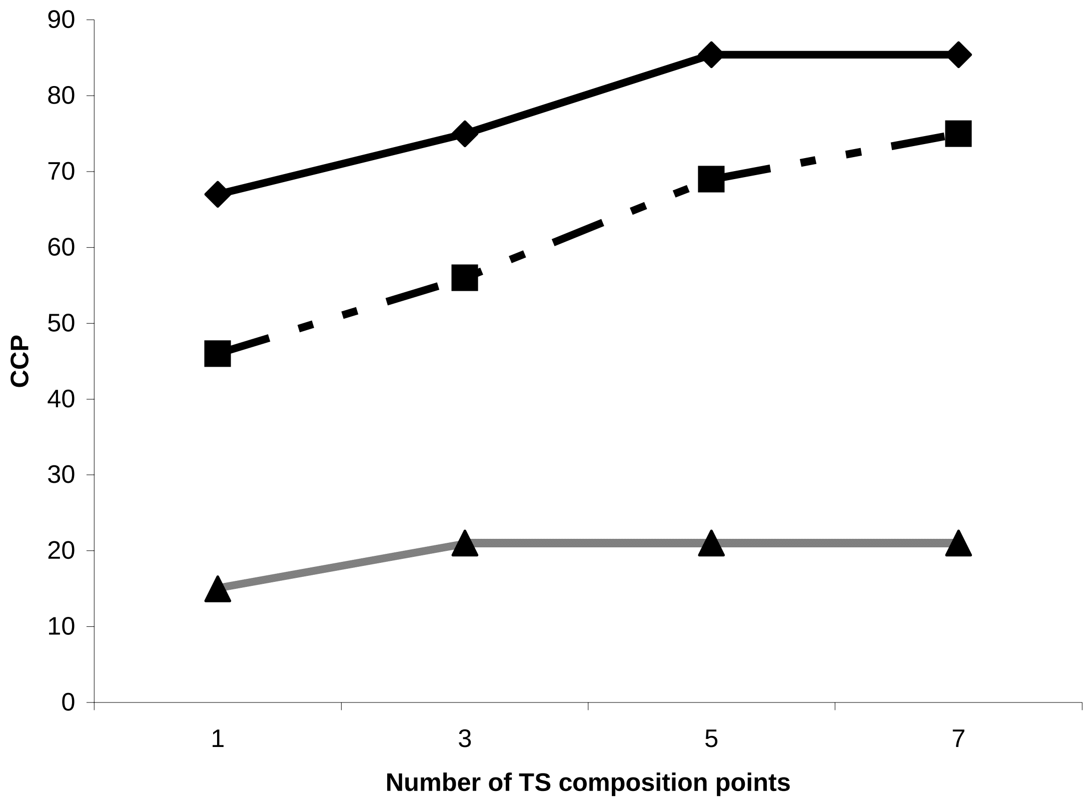


Figure 3.



90
80
70
60
50
40
30
20
10
0
CCP
1
3
5
7
Number of TS composition points

Figure 4.