

**Use of sample entropy to study equine gait lameness.**

by

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## Abstract

Administration of a sedative is occasionally required to perform a nerve or joint block in the horse during the course of a lameness examination. Because sedatives have analgesic properties, we investigated as to whether a sedative could ameliorate lameness. An improvement in gait after administration of a sedative could erroneously be attributed to a nerve or joint block performed at the same time. This study used a computerized gait analysis system (Lameness Locator) to objectively examine the effects of the sedative detomidine on the gait of naturally lame horses. The gait analysis system measures symmetry of motion. Sound horses have a symmetrical gait at the trot and lameness causes asymmetry, which is detected and quantified by the Lameness Locator. We utilized calculation of Sample Entropy to determine the complexity of system. The horses were trotted in a straight line and evaluated using inertial sensors. A trend in dynamic stability was observed with calculation of Sample Entropy of recorded head and pelvic acceleration data. At first the study between the lame and sound horse proved increase in sample entropy. Stability was unaffected after administration of sedatives, which is shown by statistically insignificant entropy value change.

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## Chapter 1

### Introduction

Archaeological and palaeological studies suggest that humans started domesticating horses since about 3500 BC.[24][21] Horses had been be very important part of human history as they helped advance human communication and transportation, accelerating global change. After invention of engine, use of horse is decreased but still in some part of the world they are used for transportation for different geographical reasons. Also in modern culture there is an increasing interest in use of horses for racing and riding activities. This has attracted scientific communities to study equine biomechanics and injuries[6].

Lameness detection is easy when lameness is in moderate to severe degree as the effect can be easily observed. But the real problem starts when lameness is in mild to moderate degree and early detection is needed. There is confusion and disagreement because of the subjective evaluation which differs on the level of skills and teaching.

Orthopedic disorders which lead to lameness in horses is main cause of economic loss to equine racing industry.[3][20]Hence the ability to detect lameness by observing movement is a skill that must be acquired by the equine clinician. Generally equine clinician observes certain pattern in movement of head and pelvic and correlate it to lameness. But it differs as there is no definite standard in industry. This type of subjective evaluation would not help in early detection of lameness. Clinician is not able to capture the small change in locomotion pattern because of low image capturing frequency (15 to 20 frames per second) of human vision.[18] And because of this mild to moderate lameness is very difficult to detect and quantify.

Also there is main concern in veterinarians, about effect of sedation during lameness examination. Many clinicians are reluctant to use of tranquilizer or sedatives during lameness examination as it is believed to affect the identification of subtle lameness.

Stability of any biological movement can be defined as its tolerance to external and internal kinematic perturbations.[11] In order to sustain healthy functional movement, minor adjustments in movements are made by the nervous system. This locomotion involves repetitive and cyclic pattern of body and limb segments[4]. And we should be able to analyze them as a mechanical system and compare the changes occurring in the body dynamics due to lameness. Movement of body center plays an important role during movement as it allows horse to reduce the pressure on lame limb and shift the body weight[8]. For last two decades with the help of high speed camera capturing devices and inertial sensors scientists have studied the change in the movement dynamics of horse. The focus of these studies have been the body center mass movement, change in the neck and pelvis movement during the stride cycles.[13]

Most intriguing part about any biological movement is its complexity and its self adjusting nature to maintain balance. Chaotic nature of the human gait has been studied for a long time for cause of poor dynamic stability in elderly patients[14]. We are trying to use similar approach to study equine stability. Quantifying stability is a very difficult problem. A periodic nature of the movement is necessarily not best notion for its stability. In fact, in many biological signals like human heart rate chaotic nature is considered to be healthy[27]. In the past variation in movement while performing repetitive task was considered as random noise, but study has proved otherwise. In fact for stable gait this chaotic nature is vary important. Chaotic movement is not as same as randomness. Different nonlinear methods have been developed to study complexity of this chaotic movement such as lyapunov exponent, entropy. Goal of this study is to implement entropy to differentiate level of complexity in different control groups, and to find its correlation to stability of gait.

Any dynamic system could be analyzed with the help of chaos theory. The difference between a cyclic motion and chaotic one is degree of randomness. As we can tell cyclic motion has zero randomness and we can predict the motion easily. But for dynamic motion, the slight change in initial condition amounts to unpredictability. If we can define a parameter to characterize the unpredictability in the system, then we would be able to differentiate the motion.

Numerous criteria have been suggested before to define chaotic behavior which are based on two aspects, random behavior of the system and initial condition dependence. So the first approach analysis deals with randomness of signal we obtained on real time period like entropy, correlation dimension. The second approach mainly focuses on variation in trajectory with small change in the initial conditions. We would focus this study based on the time signal analysis to get entropy.

Chapter 2 is divided into two parts. At first we would examine the different parameters for the study of equine gait and the development done so far.

In the second section we should get familiar the concept of the entropy which originated from information technology and found great use in the study of biological signals. The base of entropy used in this study is based on information theory. Shannon developed entropy to quantify the amount of information obtained in communication signal. The equivalence of the dynamic entropy with Shannon's communication theoretic entropy under certain plausible assumptions is proved. We would also investigate different algorithms and methods to calculate entropy. And finally we would examine the usefulness of the study of entropy to analyze gait. We would

Chapter 3 is a Method section in which we would focus on the tools used to get the head and pelvic acceleration data for our study. We would introduce the signal processing methods used to get filtered data. And finally how computational sample entropy is calculated with consideration of our current data. We have done two studies, first to find relation between effect of change in gait and sample entropy. Second we used the results obtained from our

first study to tackle important question of whether the sedation affects gait during lameness examination.

Chapter 4 would summarize all the results obtained and statistical analysis done. And finally in last two chapter we would discuss the conclusion of our study and future direction.

## Chapter 2

### Literature review

Gait analysis is most important step for lameness detection. The need for objective evaluation means a better understanding about the mechanics of this biological motion. In the first section of this review we would examine definitions and parameters for gait dynamics and measurement methods. In the second section we would evaluate different nonlinear methods which have been used to analyze the gait data. We would go through the different types of studies that have been done so far in this field. The major focus of this review is about the progress that is made on the dynamics of equine motion and possible methods which could be used to analyze lameness.

#### **2.1 Equine gait dynamics**

Horse moves with the help of its musculature in the body. We would first define the basic anatomy structure and terminology which is used in equine gait study.

##### **2.1.1 Basic structure anatomy**

Before we can understand actual horse movement we need to become familiar with the horse anatomy and body structure responsible for movement. Two major parts of the skeleton shown in figure are axial skeleton and appendicular skeleton. Axial skeleton includes skull, spinal column, ribs and breastbones, whereas appendicular skeleton consist of pelvis and limbs. Longs(leg) bones are the actual bones which are responsible for support and movement of body. Short bones in joints absorbs impact vibrations. Joints and ligaments binds and hold bones together.[12]

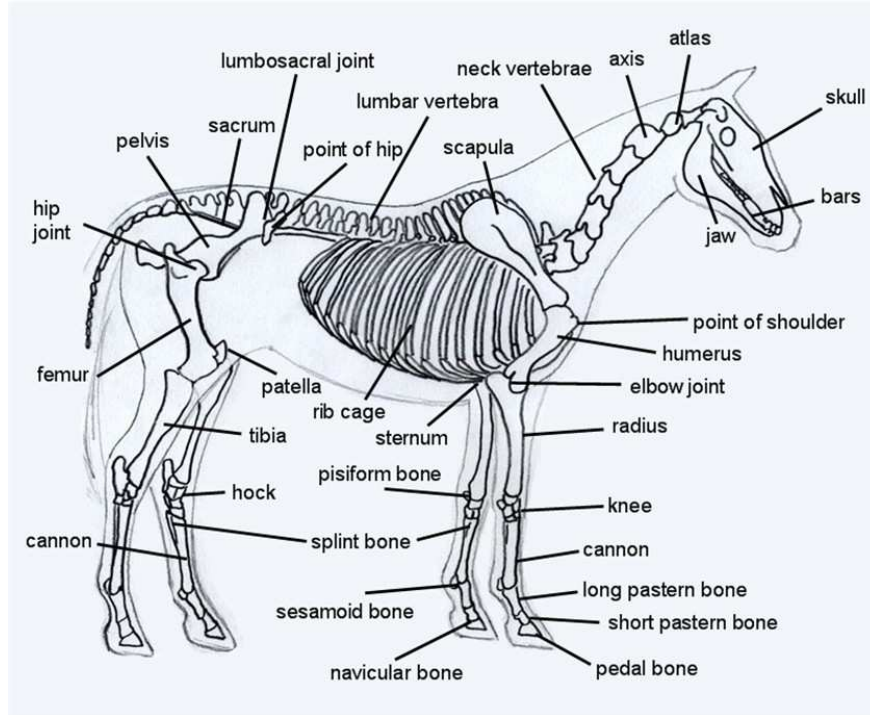


Figure 2.1: Sketch of the skeleton of horse, from Equinespot[1], shows the two major parts of the movement of horse

### 2.1.2 Horse movement mechanism

A gait is defined as a coordinated and rhythmical movement of body segments in particular fashion which gives forward motion to the body. Gait could be symmetrical or asymmetrical. The stride is movement of limb in a cyclic pattern which is repeated continuously during the movement. To complete each stride it goes through two phases as shown in figure 2.2, stance phase when the limb is in contact with the ground and a swing phase is when it is not in contact. Also we can divide the stride in 4 basic movements. Impact is when limb hits the ground, stance when it supports the body and stores the energy, thrust when it pushes the ground using this energy and finally flight when the limb is moving forward through air. Also if we consider the whole cycle of all limbs, we have a suspension phase when no limb is in contact with the ground.[19]

We can define and study the whole motion with some definite parameters like, stride frequency, stride duration and stride length. Stride frequency is number of strides observed

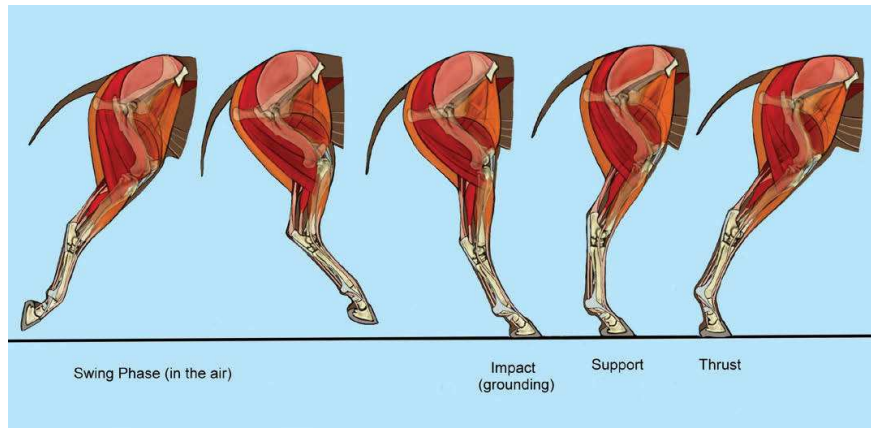


Figure 2.2: A complete stride cycle separated by swing and stance phase from Equine wellness magazine.[2] Also the stance phase was further distinguished with impact, support and thrust phase

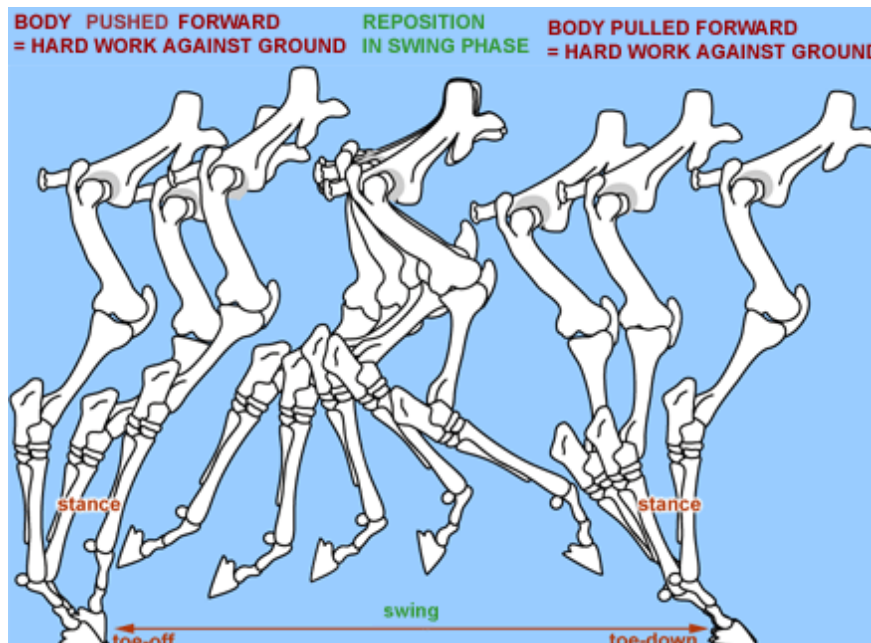


Figure 2.3: The motion of hind leg during swing and stance. The specific motion of joints provide thrust for forward motion. [23]

in a second. Stride duration is inverse of stride frequency which is basically time taken for a single stride. Stride length corresponds to the distance traveled by hoof during successive impacts on the ground.

Combination of four limbs give horse diversity in gait pattern. The most natural gaits observed in increasing order of the speed of motion are walk, trot, canter and gallop. A walk is four beat gait in which leg movement pattern is left hind, left front, right hind and right front leg. It also cycles from three to two legs on the ground. A trot is a very symmetrical two beat gait in which horse moves its legs in unison diagonal pair. There is also suspension phase between two beats. Canter is a 3 beat gait with a sequence of either of any hind leg followed by opposite diagonal fore and hind limbs and finally remaining fore limb. Gallop is fastest natural gait with four separate beats. Sequence of beats is as either of any hind leg followed by opposite hind leg then opposite fore limb and finally remaining fore limb. In this study the motion would be studied by trotting horse with equivalent stride frequency for all experiments.

## **2.2 Equine gait measuring techniques**

For studies done so far on this topic we can divide the approach into two categories. First approach is kinetic which is to study the cause of the motion and related parameters. This type of study is concerned about the force applied on the body and distribution of mass. We would be interested in analyzing kinetic parameters like force, work, energy and acceleration. It uses pressure sensor, force plates and accelerometers for measurement. Second type is kinematic study which is more concerned about actual motion related to temporal and spatial change in body segments like linear and angular displacements, velocity and acceleration.

### **2.2.1 Kinetic Analysis**

Calculating parameters like force and acceleration proved to be important in locomotion research and finding the cause of lameness. For the first time Marey(1873) used pressure



sensor in shoes under the hoof and accelerometers to limbs to find out the contact duration. Usually three different methods can be implemented for kinetic analysis. Sensors can be either installed on the ground or we can use force shoe device and lastly we can use accelerometers. Bjorck(1958) used strain gauge device built into horseshoe to evaluate horizontal and vertical force. The force plates can provide force amplitude and orientation the co-ordinates of the point of application of force and the moment value.[?] [?] Main difficulties with this measurements are extra weight added because of shoes or limited experimental area for horse motion. The results we acquired by these methods are limited for laboratory conditions. Accelerometers can be used to measure body accelerations. The acceleration vector is proportional to the resultant force applied to the body where sensor is attached. The main advantage of using accelerometers is simplicity of measurement technique both in field and laboratory conditions.

### **2.2.2 Kinematic Analysis**

Analysis of locomotion of different parts of body is performed by capturing it with camera. The modern approach involves attaching marker to important parts of the body and analyzing these points to get the idea about the overall motion. With the help of these recordings we can study things like joint kinematics, change in different parts of body with external and internal factors. Nowadays high speed cameras and computer are used to capture and analyze this motion in detail. The only problem with this method is that it is time consuming, expensive and constrain our study in closed environment. There are other methods to study kinematics of motion. Many use electrogoniometers(elgons) to study metacarpopalangeal joints.This Kinematic study method also offer us a way to evaluate kinetic aspects like horizontal and vertical force between hoof and ground.

### **2.2.3 Balance and movement**

For a long time research is done to study science behind the equine motion. In particular the balancing mechanism during the whole stride give us a great insight in understanding kinetics of a body. Determination and analysis of body center is important as it help us in understanding load distribution in legs. Especially lameness study would be benefited from this as a lame horse would try to shift its body center such that load on lame leg is reduced.[8]

Calculation of body centre of mass(BCM) is a key part of biomechanical analysis and not easier one. BCM movement is a key research area for gait analysis in humans. Hence similar approach and techniques have been develeoped to calculcate and analyze horse. Earliest scientific study was published by Benke(1934) for finding BCM of standing horse[5]. But the model was not able to find BCM for moving horse. But Knoll(1934) first time made attempt to calculate BCM in moving horse[16]. But still limited database on the position of segmental centres of mass and techincal difficulty in calculating large amount of data analysis made it difficult to calculate accurate BCM. With improved technology, Buchner was able to calculate accurately BCM positions.[7] He used 20 segment model for his calculations. Comparison of body center of mass movement between sound and lame horse gave some valuable information about how horse tries to balance the motion and distribute the load to reduce the force applied on the lame limb. He studied the movement of BCM and other individual body parts in all individual moving axis. His findings are really important in understanding the balance movements in horse.

### **2.2.4 Evaluation of head and pelvic movement to determine lameness**

Major study of equine locomotion is based on trotting as it is the most symmetrical gait and help us in understanding changes in body movement during lameness. The figure 2.4 highlights symmetrical, sinusoidal pattern of vertical displacement. The Forward and backward movement of BCM is very negligible. During trotting there is no trunk rotation is

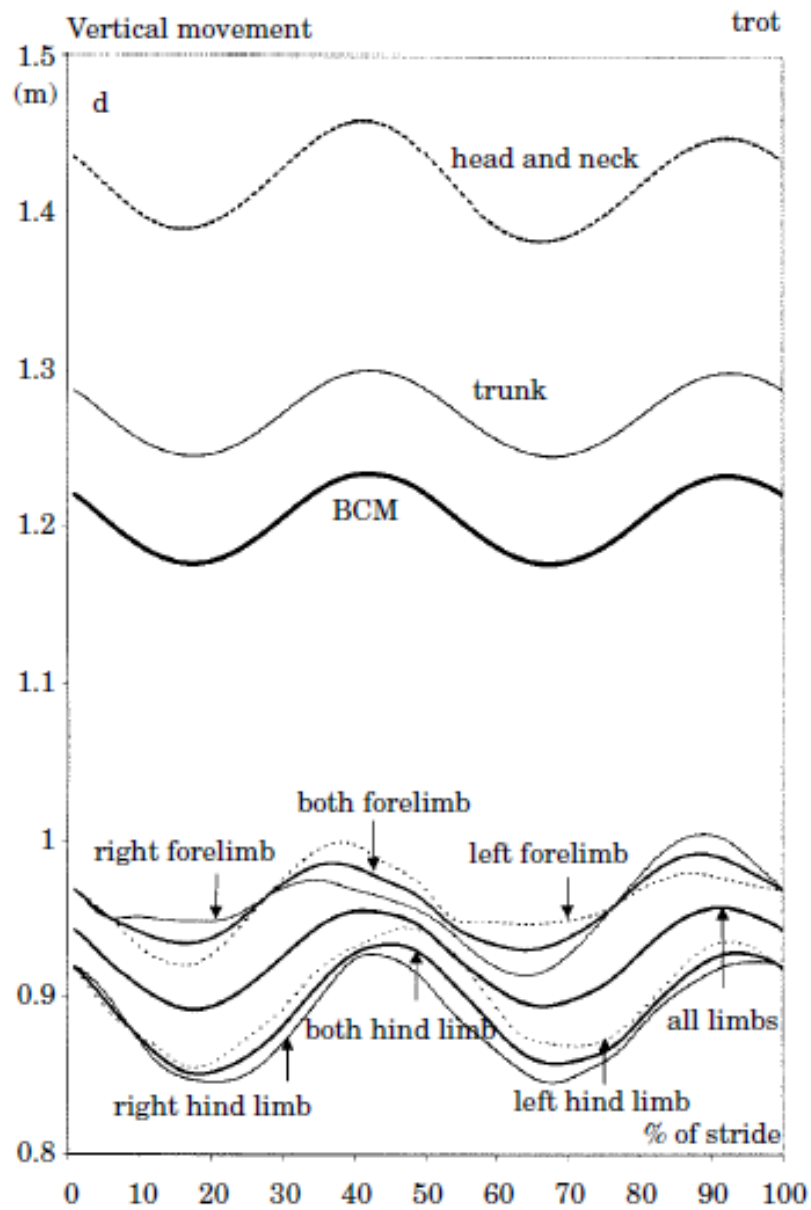


Figure 2.4: Sketch of experimental setup. Head and Pelvic movement was recorded simultaneously.

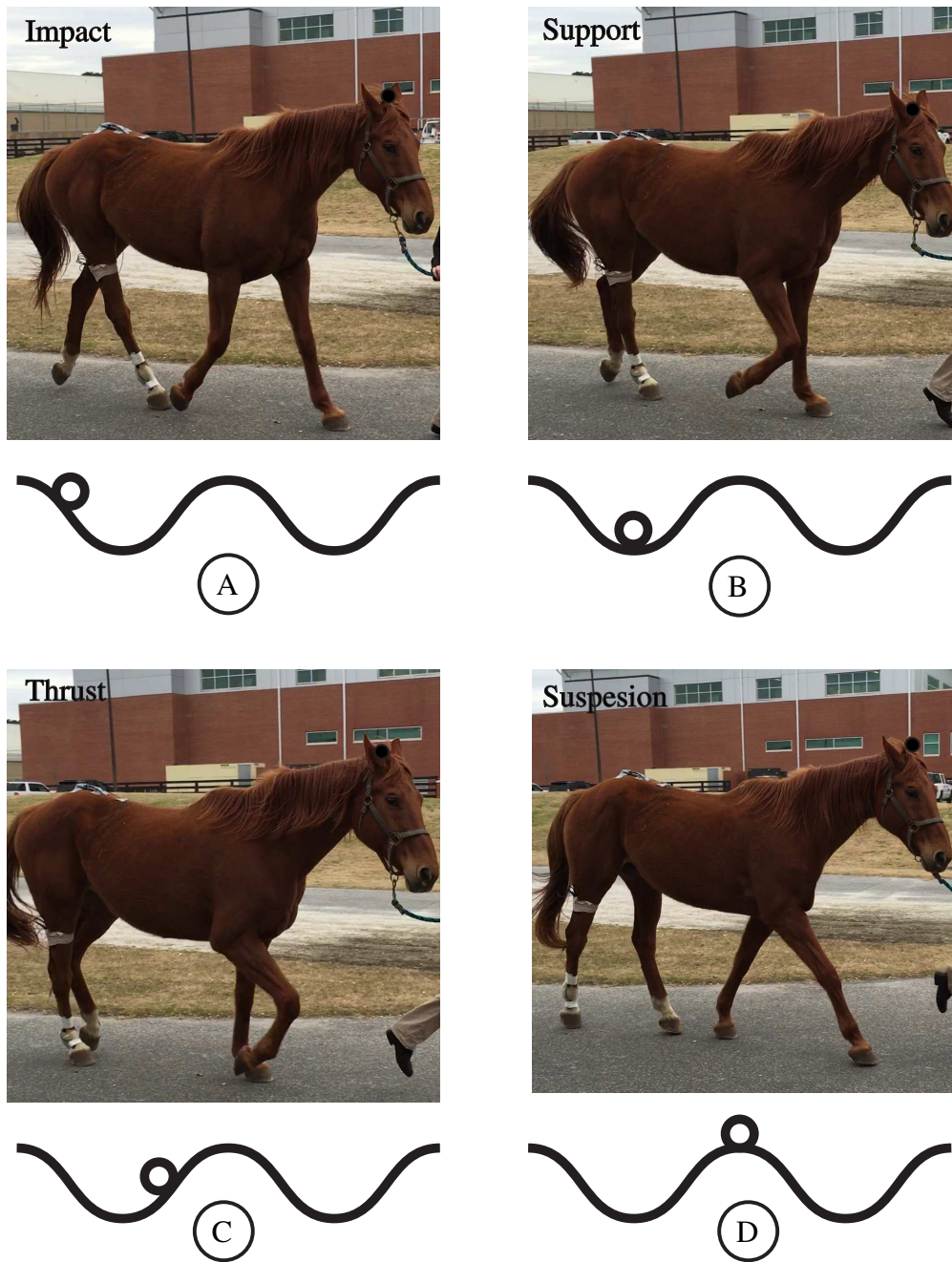


Figure 2.5: Video frames showing vertical head movement in a trotting horse corresponding to the stride cycle. (A) Just after suspension phase head start moving downward after Impact(B) First vertical minimum is lowest at mid stance of the left forelimb. Right forelimb is at midswing. (C) Head starts moving upward during thrust phase (D) vertical maximum just after lift-off of the right forelimb foot and just before impact of the left forelimb foot. Dots at the top of each video frame (Black) are the vertical head position.

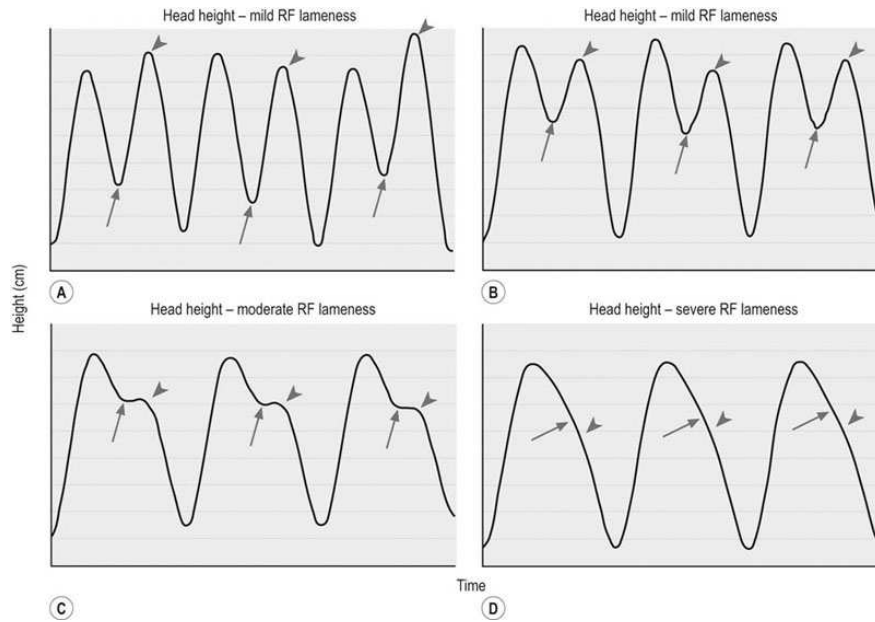


Figure 2.6: Comparison between head movement during single stride depending on severity of lameness.[18]

observed because of symmetrical leg movements so even transverse movement is very small. The most important pattern is observed in vertical direction. A sinusoidal movement of head, pelvis and BCM is observed synchronized and has two cycles in each stride. BCM movement has comparative smaller amplitude than trunk and head movements. For a sound horse head reach its maximum just before the hoof contact and minimum during the midstance of each forelimb. And during trot this movement happen twice for each stride in uniform sinwave like pattern with equal amplitude. The pertubation from this sound movement is indicative of the lameness. For a long time lameness for horse is evaluated subjectively. Main problem in the subjective evaluation is there is a lot of disagreement in different text for parameters to observe during lameness detection. A sample head neck movement for sound and lame horse is shown in figure 2.6. It highlights the asymmetry in the movement.

There is a change in amplitude of vertical head movement during stance phase of lame diagonal compared to sound one. In addition to this, during stance phase of lame diagonal, the distribution of load between fore and hindlimb is unequal. This asymmetry is mirrored into the trunk movement due to its extreme position compared to trunk. The momentum and

acceleration of these movements is also an important factor in this study. A decreased vertical head acceleration during lame diagonal stance phase decreases the momentum in the trunk and forelimb load with a synchronous unloading of hind limb. In this way unloading of the lame forelimb by the reduced vertical force is enhanced by the load to the diagonal hind limb without major positional changes of the BCM. Also it was suggested lack of compensation of vertical acceleration during stance phase of sound diagonal is because of the increase in the vertical impulse caused by the increase in the relative stance duration and the higher stride frequency of lame horses.

The change in symmetry is not same and dependent on location and degree of lameness. The first detail study about this was done by Keegan. He observed that the head moves down less during stance phase of the lame limb and up less after the stance phase of the lame limb when pain occurs maximally at hoof impact or the within the first half of the stance phase of the stride. The head moves down less during the stance phase of the lame limb when the pain occurs maximally at full weight bearing. The head moves up more after the stance phase of the lame limb when the pain occurs maximally during the second half of the stance phase of the stride. The head does not move up appreciably during stance phase of the lame until the lameness is severe. Also during hind limb lameness pelvis moves down less during stance phase of the lame limb and up less after the stance phase of the lame limb when the pain occurs maximally within the second half of the stance phase of the stride. Also it moves up less after the stance phase of the lame limb when the pain occurs maximally within the first half of the stance phase of the limb. He try to explain this sinusoidal movement with the help of frequency based kinematic model. Main hypothesis for this study was that the vertical head movement of horse is combination of 3 components: a harmonic frequency with  $2\omega$ , ( $\omega = \text{strides/s}$ ) which indicates up and down movement of head; a harmonic component with a frequency  $\omega$  describing unilateral lameness contribution to vertical head movement, and a low frequency noise like extraneous head movement. He expressed it mathematically

as:

$$y(t) = C_1 \cos(\omega t) + C_2 \sin(\omega t) + C_3 \cos(2\omega t) + C_4 \sin(2\omega t) + C_5 + C_6 t + C_7 t^{-2} + C_8 t^{-3} \quad (2.1)$$

The results obtained are interesting as it highlights the change in movement of head is complex phenomenon and it depends on different number of factors like severity of lameness and the time at which the pain is felt by horse.

We have focused in this study largely on vertical movement instead of any lateral or axial movement of head. The percentage of shift in those directions are not sufficient for percentage of redistribution of load. Though helpful but visible forward stretching of head which accompanies distinct head lowering during the stance phase of sound lamb is insufficient to play considerable role in the lameness management. Also horse changed their movement pattern in the transverse axis and moved BCM nearer to the sound fore limb.

Keegan developed a tool based on this findings which tries to generate a kinematic model of lameness. The study postulates some important theories on head and pelvic movement during lameness. The study was done by capturing the movement horse on cameras and then measured movement was analyzed with the help of computer assisted gait analyzing equipment. In the next part of this study we would introduce different methods which have been used to study and analyze gait

### **2.3 Entropy**

Now we are going to discuss the basic conceptual background behind entropy calculation and its usefulness in measuring real world deterministic systems. Origin of entropy is from information technology. With gradual modifications theoretical model was converted to tackle time signal complexity. Also we would study implementation of entropy to gait dynamics.

### 2.3.1 Entropy in Communication theory

In this section we would establish the solid background on Shannon entropy and we would only focus on certain aspect of this entropy which deals with a system whose probability of future signal is dependent on the entire past history. This helps in facilitating a connection with entropy of dynamical system. The concept of entropy in information systems was first developed by Claude E. Shannon in 1948 in his publication as to describe the amount of information generated by a signal[26].

Consider a communication system where Signal  $S$  is transmitted via transmitter  $T$  and received at Receiver  $R$ . This message could be words, letters or any type of symbols. The only criteria is we are using discrete symbols  $S_1, \dots, S_n$ . The receiver is logging this signal at steps starting with time  $t_1, \dots, t_n$ .

Shannon developed a new measure to study how much new information has been developed in the signal while investigating language based communication signal. For this he simplified the concept of new information by comparing it to uncertainty or randomness of data. So in short if the signal 1 is more unpredictable than signal 2 then signal 1 has more information than signal 2. To simplify this concept, we would consider an example of output from a die. Consider two dies, one which is unbiased with all 6 outputs with equal probability and the second one which is biased with 99 percentage chance of 1 as output. Both dice are rolled 100 times. When we look at time signal output in both cases, in first case we had to give data for all 100 outputs. But in the second case we can mention only 1 different output number and experiment number at which this occur. So unbiased signal has more information than the biased signal. This helps in understanding the important relation of uncertainty and new information.

If we generalize this concept of entropy for  $n$  different symbols, we need a parameter which would be increasing as a function of  $n$ , and it would show additive property when two signals would add up increasing the information. Most suitable function would be with



logarithm given by,

$$H_{step} = - \sum_{i=1}^n p(S_i) \log(p(S_i)) \quad (2.2)$$

Where  $p()$  is the probability of each  $n$  possible outputs. As you can see greater the value of  $H_{step}$  less we can predict the signal and more information would be obtained from signal. Also if we look at the formula the greatest value of  $H_{step}$  for fixed number of  $n$  symbols would be highest if probability distribution is equal for all outputs. This coincides with notion that we considered before about biased and unbiased die experiment. But in this case we are still assuming the probability of each output is independent of the previous history of symbols which is not the case in real time signal. The new information probability is dependent on signal history and when we consider this the formula could be modified as,

$$H_k(S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_k}^{t_k}) = - \sum_{i=1}^n z(p(S_i^{t_{k+1}} / S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_k}^{t_k})) \quad (2.3)$$

where  $z(x) = x \log(x)$  and the probability of receiving  $S_i$  at time  $t_{k+1}$  is  $p(S_i^{t_{k+1}} / S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_k}^{t_k})$ . In this subscript  $k$  would emphasize that we are calculating the entropy at  $k_{th}$  step. Now if we want to calculate the uncertainty at  $t_{k+1}$  if we do not assume the previous history, namely  $S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_k}^{t_k}$  then we can take average of all  $H_k(S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_k}^{t_k})$  and weight each term of the step according to the probability we could get,

$$\bar{H}_k = - \sum_{i=1}^n p(S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_k}^{t_k}) H_k(S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_k}^{t_k}) \quad (2.4)$$

where

$$p(S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_k}^{t_k}) = p(S_{l_1}^{t_1}) p(S_{l_2}^{t_2} / S_{l_1}^{t_1}) \dots p(S_{l_k}^{t_k} / S_{l_1}^{t_1} S_{l_2}^{t_2} \dots S_{l_{k-1}}^{t_{k-1}}) \quad (2.5)$$

By taking average for length  $k$  we would be able to get average entropy at the every step of process when the signal length as  $k$ . And if we want to take the entropy of the source we

take limit when  $k$  reaches to infinity.

$$\widetilde{H}_k = \frac{1}{k} \sum_{j=0}^{k-1} \bar{H}_j \quad (2.6)$$

$$H_s = \lim_{k \rightarrow \infty} \widetilde{H}_k \quad (2.7)$$

### 2.3.2 Entropy in Dynamical System theory

The concept of the creation of unique information proposed by Shannon served as the starting point for a wide breadth of entropy measures which have since been developed. In the late 1950s, Kolmogorov and Sinai brought the concept of entropy to deterministic dynamical systems. [17] They developed Kolmogorov-Sinai entropy (abbreviated KS-entropy), which essentially serves to analogize Shannons Entropy in the context of deterministic dynamics [11]. Pincus developed Approximate entropy (ApEn) based on Handsdroff dimension calculation. This parameter is useful in distinguishing data complexity. Previous algorithms to calculate correlation dimensions needed huge number of data points to converge even for low dimensional system and affected by system noise.

Consider a standardized time series  $u_1, u_2, \dots, u_N$  of  $N$  data points. Fix  $m$ , a positive integer and  $r$ , a positive real number. For this algorithm  $m$ , indicates length of vector and  $r$  is the tolerance for accepting matches. From given time series data, form a  $N - m + 1$  vectors  $x_m(i)$  for  $\{i | 1 \leq i \leq N - m + 1\}$ , where  $x_m(i) = \{u(i+k) : 0 \leq k \leq m-1\}$

Also  $C_i^m(r)$  is the number of vector  $x_m(j)$  is within tolerance  $r$  of  $x_m(i)$ . We can define it as, for  $i, 1 \leq i \leq m-1$

$$C_i^m(r) = \frac{1}{N - m + 1} \times \Theta(r - \|x_m(i) - x_m(j)\|_\infty) \quad (2.8)$$

where is  $\Theta$  the Heavisid function and is the maximum norm defined by

$$\|x_m(i) - x_m(j)\|_\infty = \max_{k=1,2,\dots,m} (|u(i+k-1) - u(j+k-1)|) \quad (2.9)$$

From  $C_i^m(r)$  we define,

$$C^m(r) = \frac{1}{N - m + 1} \times \sum_{i=1}^{N-m+1} C_i^m(r) \quad (2.10)$$

and define  $\beta_m$  as a correlation dimension when  $m$  is sufficiently large.

$$\beta_m = \lim_{r \rightarrow 0} \lim_{N \rightarrow \infty} \log C^m(r) / \log(r) \quad (2.11)$$

But this is not very useful as for all practical examples the dimension  $m$  is small. Based on this we can similarly find the K-S entropy which could be used to calculate for time series data. We can define  $\phi^m(r)$  as,

$$\phi^m(r) = \frac{1}{N - m + 1} \sum_{i=1}^{N-m+1} \log C_i^m(r) \quad (2.12)$$

$$E - R \text{ entropy} = \lim_{r \rightarrow 0} \lim_{m \rightarrow \infty} \lim_{N \rightarrow \infty} [\phi^m(r) - \phi^{m+1}(r)] \quad (2.13)$$

This ER entropy would be very useful in distinguishing low dimension chaotic systems. But still this converged entropy has some shortcomings as it could not be applied to meaningful range of  $r$  and  $m$ . Hence for fix  $m$  and  $r$  Pincus defined,

$$ApEn(m, r) = \lim_{N \rightarrow \infty} [\phi^m(r) - \phi^{m+1}(r)] \quad (2.14)$$

And for sufficiently large  $N$  data points we can define,

$$ApEn(m, r, N) = [\phi^m(r) - \phi^{m+1}(r)] \quad (2.15)$$

Pincus developed Approximate Entropy to measure the rate of information generation of chaotic system. He estimated that this parameter would give us a good estimation about the change in complexity of data. Lake recognized the important downside in this algorithm. ApEn algorithm involves self matching which creates bias and misleading information about the data. So he formulated Sample Entropy to avoid self matching.

$B_i^m(r)$  is defined similarly as  $C_i^m(r)$  but  $j$  ranges from 1 to  $N - m$  and  $j \neq i$  ensure to exclude any self matches.

$$B_i^m(r) = \frac{1}{N - m - 1} \times \Theta(r - \|x_m(i) - x_m(j)\|_\infty) \quad (2.16)$$

Then we formulate  $B_i^m(r)$  as

$$B^m(r) = \frac{1}{N - m} \times \sum_{i=1}^{N-m} B_i^m(r) \quad (2.17)$$

Similary we define  $A_i^m(r)$  is defined for next  $m+1$  vector

$$A_i^m(r) = \frac{1}{N - m - 1} \times \Theta(r - \|x_{m+1}(i) - x_{m+1}(j)\|_\infty) \quad (2.18)$$

Then  $A^m(r)$  would be defined as probability that two sequences would match for  $m$  points

$$A^m(r) = \frac{1}{N - m} \times \sum_{i=1}^{N-m} A_i^m(r) \cdot B^m(r) \quad (2.19)$$

And finally he defined Sample Entropy as,

$$SampEn(m, r) = \lim_{N \rightarrow \infty} \left( -\ln \left( \frac{A^m(r)}{B^m(r)} \right) \right) \quad (2.20)$$

$$SampEn(m, r, N) = -\ln \left( \frac{A^m(r)}{B^m(r)} \right) \quad (2.21)$$

### 2.3.3 Use of Approximate and sample entropy in gait analysis

Effect of sedation on gait of lame horses were studied [28] which is basis for our study. This study used the median vector sum values of head movement and meadian values for hip drop and hip hike for before and after sedation. This study found that vector sun and hip drop/hike had no significant difference from sedative effect.

Entropy measures have made a number of appearances among the nonlinear dynamical measures being used in biomechanical studies. Of particular interest are uses of entropy measures to study postural balance and gait. Postural balance studies have investigated the effects of pathology and aging on the ability of subjects to balance in quiet standing on different surfaces. Entropy measures have been shown to correlate with existing indicators of the health of postural balance [10] [9]. Entropy analysis was done by Yuki Tochigi(2011), [31] for leg acceleration signal wave forms for human gait. This sample entropy study proved that age dependent decrease of motion pattern variability in gait. Reduced sample entropy suggested that with age the complexity and variability of the motion is reduced. Thomas(2017) studied impact of speed and time on human gait with sample entropy[30]. Sample entropy of stride period showed significant difference in mean with gait speed with increased entropy with speed.

A study done by McGregor(2011) [22] studied complexity of walking for running athletes, and found decreased entropy value indicating change in gait. Though he concluded that it does not necessarily mean unhealthy gait, the normal gait was affected from training. The study concluded that highly-trained runners exhibit lower complexity in their vertical and medial-lateral accelerations.

Costa [9] used entropy measures to assess variations in stride intervals for different speeds of self-paced and metronome-paced walking. Measurements were taken over one hour of consecutive strides. By comparing consecutive strides to shuffled strides, Costa noted that metronome-paced walking disturbed natural variations in stride interval.

The main focus of this study is to analyze the changes in the head acceleration during trotting. The head moves up and down twice during a single stride. In a sound horse this movement is symmetrical and sinusoidal. But this affects if horse is lame as it tries to adjust its center of body mass to reduce the pressure on the lame leg. For a long time investigators have tried to formulate and distinguish complex biological systems with the help of nonlinear dynamics or chaos. This complex behavior has been encapsulated with the help

of formulation of different parameters relating dimension and entropy. But proper estimation of these parameters is difficult considering large amount of data points required and noise factor, resulting in use of several algorithmic calculations to compute each parameter.

Before this study was done to investigate effect of sedation on gait of lame horses[28]. This study used the same head and pelvic acceleration data to analyze the motion. Head motion vector sum and hip hike/drop was calculated from this acceleration, and statistical analysis of this data proved no significant effect. We would try to apply sample entropy to same data to get different insight about the motion.

## Chapter 3

### Methods

#### 3.1 Study Design

Kinematic data was recorded from 10 lame horses and 2 sound horses; mean weight (+/- standard deviation) 460 +/- 50 kg. Lameness was determined with subjective evaluation from two of the investigators. A full clinical examination was performed on all horses to ensure that these horses satisfied the experiment's requirements. They were amendable to the trotting protocol and measurement sessions.

For our first study we would establish a relationship between lameness in gait and sample entropy. Two horses from each group(sound and lame) were trotted for 10 random trials while wearing sensors for objective evaluation using a motion analysis system (Lameness Locator, Equinosis). The signal is transmitted to a tablet PC at a 200 Hz frequency.

After that for our main study to test effect of sedation we are going to consider two groups; group A (horses administered 10 mg of detomidine HCL; Pfizer Animal Health, New York, NY) and group B (no treatment, control group). In this study same subject would act as its own control group as the administration of sedatives and treatment group trials were done after sufficient days of first trials. Horses were trotted about 25 strides every 5 minutes for 45 minutes. Again lameness locator was used for these trials.

After successful collection, data was processed in the software packages given for the IMU system used (Lameness Locator, Equinosis). These primary results was basis for our lameness examination which provided us insight for our further detail analysis. The raw sensor data collected from the system was used further in MATLAB R2016a(Mathworks,BV,USA) for the Sample Entropy Analysis with the help of SampEn algorithm developed by D.K. Lake, J.R. Moorman and C. Hanqing, PhysioToolkit-PhysioNetm[?]. To determine correlation

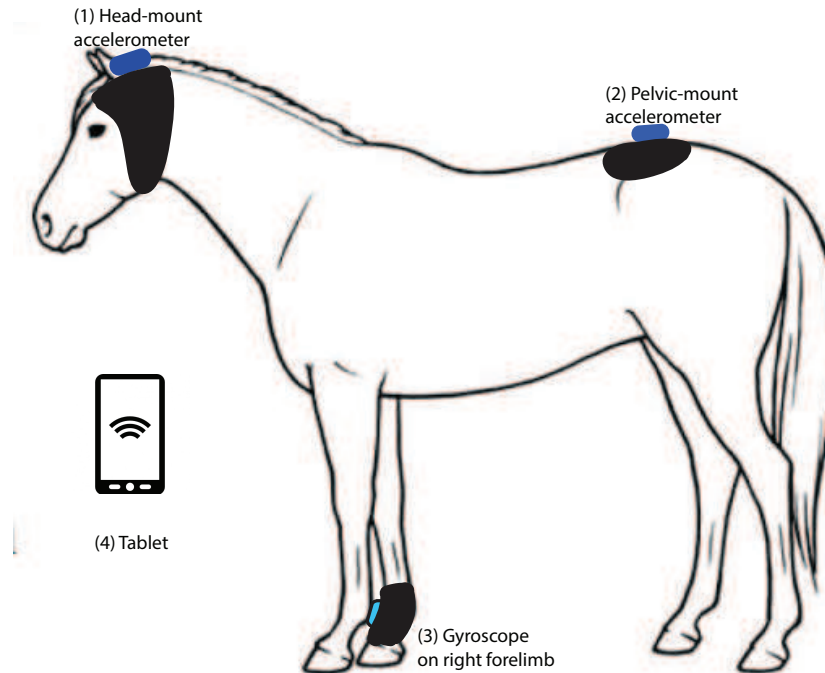


Figure 3.1: Inertial sensor placement Sketch of experimental setup. Head and Pelvic movement was recorded simultaneously.

between gait and SampEn also the effect of sedation drugs, t-test and a two-way repetitive measure ANOVA method was used respectively with IBM SPSS Statistics Subscription.

## 3.2 Data Acquisition

### 3.2.1 Instrumentation

Lameness Locator is a wireless inertial sensor-based, motion analysis system designed to objectively detect and evaluate lameness in horses. There are 4 components in this system; 3 inertial sensors and a tablet PC. Inertial sensors are attached non-invasively to horse. As shown in figure 3.1 One single axis accelerometer (head-mounted accelerometer) is mounted on the most dorsal aspect of the crown piece of the halter or to a head bumper attached to halter. Another single-axis accelerometer (pelvic-mounter accelerometer) was attached to the skin between right and left tuber sacrale. One single-axis gyroscope was attached to



dorsal aspect of the region between the metacarpophalangeal joint and coronary band of the right forelimb.

Specifications for all inertial sensors are as follows. Single-axis accelerometer transducer sensor setup on head consist of a noninverting amplifier, low-pass filter design (resolution, 20mV/G [G (acceleration due to gravity) = 9.8 m/s<sup>2</sup>]; gain, 43.5X; cutoff frequency, 50Hz). The accelerometer transducers measure the combination of gravitational and unidirectional inertial acceleration. Single-axis piezoelectric vibrating gyroscopic transducer sensor comes with a noninverting amplifier, low-pass filter design (resolution, 0.67mV/G; gain, 2X; cutoff frequency, 53Hz). The gyroscopic transducer measure right forelimb angular velocity through phenomenon of Coriolis force, which is generated when a rotational angular velocity is applied to a vibrating element[15].

### **3.2.2 Data collection and primary analysis**

After the data is collected in the system, software filter the data as shown in the figure 3.2. The start point and end point of each cycle is determined to avoid outliers during starting steps and when horse is turning around. Once the data is finalized stride splitting and double integration of the uni-axial vertical acceleration of head and pelvis would be done to calculate the vertical displacement in the sensor reference frame. Stride split was achieved by using the information from the gyroscope located in the right forelimb to identify left or right stance or swing phase. Figure gives us an example of tracing one stride of signal and how corresponding head movement values are calculated.

After the correct identification of strides and head movement is done software gives us analysis report as shown in figure with forelimb and hindlimb ray diagram and lameness values based on lameness theory proposed by Keegan(year). We would use this report as a initial confirmaion of gait of current horse into lame and sound. This analysis is based on calculation displacement of head and pelvic from acceleration values obtained with inertial sensors during stride cycles and its correlation to maximum and minimum values.

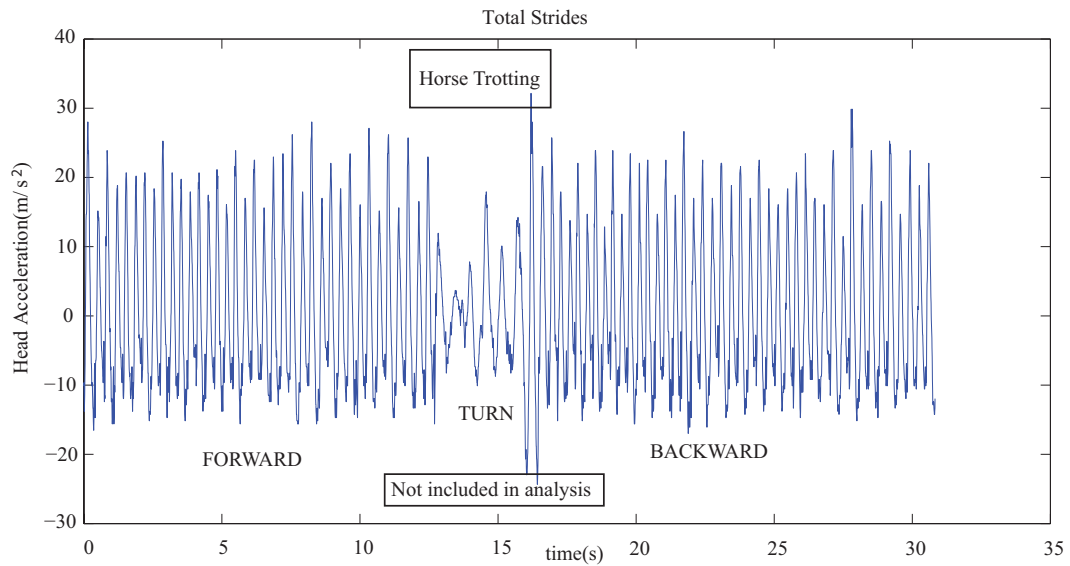


Figure 3.2: Data Collected from head accelerometer. Figure shows selection of filtered data to remove outliers

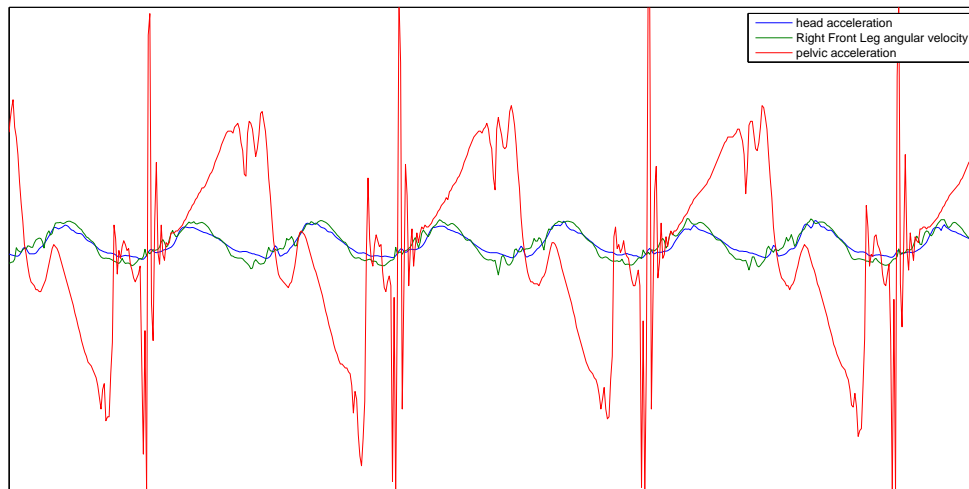
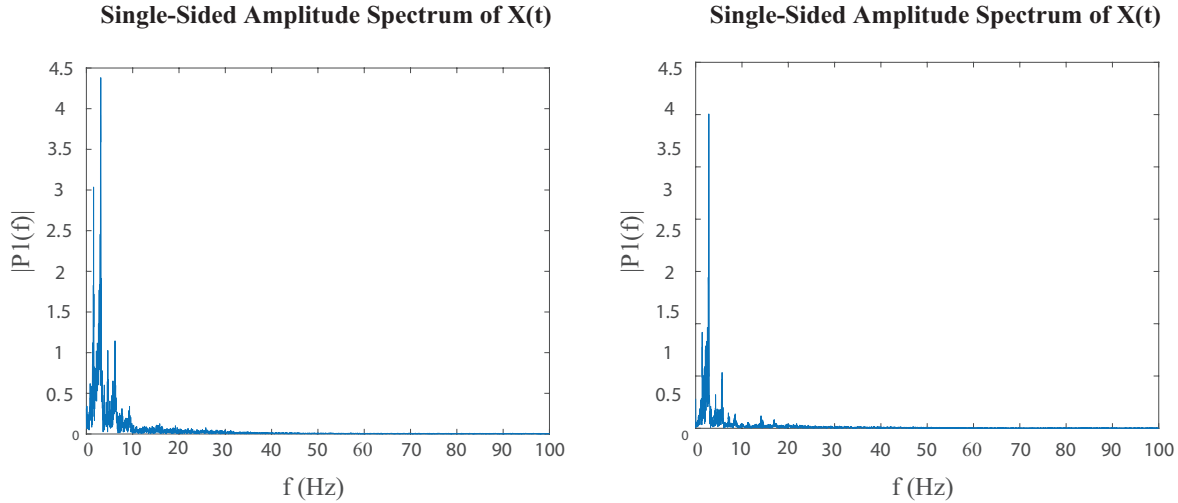


Figure 3.3: Simultaneous plot of head acceleration, Right front leg angular velocity and pelvic acceleration. This figure shows the step detection is achieved



(a) FTT for head acceleration before sedation (b) FTT for head acceleration after sedation

Figure 3.4: Fourier analysis

For our study purpose we were interested in acceleration data, so first we collected raw sensor data from software for each trials. The data was in tsv-format with a unique 32-digit hex address which was placed correctly for each trials with the help of horse and trial address tag. The raw output value in this file was digitized (8-bit) from the voltage value(+/- 5 volts). So the conversion factor was used to get actual acceleration data from this for our study. The data collected from the sensor was filtered similarly as done in the software by removing outliers.

### 3.2.3 Preprocessing of raw sensor data

Initially basic filtering was done to check and remove noise from the data. The data was detrended. . Fourier analysis was done as an initial analysis of data to get a clear picture about the frequency spectrum.

Some important aspects of horse head motion was highlighted in this analysis as presented by Keegan as the motion of head with 2 major frequencies. Similar properties were observed in the pelvic motion.

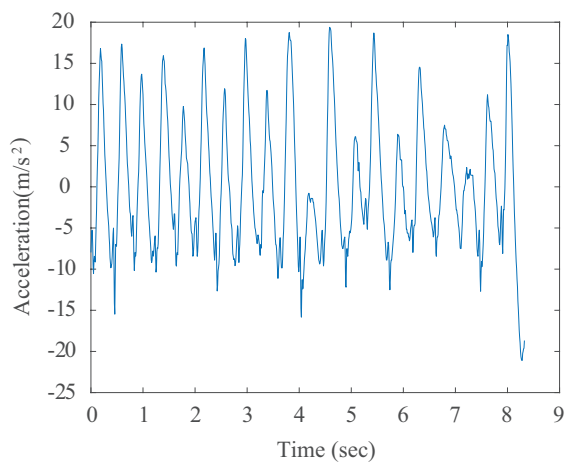
Similar algorithm was created as used in the previous section by Lameness Locator software; to recognize step using single axis gyroscope. As you can see in the (3.4) the 10 strides have been recognized by the software according to the impact during each step.

Data were time normalized in two separate manners and results were compared. First every stride was time normalized to 100 data points per stride and this helps to have same data points for each cycle regardless of varying step time. But it also affects the temporal variation. Second whole cycle was time normalized for 1000 data points with 20 strides. This helps in keeping temporal variation.[32] This data length is considered sufficient for our entropy analysis. Fourier analysis of data was done to determine major frequencies. It was observed that both data standardization gave the same results. So only data with each stride time normalized was used for our analysis.

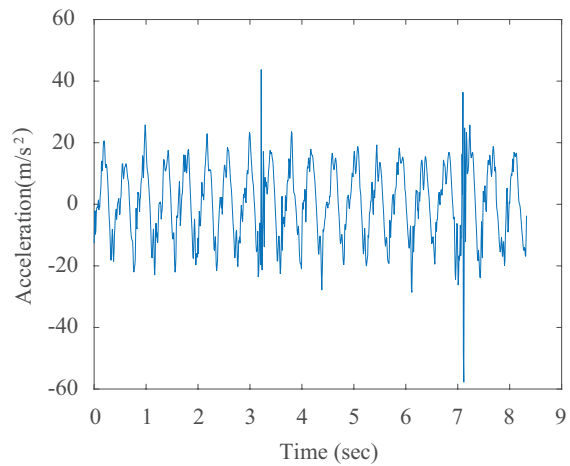
### 3.3 Sample Entropy

After signal data is segmented into strides and normalized, the entropy calculation was carried out. For each horse we had 10 repetitive reading with 5 minute time interval. The SampEn give us the probability of two data that are close (predetermined tolerance level) in  $m$ -dimensional space, remain close in  $m + 1$  dimensioned space. Greater is the probability less is the SampEn value and vice versa. Hence complexity level of two signals could be determined from this method. For the computation of SampEn, we followed here the guidelines detailed in Ramdani et al. To estimate the SampEn, the time series is standardized to obtain samples with zero-mean and unit standard deviation.

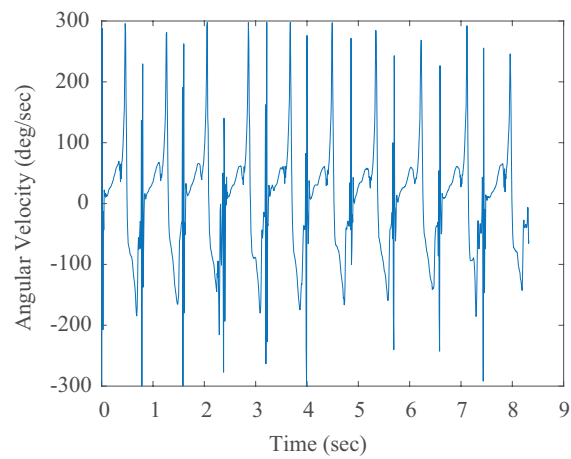
SampEn is found to be closely related to selection of  $m$  and  $r$  for short data sets. Hence we used methodology proposed by Lake for the selection of embedding dimension ( $m$ ) and tolerance( $r$ ). But before that we need to understand these two parameters and what they indicate for entropy calculations.



(a) Acceleration from head-mounted accelerometer



(b) Acceleration from pelvic-mounted accelerometer



(c) Angular velocity from single axis gyroscope

Figure 3.5: Ten Cycle data extracted from complete cycle (c) you can see sudden change in velocity which separates each cycle

### 3.3.1 Embedding dimension (m)

Embedding dimension is smallest dimension of the space required to unfold the projection of original space. Takens(1981) proposed that calculating a dimension bigger than twice the Hausdraoff dimension of the chaotic attractor accomplishes this task[29]. Pincus(1995) suggested to set  $m = 2$  or  $3$  which is based on the data that higher  $m$  values gives poor ApEn estimation because of lesser number of vectors for comparison and self counting algorithm of ApEn.[25] Though SampEn avoids self counting we need sufficient number of vectors to determine similarity in time signal.

### 3.3.2 Threshold (r)

As it was aforementioned, the statistics  $SampEn(m, r)$  can vary significantly with  $r$ . Pincus(1995) suggests that  $r$  should lie between  $0.1$  and  $0.2$  times the standard deviation (SD) of the raw signal [25]. The  $r$  value should be large enough, not only to avoid significant contribution from noise, but also to admit a reasonable number of  $x_m(i)$  vectors being within a distance  $r$ . This would ensure an acceptable estimation of the  $C_m(r)$  probability. However, with too large  $r$  values,  $SampEn(m, r)$  is unable to perform fine process distinctions and consequently, the  $r$  value selection will greatly depend on the application.

### 3.3.3 Choosing parameters

The procedure is based on to use a convergence criterion which estimate  $m$  leading to the selection of  $r$ . We calculated median SampEn for all data sets for  $m$  ( $m = 1, 2, 3, 4$ ). The convergence criteria is used to estimate best embedding dimension. It was observed that when we plot entropy values plot converge when  $m$  is equal or greater than  $3$ . . The second step is to estimate the value of  $r$  which would give maximum relative error no higher than  $0.05$ , so that  $95$  percent CI entropy estimate is  $10$  percent of its value. Also it for almost all values error was below  $95$  percent. For  $m = 3$ , the minimum of the median of  $Q(m, r)$  values was reached for a radius  $r = 0.70$ . Hence, the two optimal input parameters used for

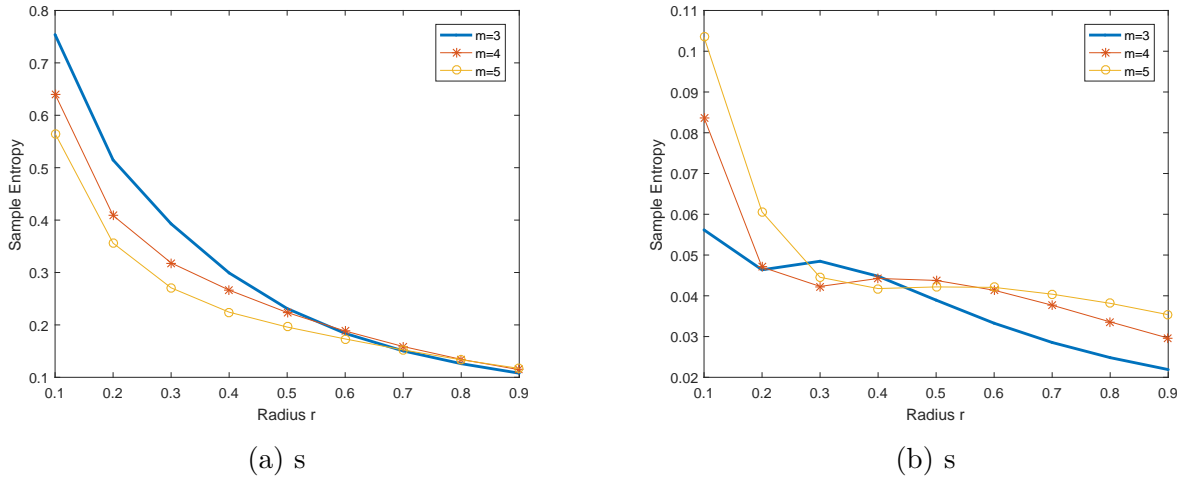


Figure 3.6: Median sample entropy and error estimation as a function of  $m$  and  $r$  (a) The median of sample entropy is observed to be highest at  $m=1$  and  $m=4$  and 5 are very close to all  $r$  values

computing the SampEn were  $m = 3$  and  $r = 0.70$ . Note that if more than one error curve displays values that are below 0.05, one would select the converging  $m$  value associated to the lowest error curve. This optimal  $r$  value is higher than the recommended values of the tolerance for computing SampEn (which are ranging from 0.10 to 0.20).

### 3.4 Statistical analysis

To obtain more clear picture about the results obtained detailed statistical analysis was done to assess the ability of entropy to characterize difference in motion before and after the sedation. First independent t-test would be performed to find if there is any significant difference between two means of sample entropy for sound and lame horse. Then a two way repeated-measure analysis of variance (ANOVA) would be used to investigate the significance of change in entropy measure. This result would be interpreted based on three comparisons. We would first compare the change of time as a factor in analysis after sedation. Second we would compare the our two control groups and if the difference is significant. And final comparison would impact of time and sedation has on horse gait.

This analysis is based on three metrics; F-statistic, p-value (significance level). F statistic is used to decide whether the analysis supports or rejects your null hypothesis in this case which is that there is an effect of sedation on the gait. It represents the ratio of the between-group variability to the within-group variability. This allows one to assess whether the variations between the two groups reflect variations that would naturally occur from two samples of the same population or whether the variations are meaningful. An F-statistic of 1 corresponds to when the between-group variation is equal to the within-group variation and means the two groups are likely samples of the same population. Increasingly large F-statistics reflect increasingly more meaningful differences between the two groups. The presentation of an F-statistic is accompanied by two measures of the degrees-of-freedom of the system under consideration;  $dfb$  and  $dfw$ .  $dfb$  represents the between-group degrees of freedom and is equal to the number of groups minus one.  $dfw$  represents the within group degrees of freedom; in our case this would point out the change with temporal variation and is equal to the sum of one less than the number observations in each group.

Although the F-statistic provides insight about the nature of within group and between group variations, it is not easily interpreted. We therefore interpret the meaning of the F-statistic based on its corresponding significance level. The significance level, or p-value, is a common numerical value in statistical hypothesis testing. Formally, it corresponds to the probability of incurring a Type I error; when the null-hypothesis is incorrectly rejected. In the contexts of the ANOVA described above, the null-hypothesis would be that both groups are samples of the same population (there is no statistically meaningful difference between the results). Therefore, the significance level, or p-value, can be thought of as the probability that the two samples belong to the same population. Following this logic, the smaller the p-value, the more significant the difference between the two groups. Typically,  $p < 0.05$  represents the least strict criteria for rejecting the null hypothesis. By considering the effect size, F-statistic and significance level together, we gain good insight into the differences between two groups.



## Chapter 4

### Results

This chapter encompasses a presentation of the research results organized around the two research questions.

1. Is there any significant difference between the sample entropy of lame and sound gait?
2. Is there any significant difference in sample entropy after sedation on groups. Also to find if there is any interaction between time of the trial and treatment?

**Hypothesis 1. There is statistically significant difference on sample entropy value of equine gait of sound horse and lame horse.**

For this study we took 20 random trials from 2 sound horse and another 20 random trials from 2 lame horse. The head acceleration data taken from Lameness Locator was used to calculate sample entropy (Table 4.1).

The group of horse with sound gait (number of readings taken for each group( $N = 20$ ) was associated with sample entropy mean  $M = 0.413$  with standard deviation( $SD = 0.0486$ ). By comparison the group of horse with lameness in gait was associated with numerically smaller and sample entropy mean  $M = 0.297$  with standard deviation ( $SD = 0.015$ )(Table 4.2). To test the hypothesis that there is a statistically significant difference between mean sample entropy and independent samples t-test was performed.

As explained in the previous chapter we would test the data for normality and homogeneity of variance. Readings taken for lame and sound horse were sufficiently normal for the purpose of conducting t test . Table 4.3 shows that skew for the data is  $0.517 (< |2.0|)$  and Kurtosis is  $-1.245 (< |9.0|)$  (find paper for schmider 2010).

Table 4.1: Sample entropy Values for Head acceleration. Comparison is done between the sound and lame gait. Total 20 readings were taken for each condition from 2 horses from each category.

No.	Sample Entropy for Sound gait	Sample Entropy for Lame Gait
1	0.405	0.292
2	0.448	0.285
3	0.441	0.274
4	0.401	0.287
5	0.347	0.293
6	0.446	0.291
7	0.333	0.281
8	0.354	0.288
9	0.356	0.3
10	0.421	0.315
11	0.4	0.321
12	0.324	0.308
13	0.437	0.273
14	0.44	0.318
15	0.495	0.28
16	0.437	0.303
17	0.475	0.304
18	0.473	0.329
19	0.425	0.289
20	0.408	0.312

Table 4.2: Total independent 20 readings were taken for lame and sound horse and the mean is compared in this table.

*Group Statistics*

Gait_type	N	Mean	Std. Deviation	Std. Error Mean
SampEn	Sound gait pattern	20	0.41327	0.048697
	Lame gait pattern	20	0.29717	0.015991

Table 4.3: Normality test for the given data

*Descriptives*

	Statistic	Std. Error
SampEn	Skewness	0.517(< 2.0)
	Kurtosis	-1.245(< 9.0)

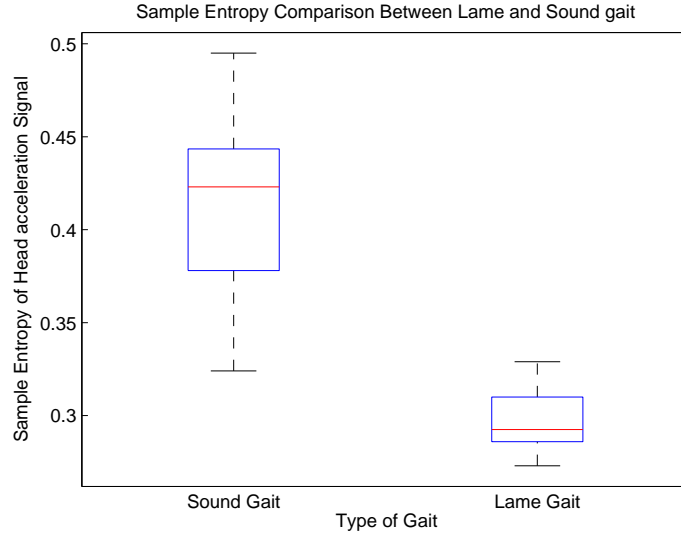


Figure 4.1: Figure show comparison of sample entropy between sound and lame gait

Additionally the assumption of homogeneity of variances was tested and satisfied via Levene’s  $F$  test,  $F(38) = 15.947, p < 0.001$  where degree of freedom(df) = 38. As  $p$  is less than 0.05 this test was satisfied. We performed independent sample  $t$  test on IBM SPSS Statistics. The independent samples  $t$ -test was associated with a statistically significant effect,  $t(38) = 10.13, p < 0.001 (< 0.05)$  (Table 4.4). Thus sound horse gait was associated with statistically significantly larger mean sample entropy than lame horse gait.

Table 4.4: Independent Sample  $t$  test was done between sound and lame gait sample entropy

*Independent Samples Test*

t-test for Equality of Means							
	t	df	Sig.(P) (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						Lower	Upper
SampEn	10.130	38.000	5.8E-10	0.116	0.011	0.092	0.139

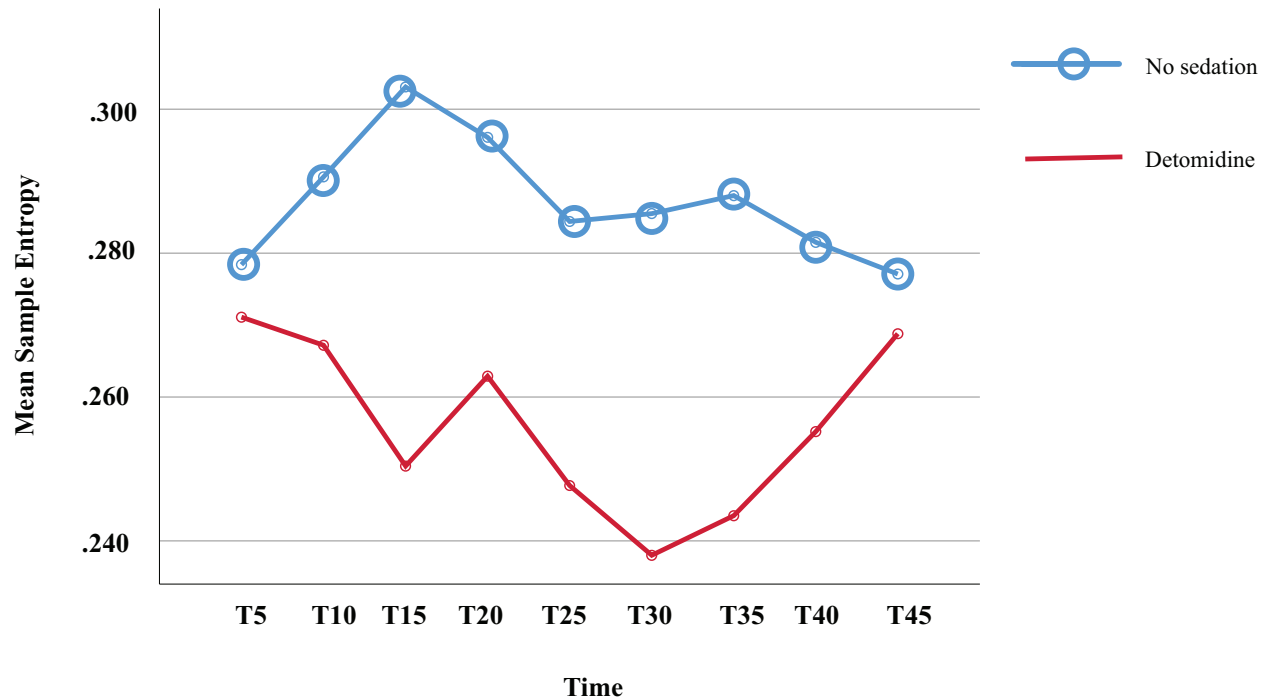


Figure 4.2: Comparison of mean of sample entropy between two treatment groups over time

**Hypothesis 2. There is a statistically significant difference in sample entropy value of equine gait of control group with no sedation and treatment group who was administrated with detomidine.**

To answer these research questions, a general linear model using two way factorial repeated measures ANOVA in SPSS software was used to analyze the sample entropy data between the nine time periods (T5, T10, T15,..., T45) , treatment and control groups (Table 4.5).

The group of lame horse who are not sedated (group 1) has a sample entropy mean  $M = 0.287$  with standard deviation( $SD = 0.023$ ). By comparison the same group of horse when sedated (group 2) has sample entropy mean  $M = 0.256$  with standard deviation ( $SD = 0.020$ )(Table ??). Also we took repetitive measures at 5 minutes time interval to see if there is any interaction between kind of treatment and time. To test the hypothesis that there is a statistically significant difference between mean sample entropy and interaction two way ANOVA repetitive analysis was performed.

Table 4.5: Sample entropy Values for Head acceleration before and after sedation

Treatment	Subjects	Time of Test								
		T5	T10	T15	T20	T25	T30	T35	T40	T45
No sedation (group 1)	S1	0.272	0.27	0.288	0.275	0.272	0.228	0.274	0.224	0.251
	S2	0.258	0.266	0.262	0.266	0.264	0.306	0.257	0.286	0.269
	S3	0.293	0.262	0.276	0.303	0.304	0.278	0.252	0.288	0.277
	S4	0.273	0.302	0.345	0.288	0.298	0.317	0.314	0.308	0.301
	S5	0.212	0.242	0.217	0.246	0.2	0.156	0.156	0.237	0.177
	S6	0.16	0.165	0.191	0.203	0.142	0.139	0.173	0.134	0.173
	S7	0.366	0.399	0.416	0.331	0.362	0.355	0.365	0.367	0.366
	S8	0.352	0.394	0.447	0.439	0.424	0.393	0.375	0.394	0.375
	S9	0.333	0.353	0.337	0.345	0.338	0.357	0.363	0.332	0.344
	S10	0.265	0.253	0.252	0.265	0.24	0.326	0.351	0.245	0.238
Detomidine (group 2)	S1	0.311	0.345	0.287	0.338	0.226	0.229	0.221	0.211	0.25
	S2	0.279	0.313	0.318	0.224	0.219	0.273	0.292	0.307	0.313
	S3	0.197	0.217	0.213	0.207	0.209	0.197	0.213	0.217	0.213
	S4	0.313	0.291	0.265	0.291	0.256	0.26	0.278	0.285	0.29
	S5	0.217	0.16	0.142	0.153	0.166	0.166	0.161	0.177	0.161
	S6	0.191	0.202	0.167	0.184	0.169	0.153	0.185	0.172	0.194
	S7	0.305	0.338	0.31	0.286	0.307	0.275	0.242	0.311	0.292
	S8	0.317	0.242	0.241	0.28	0.269	0.196	0.207	0.235	0.236
	S9	0.328	0.335	0.328	0.444	0.43	0.421	0.415	0.344	0.419
	S10	0.253	0.229	0.233	0.222	0.226	0.21	0.221	0.293	0.32

Table 4.6: Mean comparison Between two treatment groups

*Estimates*

Measure: MEASURE\_1

Treatment	Mean	Std. Deviation	95% Confidence Interval	
			Lower Bound	Upper Bound
1	0.287	0.023	0.236	0.338
2	0.256	0.020	0.211	0.301

As shown in Table 4.6 and figure 4.2 mean for no sedation is less compared to that of Detomidine. Now we need to find that wheter this difference is statistically significant or not.

Now we are going to check three effects. First we would be measuring whether time alone has any significant effect on the sample entropy of head acceleration or not. Then we are going to check whether the treatment (sedation) has any similar affect. And lastly we would like to verify any changes because of the interaction between the time and treatment

Table 4.7 shows the results of the ANOVA with corrected F values. The output is split into sections that refer to each of the effects in model and error terms associated with these effects. Also it includes the significance values of the F-ratios. If these values are less than 0.05 then we can say that effect is significant. To test the first effect of change with time (T5, T10,..., T45)  $F(6.345, 114.208) = 0.940$ ,  $p = 0.473$  ( Huynch Fedt meathod). As p value is not less than 0.05, the mean at different time interval does not have any significant change. The main effect of treatment yielded an F ratio of  $F(1, 18) = 1.063$ ,  $p = 0.316$ , indicating that the treatment effect was also non-significant. The interaction effect between time and treatment was non significant ,  $F(6.345, 114.208) = 1.526$ ,  $p = 0.172$ ,

Table 4.7: Testes of within subject effects like time of testing and its interaction with treatment

*Tests of Within-Subjects Effects*  
Measure: MEASURE\_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Squared	Eta
Time	Sphericity Assumed	0.007	8	0.001	0.940	0.486	0.050	
	Greenhouse-Geisser	0.007	4.411	0.001	0.940	0.452	0.050	
	Huynh-Feldt	0.007	6.345	0.001	0.940	0.473	0.050	
	Lower-bound	0.007	1.000	0.007	0.940	0.345	0.050	
Time * Treatment_group	Sphericity Assumed	0.011	8	0.001	1.526	0.153	0.078	
	Greenhouse-Geisser	0.011	4.411	0.002	1.526	0.198	0.078	
	Huynh-Feldt	0.011	6.345	0.002	1.526	0.172	0.078	
	Lower-bound	0.011	1.000	0.011	1.526	0.233	0.078	
Error(Time)	Sphericity Assumed	0.125	144	0.001				
	Greenhouse-Geisser	0.125	79.398	0.002				
	Huynh-Feldt	0.125	114.208	0.001				
	Lower-bound	0.125	18.000	0.007				

## Chapter 5

### Discussion and Future work

It had been suggested that because of lameness with the pain during gait the stability is disturbed. But the correlation between the complexity and stability is often debating topic. Existence evidence suggest that the head and pelvic movement gives most important area to examine for lameness. But only variability does not gives us the important picture about how body handles kinematic variability factor like lameness i.e. control of disturbances in regular movements. Many previous research had suggested that the variation from regular cyclic motion should be considered negative. But balance in gait is a complex phenomena. The changing pattern due to internal external abnormalities on the gait would be complex. The result we found during comparison of lame and sound horse supports these findings. The complexity of equine motion is increased with sound movement.

Also for a long time clinicians are trying to find the effects of sedation on lameness examinations. Sample entropy analyses revealed that the stability was not significantly influenced by the administrating 10 mg detomidine.

Diagnostic analgesic is important component in lameness examination and it is important to notice the changes that would occur in evaluation of lameness. Local anesthesia is commonly used during lameness examination to confirm or identify the site of pain. Also it is important to observe the effect of sedation with time and this study suggest the with time no significant change was observed.

Also we have to consider the possibility of some shortcomings in entropy study. Correlation between healthy system and complexity of time signal obtained is not proved criteria. The current hypothesis is largely based on the analysis of healthy horse locomotion and

based on that it was decided that high entropy indicates higher complexity and healthier motion.

Neuromuscular control of stability was unaffected by sedation. There are other several possible factors which need to be studied for this trend. The pain caused area and sedation techniques may effect this also. Feedback delay is widely accepted as a destabilizing influence on control systems which could also be important factor considering improved gait. Sedation could cause increased delay in the active recruitment and neural feedback relative to the movement trajectory. Therefore, it is not surprising that neuro-control of dynamic stability was improved after sedation.

If we considered the current system is healthy then future possibilities could be examined. The most important paramter to study which was observed to be the kinematic angles during locomotion. As the hind leg dynamics is main power source for whole motion, it would be interesting to establish a entropy analysis on foot contact and angle dynamics in hind limb for further studies.

Sample entropy is sensitive to sampling frequency and length of data sets. Also the extent of nonlinear dynamics in equine gait is unclear. But the entropy measure is able to show statistically significant difference between two gaits. This also supported the fact that lower entropy in gait is healthier than higher entropy. Although further investigation is necessary to support the fact.

## **5.1 Work done by author**

For a long time human gait is analysed using nonlinear methods like sample entropy. But for the first time we applied entropy to equine gait analysis. In the present work, we have shown that, using an appropriate methodology, the SampEn algorithm is able to characterize complexity features of equine gait dynamics in terms of their irregularity. Using the proposed approach for selecting the input parameters of the algorithm, the SampEn



could be a good dynamical signature to characterize the postural effects of sedation and lameness. Such clinical applications represent interesting research directions to explore.

Appendix A  
Preprocessing of data

```
load CC605.dat
convertunit(CC605);
fs = 200; % frequency of data

Ts = 1/fs; %Time Period for each reading

NP = length(CC605); % Total Number of points
N=1:NP; % Numericline

TP = (NP-1)*Ts; % Total Time of reading
T=0:Ts:TP; % Timeline

plot(T,ans(:,1))
title('Total Strides ')
xlabel('time(s)')
ylabel('Head Acceleration (m/s^2)')
print('-depsc', 'headacc');

function acc = convertunit(rawacc)
acc = (rawacc - 128)*6*9.8/128;
end

function legvel = convertunit2(rawleg)
```

```

legvel = (rawleg - 128) * 300 / 128;
end

clear all

clc

close all

dd = dir('*.dat');
% figure('Visible','off')
fileNames = {dd.name};
data = cell(numel(fileNames), 2);
data(:, 1) = regexp(fileNames, '.dat', '');

for ii = 1:numel(fileNames)
    data{ii, 2} = dlmread(fileNames{ii});
    t = data{ii, 2};
    [segdata, segdata1] = Steptime(t);
    filename = [sprintf(data{ii, 1}), num2str(1), sprintf('.dat')];
    save(filename, 'segdata', '-ascii');
    movefile(filename, 'profile')
    filename1 = [sprintf(data{ii, 1}), num2str(2), sprintf('.dat')];
    save(filename1, 'segdata1', '-ascii');
    movefile(filename1, 'profile')
%     subplot(3, 1, 1)
%     plot(data{ii, 2}(1:end, 1));
%     subplot(3, 1, 2)
%     plot(data{ii, 2}(1:end, 2));
%     subplot(3, 1, 3)
%     plot(data{ii, 2}(1:end, 3));

```

```

% print('-depsec', data{ii,1});
end

function [segdata,segdata1] = Steptime(horsedata);

fs = 200; % frequency of data

Ts = 1/fs; %Time Period for each reading

NP = length(horsedata); % Total Number of points
N=1:NP; % Numericline

TP = (NP-1)*Ts; % Total Time of reading
T=0:Ts:TP; % Timeline

headacc = horsedata(:,1);%Head Acceleration
gyrovel = horsedata(:,2);% Right Leg Angular Velocity
pelacc = horsedata(:,3); %Pelvic Acceleration

%We would separate Data based on Right Leg Angular Velocity

% Take a double difference to exactly locate when foot touches the ground

u = diff(gyrovel);
v = diff(u);

%Invert the graph as we need minimum points and shift by 128 to move to
%centerline

```

```

invertedgyrovel = -gyrovel + 128;
invertedv = -v + 128;

%Peak Analysis of double difference
NT = length(invertedv);
figure;
plot(NT,invertedv);
[pks, locs] = findpeaks(invertedv, 'MinPeakHeight',50, 'MinPeakDistance',100, '
pks1=invertedgyrovel(locs);
figure;
plot(N,invertedgyrovel);
hold on;
plot(N(locs), pks1, 'o', 'MarkerSize',12);

%Numbering the peaks

for k= 1:numel(pks)
text(N(locs(k)), pks1(k), num2str(k));
end
title('Counting strides');
xlabel('Time (s)');
ylabel('Inverted head acceleration (m/s^2)');
hold off;

% User Input for the start point

```

```

% prompt = 'From which peak to start? ';
% x = input(prompt);
% w = waitforbuttonpress;
% if w == 0
%     disp('Button click ')
% else
%     disp('Key press ')
% end

```

```

prompt = {'From which peak to start?'};
dlg_title = 'Input';
num_lines = 1;
x = inputdlg(prompt,dlg_title ,num_lines);
x = str2num(x{1,1});

```

```

% To eliminate Outliers in stride duration
q = diff(locs);
y = quantile(q,[0.25, 0.5, 0.75]);
r = iqr(q);
stllim = y(1)-1.5*r;
stulim = y(3)+1.5*r;

```

```

cycles = 10;

```

```

%creating step data for 10 cycles
A = locs(x:x+cycles);
s = diff(A);

```

```

if s(s < stulim)
    segdata = horsedata(A(1):A(end),:);
end
%Linear Lenth Normalisation for whole cycle
LC = 1500;
TLC = 1:(length(segdata)-2)/(LC-1):(length(segdata)-1);
LEC = LC/cycles;

NLC = 1:(length(segdata)-1); % NumericLine

segdata = interp1(NLC, segdata(1:end-1,:), TLC);

for st=1:cycles
    NLEC = 1:length(horsedata(A(st):(A(st+1)-1)));
    TLEC = 1:(length(horsedata(A(st):A(st+1)))-2)/(LEC-1):(length(horsedata(A(st)
segcycledata = interp1(NLEC, horsedata(A(st):(A(st+1)-1),:), TLEC);
    if st ==1;
        segdata1 = segcycledata;
    else
        segdata1 = vertcat(segdata1, segcycledata(2:end,:));
    end
end

% headacc = headacc - 128;
% headacc = (headacc * 6 * 9.81)/128;

```

## Appendix B

### Sample entropy calculation

```
clear all, clc;
d=uigetdir('', 'Select Input-folder '); %select the input-folder that contains
cd(d);
list = dir;
list = list([list.isdir]);
list = list(~ismember({list.name},{'.' '..'}));
l=length(list);
for i=1:l
    oldfolder = cd(list(i).name);
    dd = dir('*.*dat');
    fileNames = {dd.name};
    data = cell(numel(fileNames),2);
    data(:,1) = regexp(fileNames, '\.dat', '');
    numberOfFiles = numel(fileNames);
    for ii = 1:numberOfFiles
        data{ii,2} = dlmread(fileNames{ii});
        [head, leg, pelvic] = data_separation(data{ii,2});
        headacc = convertunit(head);
        pelvicacc = convertunit(pelvic);
        legvel = convertunit2(leg);
        filenamehead = [sprintf(data{ii,1}), sprintf('head.dat')];
        filenameleg = [sprintf(data{ii,1}), sprintf('leg.dat')];
```



```

        filenamepelvic = [sprintf(data{ii,1}),sprintf('pelvic.dat')];
        save(filenamehead , 'headacc ', '-ascii ');
        movefile(filenamehead , 'headacc ');
        save(filenamepelvic , 'pelvicacc ', '-ascii ');
        movefile(filenamepelvic , 'pelvicacc ');
        save(filenameeleg , 'legvel ', '-ascii ');
        movefile(filenameeleg , 'legvel ');
    end

        cd(olddfolder);

end

clear all; clc; close all
rnum=9;
m=5;
% r = 0.15;
clc;
datafiles = dir('*.dat');
numfiles = length(datafiles);
mydata = cell(1,numfiles);
for k = 1:numfiles
    clear e A B;
    mydata{k}=importdata(datafiles(k).name);
    mydata{k} = (mydata{k} - min(mydata{k})) / ( max(mydata{k}) - min(mydata{k}));
    [b a]=butter(2,0.1,'low');
    mydata{k} = filter(b,a,mydata{k});
% main calculation and display
% figure(k);
for i = 1:rnum

```

```

    r = i*0.1;
    [e,se ,A,B] = sampen(mydata{k}(:,1), m , r ,1 ,0 ,1);
    for j =1:m
        se_entpy(j ,i ,k) = e(j);
        stderror(j ,i ,k)= se(j);
    end
end
end
for j =3:m
for i = 1:rnum

for k = 1:numfiles
    if k==1
        initialen(j-2,i)=se_entpy(j ,i ,k);
        initialerror(j-2,i)=stderror(j ,i ,k);
    else
        initialen(j-2,i) = initialen(j-2,i) + se_entpy(j ,i ,k);
        initialerror(j-2,i) = initialerror(j-2,i) + stderror(j ,i ,k);
    end
end
end
end
finalerror = initialerror/(numfiles-2);
finalse = initialen/(numfiles-2);
m = 1:5;
rnum = 0.1:0.1:0.9;
p = plot(rnum,finalse);

```

```

    legend ( 'm=3 ', 'm=4 ', 'm=5 ')
    xlabel ( 'Radius r ')
    ylabel ( 'Sample Entropy ')
    p(1).Marker = '.';
    p(2).Marker = '*';
    p(3).Marker = 'o';
    p(1).LineWidth = 2;
    figure;

p1 = plot (rnum, finalerror);
    legend ( 'm=3 ', 'm=4 ', 'm=5 ')
    xlabel ( 'Radius r ')
    ylabel ( 'Sample Entropy ')
    p1(1).Marker = '.';
    p1(2).Marker = '*';
    p1(3).Marker = 'o';
    p1(1).LineWidth = 2;

function [e, se, A, B]=sampen(y, M, r, sflag, cflag, vflag)
%function e=sampen(y, M, r);
%
%Input Parameters
%
%y input signal vector
%M maximum template length (default M=5)
%r matching threshold (default r=.2)
%
%Output Parameters
%
```

```

%e sample entropy estimates for m=0,1,...,M-1
%
%Full usage:
%
%[e,se,A,B]=sampen(y,m,r,sflag,cflag,vflag)
%
%Input Parameters
%
% sflag    flag to standardize signal (default yes/sflag=1)
% cflag    flag to use fast C code (default yes/cflag=1)
% vflag    flag to calculate standard errors (default no/vflag=0)
%
%Output Parameters
%
%se standard error estimates for m=0,1,...,M-1
%A number of matches for m=1,...,M
%B number of matches for m=0,...,M-1
% (excluding last point in Matlab version)

if ~exist('M')|isempty(M),M=5;end
if ~exist('r')|isempty(r),r=.2;end
if ~exist('sflag')|isempty(sflag),sflag=1;end
if ~exist('cflag')|isempty(cflag),cflag=1;end
if ~exist('vflag')|isempty(cflag),vflag=0;end
y=y(:);
n=length(y);
if sflag>0

```

```

y=y-mean(y);
s=sqrt(mean(y.^2));
y=y/s;
end
if nargout>1
    if vflag>0
        se=sampense(y,M,r);
    else
        se=[];
    end
end
if cflag>0
    [match,R]=cmatches(y,n,r);
    match=double(match);
else
    [e,A,B]=sampenc(y,M,r);
    return
end
k=length(match);
if k<M
    match((k+1):M)=0;
end
N=n*(n-1)/2;
A=match(1:M);
B=[N;A(1:(M-1))];
N=n*(n-1)/2;
p=A./B;

```

```

e=-log(p);

function [e,A,B]=sampenc(y,M,r);
%function [e,A,B]=sampenc(y,M,r);
%
%Input
%
%y input data
%M maximum template length
%r matching tolerance
%
%Output
%
%e sample entropy estimates for m=0,1,...,M-1
%A number of matches for m=1,...,M
%B number of matches for m=0,...,M-1 excluding last point

n=length(y);
lastrun=zeros(1,n);
run=zeros(1,n);
A=zeros(M,1);
B=zeros(M,1);
p=zeros(M,1);
e=zeros(M,1);
for i=1:(n-1)
    nj=n-i;
    y1=y(i);
    for jj=1:nj

```

```

j=jj+i;
if abs(y(j)-y1)<r
    run(jj)=lastrun(jj)+1;
    M1=min(M,run(jj));
    for m=1:M1
        A(m)=A(m)+1;
        if j<n
            B(m)=B(m)+1;
        end
    end
end
else
    run(jj)=0;
end
end
for j=1:nj
    lastrun(j)=run(j);
end
end
N=n*(n-1)/2;
B=[N;B(1:(M-1))];
p=A./B;
e=-log(p);

function [se,e]=sampense(y,M,r)
%function [e,A,B]=sampense(y,M,r);
%
%Input
%
```

```

%y input data
%M maximum template length
%r matching tolerance
%
%Output
%
%se standard error estimates for m=0,1,...,M-1
%e sample entropy estimates for m=0,1,...,M-1

[F1,R1,F2,R2]=makerun(y,M,r);
F=F1+F2;
n=length(y);
dd=1;
K0=sum(F.*(F-1));
K(1,:)=K0;
for m=1:M
    for d=1:min(m+1,M)
        i1=(d+1):n;
        i2=i1-d;
        nm1=F1(i1,m);
        nm2=F2(i1,m);
        nm3=F1(i2,m);
        nm4=F2(i2,m);
        nm1=nm1-sum(R1(i1,1:(dd-1))>=m,2);
        nm2=nm2-sum(R2(i1,1:(2*d))>=m,2);
        nm3=nm3-sum(R1(i2,1:(2*d-1))>=m,2);
        nm4=nm4-sum(R2(i2,1:(dd-1))>=m,2);
    end
end

```



```

        K(d+1,m)=2*sum((nm1+nm2).*(nm3+nm4));
    end
end

n1=zeros(M,1);
n2=zeros(M,1);
n1(1)=n*(n-1)*(n-2);
for m=1:(M-1),
    n1(m+1)=sum(K(1:(m+1),m));
end
for m=1:M,
    n2(m)=sum(K(1:m,m));
end

A=sum(F)'/2;
N=n*(n-1)/2;
B=[N;A(1:(M-1))];
p=A./B;
e=-log(p);

vp=p.*(1-p)./B+max((n2-n1.*p.^2)./B.^2,0);
sp=sqrt(vp);
se=sp./p;

function [F1,R1,F2,R2]=makerun(y,M,r);
%function [F1,R1,F2,R2]=makerun(y,M,r);
%
```

```

%Input
%
%y input data
%M maximum template length
%r matching tolerance
%
%Output
%
%F1 matches with future points
%R1 runs with future points
%F2 matches with past points
%R2 runs with past points

n=length(y);
run1=zeros(1,n);
MM=2*M;
R1=zeros(n,MM);
R2=zeros(n,MM);
F=zeros(n,M);
F1=zeros(n,M);
for i=1:(n-1)
    j=(i+1):n;
    match=abs(y(j)-y(i))<r;
    k=find(match);
    nj=length(j);
    run=zeros(1,length(j));
    run(k)=run1(k)+1;

```

```

    for m=1:M
        k=find(run>=m);
        nm=length(k);
        F1(i,m)=nm;
        F(i,m)=F(i,m)+nm;
        F(i+k,m)=F(i+k,m)+1;
    end
    nj=min(nj,MM);
    k=(1:nj);
    R1(i,k)=run(k);
    run1=run;
end
for i=1:n
    nj=min(MM,i-1);
    for j=1:nj
        R2(i,j)=R1(i-j,j);
    end
end
end
F2=F-F1;

function [e,A,B]=cross_sampen(x,y,M,r,sflag)
%function [e,A,B]=cross_sampen(x,y,M,r,sflag);
%
%Input
%
%x,y input data
%M maximum template length
%r matching tolerance

```

```

% sflag    flag to standardize signals (default yes/sflag=1)
%
% Output
%
% e sample entropy estimates for m=0,1,...,M-1
% A number of matches for m=1,...,M
% B number of matches for m=0,...,M-1 excluding last point

if ~exist('M')|isempty(M),M=5;end
if ~exist('r')|isempty(r),r=.2;end
if ~exist('sflag')|isempty(sflag),sflag=1;end
y=y(:);
x=x(:);
ny=length(y);
nx=length(x);
if sflag>0
    y=y-mean(y);
    sy=sqrt(mean(y.^2));
    y=y/sy;
    x=x-mean(x);
    sx=sqrt(mean(x.^2));
    y=y/sx;
end

lastrun=zeros(nx,1);
run=zeros(nx,1);
A=zeros(M,1);

```

```

B=zeros(M,1);
p=zeros(M,1);
e=zeros(M,1);
for i=1:ny
    for j=1:nx
        if abs(x(j)-y(i))<r
            run(j)=lastrun(j)+1;
            M1=min(M,run(j));
            for m=1:M1
                A(m)=A(m)+1;
                if (i<ny)&(j<nx)
                    B(m)=B(m)+1;
                end
            end
        end
    else
        run(j)=0;
    end
end
for j=1:nx
    lastrun(j)=run(j);
end
end
N=ny*nx;
B=[N;B(1:(M-1))];
p=A./B;
e=-log(p);

```

Appendix C  
Statistical analysis

```
clear all; clc; close all
datafiles = dir('*.dat');
numfiles = length(datafiles);
mydata = cell(1,numfiles);
for k = 1:numfiles
    mydata{k}=importdata(datafiles(k).name);
    [p,tbl]=anova2(mydata{k}(:,2:end),1)
end
```

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