IJCSI International Journal of Computer Science Issues, Vol. 10, Issue 2, No 3, March 2013
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org

Spectral Characterization of Stride-to-Stride Variability in Children Gait Motion

Hedi Khammari, Azeemsha Thacham Poyil, *Taif University, KSA*

***Abstract*—In this paper, we present a study of stride variations and their dependency on human physical parameters and dynamics. We concentrated on the stride to stride intervals on 50 different subjects. The effects of age, height, weight, length of legs and the speed of walking are researched and analyzed against the stride time variations for each subject. It can happen that a subject during the initial and end stages of walking, display some non-uniform stride movements. So, in order to achieve a stable data for analysis, the initial and final samples of stride are truncated. It is understood that the variations in stride at consecutive steps denote instability in walking, which is considered as abnormal in case in adults. In case of children these studies help in assessing the progress in the stability of stride movements as the age progresses. The result of this study can be applied to enhance progress in stride stability by providing adequate feedback to the individuals. For example, for a young person, the analysis of weight against his stride stability may be used to help him control his food or to automatically adjust treadmill speed in Gymnasium. For a child this analysis may be used to anticipate/predict his stride stability in future and provide proper training to improve the irregular patterns according to the feedback. The first and second harmonics of the stride variations are considered for the analysis. The mean and standard deviation of these harmonics are calculated in time domain as well as frequency domain and are used in presentation of parameters. The mean values are analyzed against the age, height, weight and speed of all the subjects. The information contained in the spectral components of stride cycle and their correspondence with the physical parameters, are demonstrated with the help of different plots and parameters.**

***Index Terms*—Gait Signal, Harmonics, Stride length, Spectral Analysis, Stride variations, Fast Fourier Transform**

I. Introduction

The potential of gait as a biometric was proved on different databases including many subjects with multiple samples. For this purpose, we have chosen children maturation gait dataset from PhysioNet database to enable the investigation of gait as a biometric. Such database includes a huge collection of recorded physiologic signals. The extraction of discrete parameters from human gait motions has been a major area of research for many years. The numerous medical applications of these studies are the reason behind it. In this paper we present a detailed study of the stride movements of 50 children having ages between 3 and 14 years. To start with, some generic terms and methods in gait signal analysis are to be described. The stride interval of a gait motion is defined as the time from one heel strike to the next heel strike of the same foot [2]. Cadence or walking rate is calculated in steps per minute. Velocity, the product of cadence and step length, is expressed in units of distance per time [14], [15].

It is noticed that the stride interval in children in the beginning of their walking ages are highly unstable. These variations get reduced gradually as the age progresses and become stabilized to some extent. There are many physical factors which determine the stability of the stride interval. In this paper the study concentrates on the parameters like age, height, weight, length of legs and the speed of walking using different spectral and statistical methods. In the beginning of the work, the time series of stride cycles for each subject is analyzed using their standard deviation and their mean values. In the later steps, the subjects are analyzed in their frequency domain, concentrating mainly on their first and second harmonics.

"This work was supported by Taif University, KSA".

Hedi Khammari was with Electrical Engineering Department, National School of Applied Sciences and Technology of Kairouan, Tunis till 2009. He is now Assistant Professor in the Computer Engineering Department of Taif University, Taif, KSA.

Azeemsha Thacham Poyil was with Robert Bosch India till 2011. He is now with the Computer Engineering Department of Taif University, Taif, KSA.

II. Background and Related Work

Study of correlations between stride cycles and the physical parameters like age, height, weight had been done by many researchers at times. The variations in stride at consecutive steps denote instability in walking, which is considered as abnormal in case in adults. Chiraz Ben Abdelkader et al researched on the view-invariant estimation of height and stride for gait recognition [1]. The work presents a parametric method to identify people in a low resolution video by estimating the stride parameters namely the cadence and the height. Stride length and cadence are taken as stride parameters. A work by Hausdorff et al demonstrates a good analysis of stride variations in children. It states that mature stride dynamics will not be completely developed even in 7-yr-old children and also the different aspects of stride dynamics attain maturation at different ages. Statistical and temporal measurements are used in the analysis [2]. In another work by Rajagopalan et al, a higher order spectrum approach based on stride length for detecting human motion is described [3]. Here the human video images are being analyzed. Gait analysis has been carried out in the work by Mario Manca and team, where the repeatability of protocol is described for gait analysis in adult subjects [4]. Another work by Ahmed Mostayed et al describes the abnormal gait detection and analysis using Discrete Fourier Transform (DFT). The work concentrates on analysis of joint angle characteristics in frequency domain and harmonic coefficient recognition [5]. And it is not dealing with stride cycle variations as such. The research by Liang Zhang and team presented a novel constraint-based method to adapt the captured gait motions to new paths while preserving the original gait style [6]. In another research work, Alberto Ferrari et al, does a quantitative comparison of five current protocols in gait analysis. Here they present a comparison study about five worldwide representative protocols by analyzing kinematics and kinetics of gait cycles [7]. An analysis of the video content of humans walking towards a camera, revealed the nonlinear nature of fronto-normal human gait consequently the use of nonlinear theory for automatic identification of humans gait is motivated [8]. In another interesting work by Hyun G. Kang, the effects of walking speed, strength and range of motion on gait stability in healthy older adults are discussed [9]. The study concentrates on how age and walking speed affect independently the dynamic stability during walking. It is also investigated if the dynamic stability in old adults is improved by walking slower, and how leg strength affected the stability of walking. The research also states that the walking stability in both younger and older adults is improved by slow walking, in spite of increased variability. This measure of instability during walk is a good indicator of future risk of fall [9]. The research by Toby Weilun Lao demonstrates an approach to implement estimation and recognition of human motion from video sequences [10]. Jeffrey M Hausdorff published a work on methods and modeling for measuring the gait variability [11].The paper describes the study of stride-to-stride fluctuations in walking, and how it offers a complementary way of quantifying locomotion and its changes with aging [11]. There is another research paper by Valery B. Kokshenev on the dynamics of human walking at steady speeds [12]. And T. Karnikb presented a work about using motion analysis data for foot-floor contact detection [13]. The major purpose of this work is to obtain the stride data almost instantaneously, but the work doesn't deal with how the measured data can be interpreted effectively.

Even though there are many researches as described above which propose and demonstrate methods to describe the variations in stride cycle and its dependency on physical parameters, we find there is still a scope for more study and analysis to describe these dependencies systematically. Many of the above researches do not concentrate on using the stride intervals as a parameter for the study of gait motions; instead do concentrate on other gait parameters. In some of them they do work on the stride intervals, but that doesn't describe in detail the dependency on different physical parameters. We present in this paper, some systematic study methods and results regarding how the first and second harmonics of the stride variations behave with respect to the age, weight, height and velocity of the subjects.

III. Method for Analysis

The stride to stride intervals of 50 subjects are taken from children of ages between 3 years and 14 years. The time and frequency contents are analyzed to get an overview about the stride variations. We have used database available in PhysioNet, an example of which is shown in the Table I [2].

TABLE I
DATABASE OF SUBJECT FEATURES CORRESPONDING TO STRIDE DATA

Subject-ID (1-50)	Age (months)	Gender	Height (Inches)	Weight (lbs)	leg-length (Inches)	Speed (m/sec)
1	40	M	40.5	43	23	1.04289
2	45	F	40	35	20	1.05322
3	47	F	39.5	35	21	0.98953
4	48	M	40	37	20	1.01551
5	49	M	39	36	20	0.82461
6	49	F	40	30	21	1.00591
7	52	F	43	50	22	1.02284
8	52	F	41	34	21	0.89579
9	54	F	41.5	37	20	1.1377
10	54	M	44	41	22	1.05846

The time domain representation of a stride signal for a subject of age 40 months and height 40.5 inches in which the stride interval is given on y axis and the actual time of occurrence of this stride on x axis is shown in Fig.1.

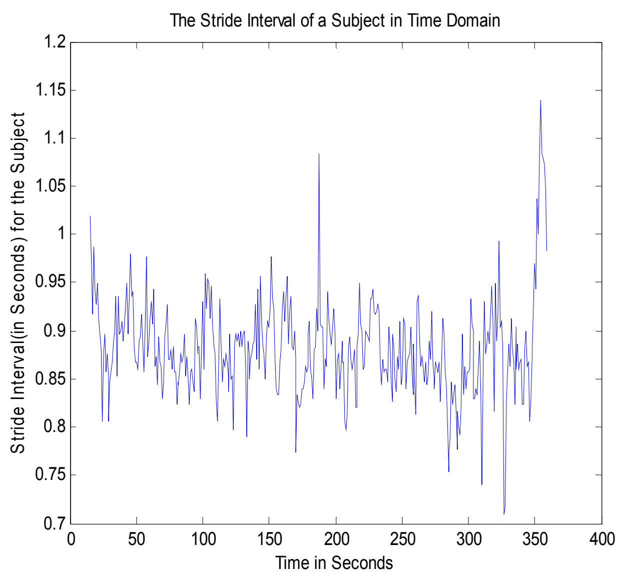

Fig.1. Stride Signal in Time Domain

Similarly, the frequency spectrum of the same subject is plotted as shown in Fig.2, with the spectral amplitudes on y axis and the corresponding frequencies (rate of variations) on the x axis.

We customized the length of each subject to 400 samples in each subject, in order to ease our calculations. It can happen that a subject during the initial and end stages of walking, display some non-uniform stride movements. Some numbers of initial and final samples are truncated in the calculations, in order to avoid the possible unstable stride cycles during the start and end of walk.

In the next part of the analysis, the standard deviation of each subject in time domain is calculated. The measure of the standard deviation of stride intervals of each subject, with respect to its mean value gives good information about the stride variations.

And in the next step, frequency analysis is carried out. Frequency spectrum analysis is the standard method adopted for analyzing the dynamics of a stride pattern. For calculating the Fourier spectrum coefficients using FFT algorithms, we took the stride to stride interval as the time varying parameter. So a spectral representation of this data will imply how frequently the stride parameters are varying with respect to time. A non-overlapped window of length 64 is adopted to split the time sequence in to different blocks. This produces the number of analysis frames,

Number of Frames = Signal Length/Window Length

FFT algorithm is run for all the different frames one by one. The number of components in the FFT is calculated by measuring the next power of 2 from the Window Length. The DC Fourier component in the frequency spectrum is large compared to the fundamental and higher harmonics, thus it is not considered for study here. We firstly investigate the role of the fundamental and higher harmonic of order 2, taken for each frame.

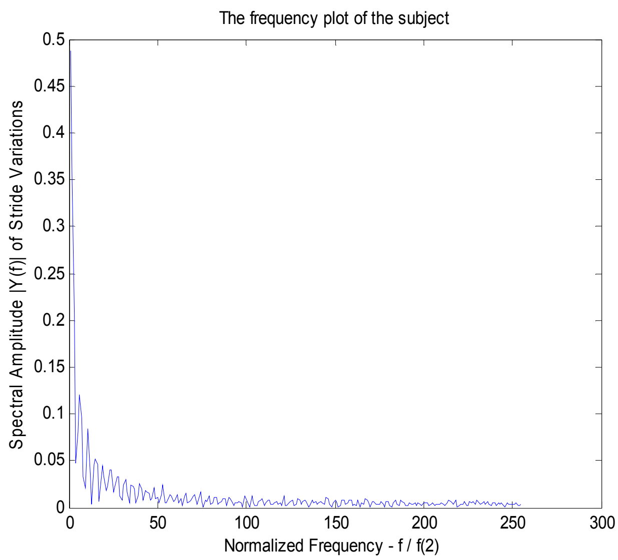

Fig.2 Frequency Spectrum with Normalized Frequency

Here we split up the analysis into multiple stages. In the first stage, we plotted the standard deviation of first and second harmonics of all the subjects. And the same is repeated for all the 50 subjects so that we get a list of the mean and standard deviation values for all the subjects. In the second stage, the spectral amplitudes of the first and second harmonics for all the subjects are studied. In the next stage, we studied the stride harmonics against the age groups, to see the dependencies of stride variation with respect to age of a subject. The next stage studies about the subject height and the harmonics and in further steps, about the subject weight, leg length and the velocity of movement of the subjects. In all the cases, the amplitudes of both the first and second harmonics are compared. At last the ratio of subject height to weight is studied against the harmonics and later the ratio of leg length to weight also. We use a database of the physical description about all the subjects for the above studies. This includes the age, height, weight, velocity information about all the subjects.

IV. RESULTS

The above methods are implemented in MATLAB using the datasets corresponding to 50 subjects, which are taken from children of ages between 3 and 14 years old. After applying the algorithms for statistical representation and spectral decomposition of stride data, we obtained a set of results which help in describing the dependencies of stride parameters with physical features like age, height etc.

We analyzed the mean value of stride variations for all the subjects as shown in Fig.3. In a detailed look at this plot, it is found that the mean value shows almost a gradual increase as the age progresses. For example, a 3 year old child shows an average stride interval of 0.9, whereas a 14 year old child shows an average value of nearly 1.2. If we look at these mean values in a different angle, we can also identify three different groups with close mean values; one group between 3 years and 5 years, a second group between 6.5 years and 8 years and a third group of ages between 11 and 14 years. In an overall viewpoint we can say that for this range of ages (children), we have roughly the same mean value.

Fig.4 shows a plot of standard deviation of the stride data in time domain with respect to each subject. The figure implies that more that 80% of the deviations are found within the value of 0.05 and there are only few random variations in case of some subjects. The subject numbers are selected and also plotted in the increasing order of ages.

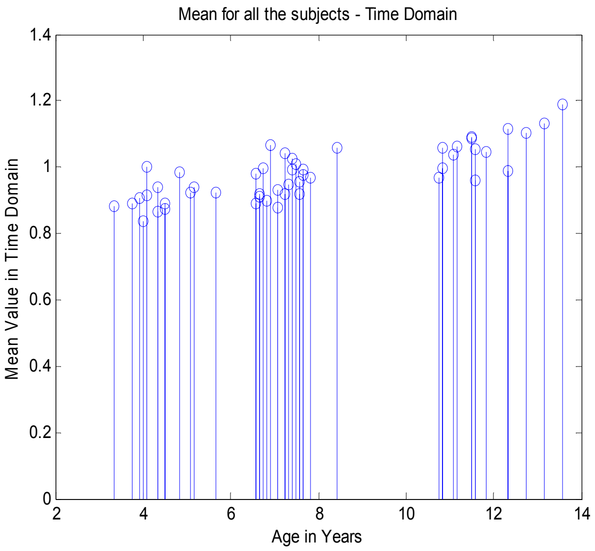

Fig.3. Mean Value of Stride Periods for Different Ages

Fig.5. Standard Deviation of Subjects in Time Domain with Respect to Age

As seen in Fig.5, children of ages till 8 years show a higher variation in stride cycle in comparison with the ages from 8 to 14 years. So we can state that, as the age increases we find a better stability in the stride variations of subjects.

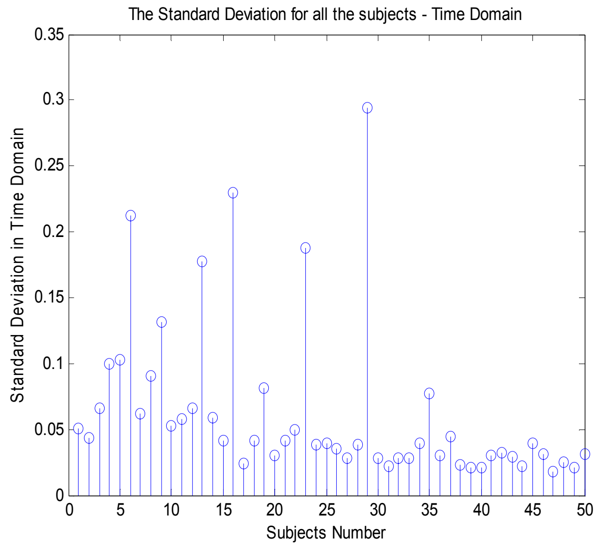

Fig.4. Standard Deviation of Subjects in Time Domain

Fig.6 shows the result of applying the standard deviation in spectral domain. Standard deviation of the first and second harmonics of all the subjects is plotted by taking different window frames of each subject's stride data. In the figure, the x axis represents the subject number and the y axis, the standard deviation of the spectral components corresponding to first and second harmonics. The blue color represents the first harmonics and red color represents second harmonics.

We can see that the standard deviation of first harmonics components of the stride variations dominate in amplitude in comparison with second harmonics. This is the case for most of the subjects. This implies that more than 90% of the subjects exhibit a high amount of variations in stride to stride period at lower harmonics. Similar to the previous case, the subject numbers are selected and plotted in the increasing order of ages. So the plot also implies that, as the age increases, the first and second harmonics of stride variations show a better stability, since the deviations are lesser for the higher values of x axis.

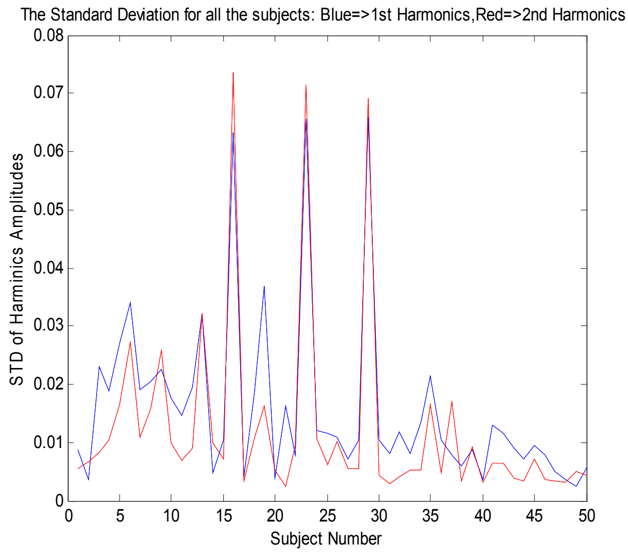

Fig.6. Standard Deviation of Spectral Components

As the next stage, we plotted the spectral amplitudes of the first and second harmonics directly against the subject numbers. In comparison with the previous step, we did not go

IJCSI International Journal of Computer Science Issues, Vol. 10, Issue 2, No 3, March 2013
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org

for measuring the standard deviation. The response is as shown in Fig.7. We can see a similar result with increased stability in stride variations at the higher subject numbers.

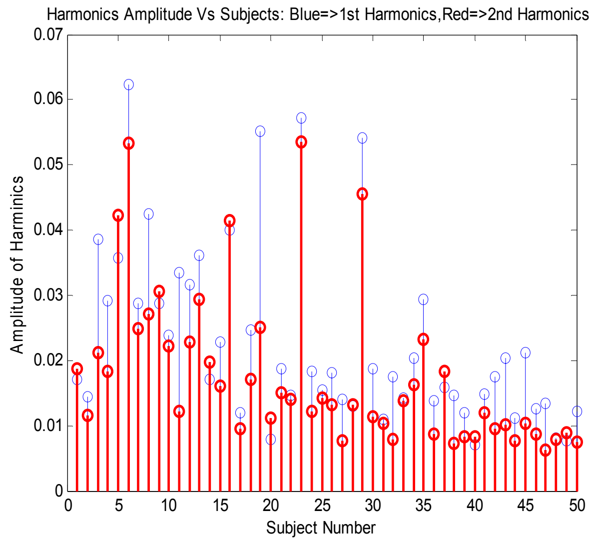

Fig.7. Spectral Amplitudes of all the Subjects – 1st and 2nd Harmonics

The difference in spectral amplitudes between the first and second harmonics is plotted as in Fig.8. It is visible from the figure that the difference in spectral amplitudes in majority is in positive direction. This indicates that the first harmonics of stride variations dominate in most of the cases in comparison with the second harmonics.

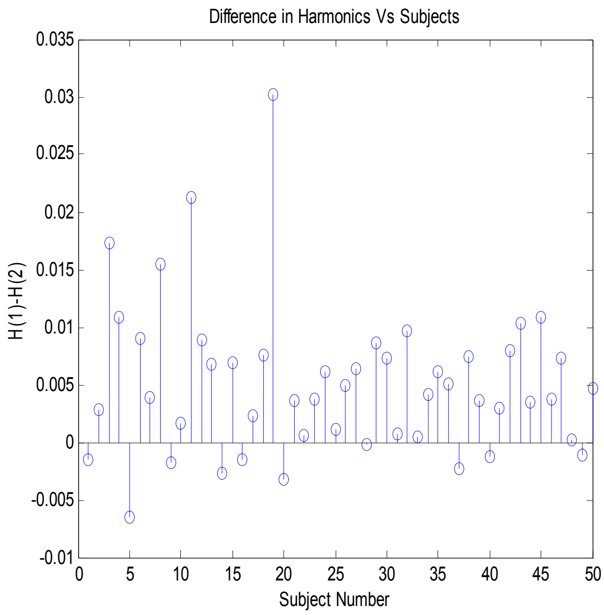

Fig.8. Difference in Spectral Amplitudes – 1st and 2nd Harmonics

Fig.9 plots the ratio of amplitudes of first harmonics to second harmonics of stride data against the subject numbers. This gives a picture of how the first harmonics dominate over the second harmonics components of many of the subjects. In the figure we can see only few cases where the height of the H(1)/H(2) axis going below the value 1.

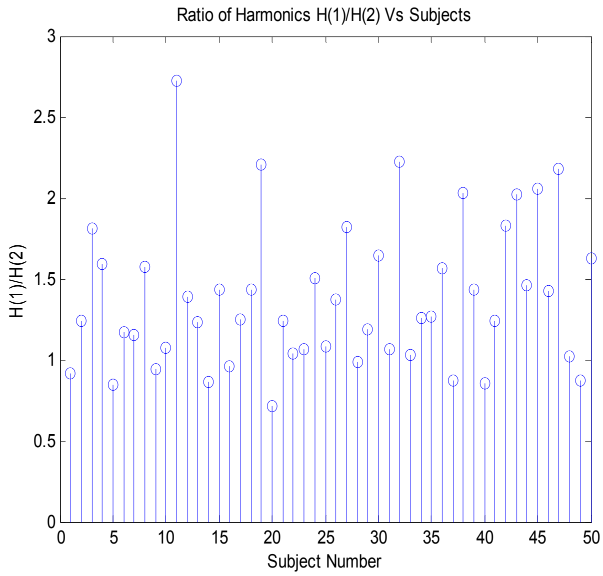

Fig.9. Ratio of 1st to 2nd Harmonics

The next step gave us a result as shown in Fig.10. The plot represents different age groups along x axis and the harmonics of stride variation along y axis. There is a clear display of high variations in the spectral amplitudes between the age groups of 4 years and 8 years. And as seen before, as the age reached 10 years and above, there is a comparatively stable display of spectral amplitudes

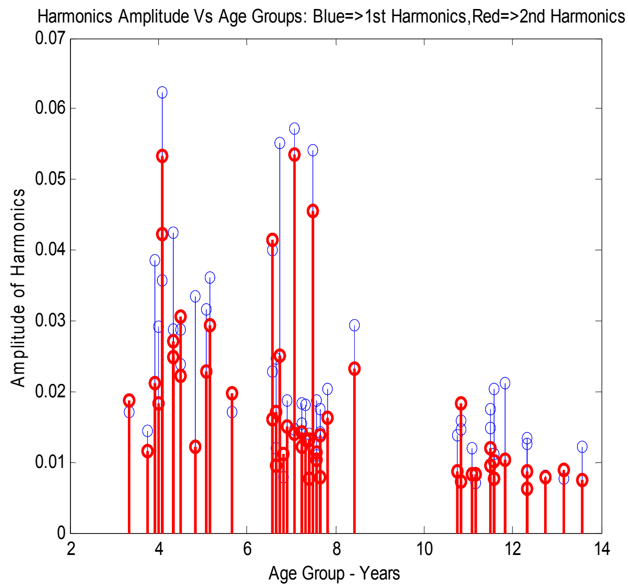

Fig.10. Spectral Amplitudes for Different Age Groups

We used the height information of each subject in the next stage of analysis, to have a study with respect to the harmonics. We plotted the height of subjects in inches along x axis and the harmonics amplitudes along y axis, as shown in

Fig.11. We noticed that there is a dependency for the stride variations on the height of subjects. As the height increases, the variations in stride interval get reduced. It is also noticed that the first harmonics of stride variations in almost all cases have higher amplitudes in comparison with the second harmonics.

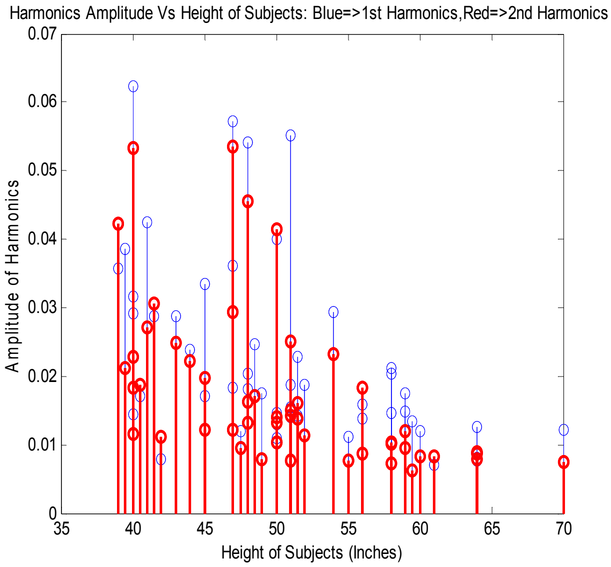

Fig.11. Spectral Amplitudes for Different Heights

The weight of individual subjects are plotted against the harmonics and analyzed in the next step. The weight is taken along the x axis and the harmonics amplitudes along the y axis. There is noticeable information in Fig.12, regarding the dependency of stride variations on the weight of subjects. The spectral components are comparatively stable from the weight values from 60 to 140 lbs, and the amplitudes show higher peaks at values less than 60 lbs. Thus, we see that the lower weights of subjects correspond to an unstable stride cycles and show higher peaks in the spectral amplitude.

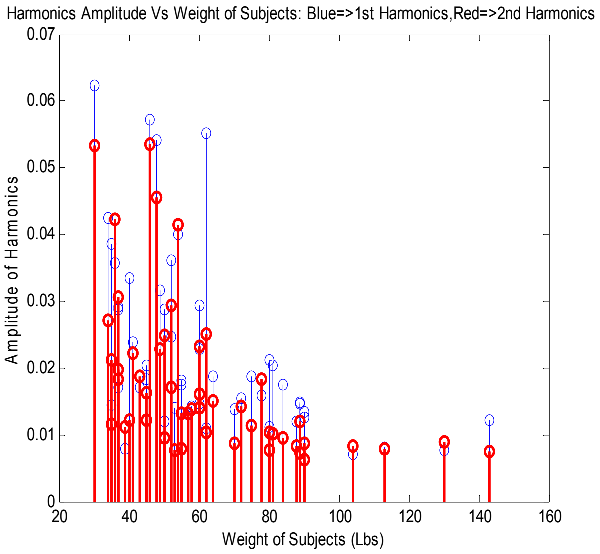

Fig.12. Spectral Amplitudes for Different Weights

In another step where the harmonics along y axis are plotted against the length of legs along the x axis, we got similar results as compared to the plot against heights of subjects. The leg lengths on the range 28 to 38 inches show a comparatively stable stride variation, in comparison with values less than 26 inches. In lower values, we get more variations, which is a sign of higher instability. As before, the first harmonics are again prominent as compared to the second harmonics. The same is visible in the plot Fig.13.

In a similar study taking into account the subject velocities, we plotted the velocities along x axis against the harmonics as in Fig.14. As seen in figure, we could not clearly conclude the dependencies due to some higher peaks even at higher velocities; but we see a higher concentration of peaks in the lower side of velocity axis. This implies that there is a possibility that, when the subject walks slowly, the probability of randomness in the stride duration is more. This may result in an unstable stride to stride interval at lower velocities.

In the next analysis, the ratio of height to weight of each subject is calculated. This ratio along the x axis is plotted against the signal harmonics along the y axis as shown in Fig.15. As before the first harmonics are found higher compared to the second harmonics components. The important observation here is that, at lower values of height to weight ratio, we find a stable and lower spectral amplitudes. And at higher ratios, the stride spectral components are found unstable. In the lower ratio region, for example around the value 0.7, for the same values of height weight ratio, we find only slight variations in the stride spectral amplitudes. This variation is found less than 0.01. Whereas in the higher ratio region for example around 1.1, for the same values of the height weight ratio, the variations are more than 0.02.

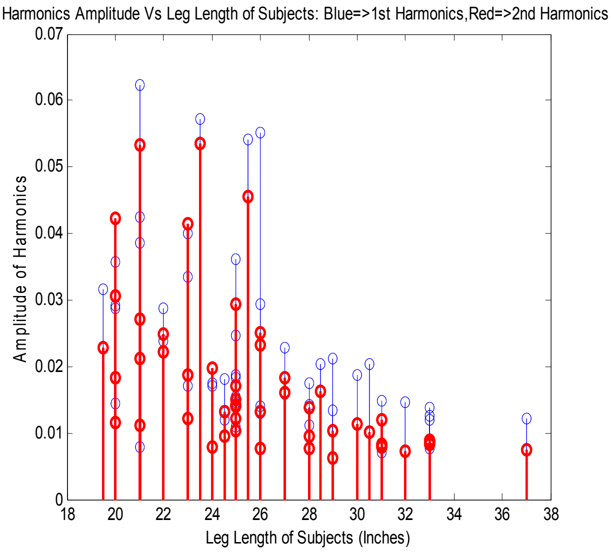

Fig.13. Spectral Amplitudes for Different Leg Lengths

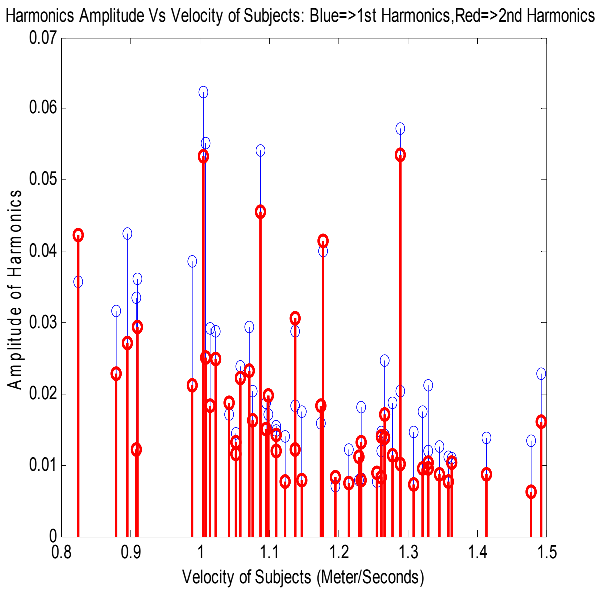

Fig.14. Spectral Amplitudes for Different Velocities

The study of the spectral components of stride distance with respect to the ratio of leg length to weight is carried out as shown in the Fig.16. The response is found almost similar to that of the previous step using height to weight ratio. Around values of the ratio, for example 0.35, we find lesser spectral amplitudes in comparison with the higher values of the ratio for example around 0.53. This gives an indication that, if the leg length increases in a higher proportion with respect to the subject weight or, if the weight does not increase in a proper way proportion with respect to the leg length, the stride variations are found to be more. This indicates instability in walking.

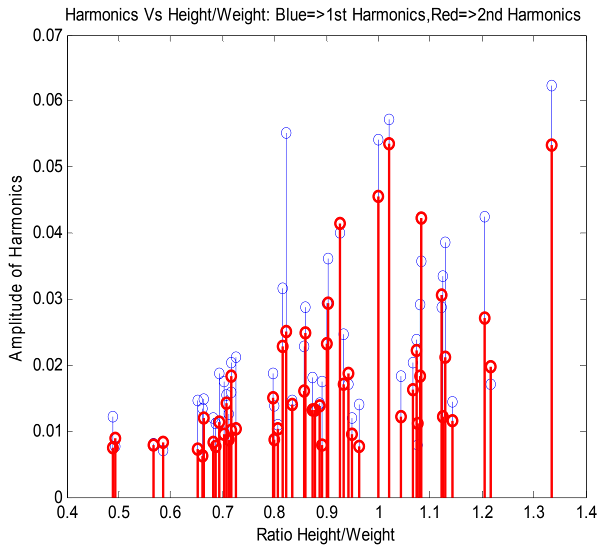

Fig.15. Spectral Amplitudes for Ratios of Heights/Weights

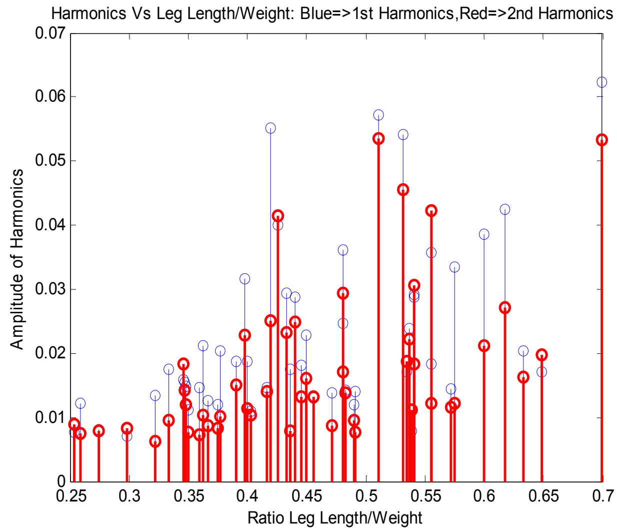

Fig.16. Spectral Amplitudes for Ratios of Leg Length/Weights

V. CONCLUSION

From the above experiments and results, we conclude that, the dependency of stride to stride intervals on the physical parameters of the subject like age, height and weight, can be effectively represented using spectral methods. The spectral decomposition of the stride data helps in analyzing this systematically. The information gathered from this study can be properly used in a feedback system to improve the physical growth of the subject. For example, in case of a child this information can be used in assessing in the stride stability as the age progresses and possibly anticipate/predict his stride stability in future and provide proper training to improve the irregular patterns according to the feedback. A young person may be informed about his body weight control, whereby the food style can be optimized in order to achieve a better stride stability. This information can also be used to automatically adjust treadmill speed in Gymnasium. Developing some optimized algorithms for meeting these needs, shall be some possible future research works in the area.

ACKNOWLEDGMENT

The authors gratefully acknowledge the directions from Physionet.org by providing maturation gait motion dataset, and thus helping the successful completion of this research paper.

REFERENCES

[1] Chiraz Ben Abdelkader, Ross Cutler, and Larry Davis, "View-invariant Estimation of Height and Stride for Gait Recognition", University of Maryland, College Park, Microsoft Research,2002

[2] J. M. Hausdorff, L. Zemany, C.K. Peng, and A. L. Goldberger "Maturation of gait dynamics: stride-to-stride variability and its temporal organization in children", American Physiological Society,1999

[3] A.N Rajagopalan and R Chellappa, "Higher-Order Spectral Analaysis of Human Motion" IEEE, 2000

[4] Mario Manca, Alberto Leardini, Stefano Cavazza , Giovanni Ferraresi , Pia Marchi , Emanuele Zanaga , Maria Grazia Benedetti "Repeatability of a new protocol for gait analysis in adult subjects" Gait & Posture 32 (2010) 282–284
[5] Ahmed Mostayed, Mohammad Mynuddin Gani Mazumder, Sikyung Kim and Se Jin Park, "Abnormal Gait Detection Using Discrete Fourier Transform", International Journal of Hybrid Information Technology, Vol.3, No.2, April, 2010
[6] Liang Zhang, Stephan Rusdorf, and Guido Brunnett, "Data-Driven On-Line Generation of Interactive Gait Motion", Chemnitz University of Technology, Germany, 2009
[7] Alberto Ferrari , Maria Grazia Benedetti , Esteban Pavan, Carlo Frigo, Dario Bettinellid, Marco Rabuffetti, Paolo Crenna, Alberto Leardini "Quantitative comparison of five current protocols in gait analysis" Gait & Posture 28 (2008) 207–216
[8] T.K.M. Lee1, M. Belkhatir, P.A. Lee, and S. Sanei, "Nonlinear Characterisation of Fronto-Normal Gait for Human Recognition", PCM 2008, LNCS 5353, pp. 466–475, 2008.© Springer-Verlag Berlin Heidelberg 2008
[9] Hyun G. Kang, Jonathan B. Dingwell, "Effects of walking speed, strength and range of motion on gait stability in healthy older adults", Journal of Biomechanics 41 (2008) 2899–2905
[10] Weilun Lao, Jungong Han, and Peter H.N. de With, "A Matching-Based Approach for Human Motion Analysis", 1Eindhoven University of Technology, 2007
[11] Jeffrey M Hausdorff, "Gait variability: methods, modeling and meaning", Journal of NeuroEngineering and Rehabilitation, Published: 20 July 2005.
[12] Valery B. Kokshenev , "Dynamics of Human Walking at Steady Speeds",Physical Review Letters, Vol 93, Number 20, 2004
[13] T. Karnik "Using motion analysis data for foot-floor contact detection", Medical & Biological Engineering & Computing 2003, Vol. 41
[14] Preis, S., A. Klemms, and K. Muller. "Gait analysis by measuring ground reaction forces in children: changes to an adaptive gait pattern between the ages of one and five years". Dev. Med. Child Neurol. 39: 228–233, 1997.
[15] Bonato P: "Advances in wearable technology and applications in physical medicine and rehabilitation". J Neuroengineering Rehabil 2005, 2:2.
[16] Ashkenazy Y, Hausdorff JM, Ivanov PC, Stanley HE: "A stochastic model of human gait dynamics". Physica A 2002, 316:662-670.
[17] Hausdorff JM, Ashkenazy Y, Peng CK, Ivanov PC, Stanley HE, Goldberger AL: "When human walking becomes random walking: fractal analysis and modeling of gait rhythm fluctuations". Physica A 2001, 302:138-147.
[18] Maki BE: "Gait changes in older adults: predictors of falls or indicators of fear". J Am Geriatr Soc 1997, 45:313-320.
[19] Nakamura T, Meguro K, Sasaki H: "Relationship between falls and stride length variability in senile dementia of the Alzheimer type". Gerontology 1996, 42:108-113.
[20] Yasutomi, S., Mori, H."A method for discriminating pedestrians based on rhythm". In: IEEE/RSG Intl Conf. on Intelligent Robots and Systems. (1994)
[21] Davis, J.W."Visual categorization of children and adult walking styles". In: AVBPA. (2001)
[22] BenAbdelkader, C., Cutler, R., Davis, L."Stride and cadence as a biometric in automatic person identification and verification". In: FGR. (2002)
[23] Murray, M., Kory, C., Clarkson, B.H., Sepic, S.B." Comparison of free and fast speed walking patterns of normal men". American Journal of Physical Medicine 45 (1966)
[24] Beck, R. J., T. P. Andriacchi, K. N. Kuo, R. W. Fermier, and J. O. Galante. "Changes in the gait patterns of growing children". J. Bone Joint Surg. Am. 63: 1452–1457, 1981.
[25] Hausdorff, J.M., M. E. Cudkowicz, R. Firtion, J.Y.Wei, and A. L. Goldberger. "Gait variability and basal ganglia disorders: stride-to-stride variations in gait cycle timing in Parkinson's and Huntington's disease". Mov. Disord. 13: 428–437, 1998.
[26] Jam Jenkins, Carla Ellis, "Using Ground Reaction Forces from Gait Analysis- Body Mass as a Weak Biometric", Western Carolina University, 2007

Hedi Khammari, PhD. He was born in Kairouan, Tunisia in 1963. He received the engineer diploma and the Master degree from National Engineering School of Tunis in 1988 and 1990 respectively. He received PhD in Electrical Engineering in 1999. He is currently Associate Professor at Taif University, Saudi Arabia. His research interests are mainly in the area of nonlinear dynamics and the application of chaos theory in different fields namely communication, electric systems and bioinformatics.

Azeemsha Thacham Poyil, M Tech. He was born in Kerala, India in 1979. He received his Bachelor degree in Electronics and Communication Engineering from Kannur University, India in 2001. Later he received his Master degree in electronics from Cochin University of Science and Technology, India in 2005. He is currently a Lecturer in Taif University, Saudi Arabia. He was previously working as specialist software engineer with Bosch Thermo Technology, Germany and Robert Bosch Engineering and Business Solutions, India in the industrial product development. His major research areas are Biomedical Signal Processing and Embedded Systems.