Estimation of the Effect of Cadence on Gait Stability in Young and Elderly People using Approximate Entropy Technique

M. Arif*[*], Y. Ohtaki[**], R. Nagatomi[***], H. Inooka**

[*] Department of Computer and Information Sciences, PIEAS, Islamabad, Pakistan
[**] Niche Lab., Tohoku University, Japan
[***] Dept. of Medicine and Science in Sports and Exercise, Tohoku University, Japan

Abstract *Walking stability of human beings varies with age and reduces in the elderly people. Lesser walking stability causes many falls in the elderly people. In this paper, we have investigated the walking stability of young and elderly subjects using approximate entropy, a non-linear time series analysis method. Our emphasis in this paper is to investigate the walking stability using a portable instrumentation that can be used in the daily life walking. The variability of the acceleration of the centre of gravity is analysed by using approximate entropy technique and is used as an index to assess the walking stability of young and elderly people. By using the proposed method, it is possible to assess the walking stability of the elderly subjects and it is observed that the walking stability of elderly subjects decreases in the lateral direction. Moreover it is also possible to suggest a walking speed to the elderly subjects that can improve their walking stability.*

1. Introduction

Normal ageing process causes many changes to neuromuscular system of a human being restricting his walking capabilities. It is very important to study the age related changes in the walking gait of elderly subjects. Because these changes sometimes result in an increase the number of falls during daily walking especially after the age of 75. Many researchers studied stability of human walking gait and it was quoted that human walking gait stability decreases with age increasing the risk of falls in elderly people. Many studies have been reported about the change in the kinematics parameters with age [1,2,3,4,5] but they require complex systems (e.g. motion capture systems) and experiments can only be performed in the laboratory environments. Some research is being done on the portable system to calculate the kinematics parameters in the daily life environment [13], but it requires many sensors attached to the body, which should be linked to a laptop computer. Our emphasis is to find some statistical index that can predict the walking stability using some kind of lightweight portable instrumentation which is easy to wear and handy to use. In this paper, we have proposed a method to predict the walking stability that can be used to predict the risk of fall in the elderly persons. In the daily life, human beings walk in various changing environment very successfully despite of the fact that a human body is a highly non-linear dynamic system. During the walking, instability occurs between the steps when we shift our weight from one leg to other. Centre of gravity (COG) of a walking person plays an important role in maintaining the dynamic stability of the walking. We change our location of COG from one foot to another foot alternatively during walking. To maintain the dynamic stability, a human walker tries to control the location of COG within the base area. The base area of a standing person is normally considered as his normal footprints. If the COG shifts outside the base area, instability occurs, which if not corrected by moving the body segments in appropriate directions, results in fall of the person. Therefore, movement of COG of a person during walking is an important index to assess the stability of his walking pattern and can be used for the prediction of the falls in the elderly people. In fact, there is no normal walking pattern and the walking pattern varies from person to person. These walking patterns are considered to be stable until and unless there is an evidence of fall of the person. During walking, human tries to generate periodic series of motions. But due to the physiological limitations, these motions do not remain exactly periodic but contains some variability or randomness in it. He does not try to correct this variability or randomness of these motions if it remains within stability limits. This variability present in the walking patterns are due to not only internal perturbation but also due to external perturbations. The amount of variability present in the walking pattern reflects the quality of neuromuscular control of the human being. Lesser the amount of variability means better neuromuscular control and walking stability. The variability or randomness of the walking pattern increases, as a person grows older. Many old people tend to lose the stability especially lateral stability. The aging effect on balance in elderly people is more prominent in the lateral direction. Elderly people take steps more laterally as compared to young people to restore the balance during walking [6,7]. In this paper, we have proposed a method to detect the variability of the COG using a portable 3D acceleration measurement system attached to the body of the subject near the COG point. Two groups of subjects participated in the experiments, namely, healthy young subjects and elderly healthy subjects. The variability of COG in analysed using approximate entropy technique, which is an excellent method of predicting the complexity or variability of deterministic as well as stochastic signals [8,9]. Approximate Entropy was mainly used in the analysis of heart rate variability [10] and endocrine hormone release pulsatility [11]. It is highly resistant to short strong transient interference (i.e. outliers or wild points). The influence of noise in the time series signal can be suppressed by properly choosing the relevant parameter of the approximate entropy algorithm. High value of the approximate entropy indicates large variability or randomness in the time series signal. The acceleration of the centre of gravity data in lateral, vertical and anterior/ posterior directions are analysed using approximate entropy technique for both groups of subjects. Effect of age on the variability or irregularity of the acceleration of COG in lateral, vertical and anterior/ posterior directions is studied in this paper.

2. Signal complexity/ variability by approximate entropy

Approximate entropy (ApEn) is a technique that can be used to quantify the irregularity or variability of the time series based on the statistics. This approach is a model free approach and can be used for a relatively short finite time series. Larger value of the approximate entropy of a time series corresponds to higher level of irregularity present in the time series. It is different from auto-correlation function and standard deviation because standard deviation used to quantify the degree of scattering of the data around their mean value. The time order of the data is immaterial. On the other hand the time order of the data is a crucial factor affecting the value of approximate entropy. ApEn is an excellent technique to predict the variability of a time series signal because it needs relatively smaller data range to calculate the approximate entropy and the influence of noise can be suppressed by properly choosing the relevant parameter of the algorithm. It can be applied to both deterministic (chaotic) and stochastic signals and/or to their combinations. In the phase flow diagram, the trajectories lying near to each other will remain close to each other in the regular type of motion and will occupy a fixed space of a certain dimension. Hence ApEn can be calculated by calculating the probability of the two phase space trajectories, which are close to each other, will remain close to each other after certain time [12].

It can be expressed as the probability of values $\boldsymbol{x}_{i+1}$ and $\boldsymbol{x}_{j+1}$ lying within a certain tolerance region of size R given that $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ lie also within region,

$$P\left(\left\|\boldsymbol{x}_{j+1}-\boldsymbol{x}_{i+1}\right\| \leq R \mid \left\|\boldsymbol{x}_j-\boldsymbol{x}_i\right\| \leq R\right) \tag{1}$$

where $\|\bullet\|$ denotes the norm (L_1 or L_2 norms). We consider an (m, J)-window which contains m samples taken at interval of J. The elements in the (m, J)-window represent the components of an embedding space $\mathbb{R}^m$. The value m is the embedding dimension. Equation (1) for m embedding dimension can be written in vector form as,

$$P\left(\left\|\boldsymbol{x}_{jm}-\boldsymbol{x}_{im}\right\| \leq R\right) \tag{2}$$

The conditional probability if the embedding dimension increases to $m+1$ can be written as

$$\frac{P\left(\left\|\boldsymbol{x}_{j(m+1)}-\boldsymbol{x}_{i(m+1)}\right\| \leq R\right)}{P\left(\left\|\boldsymbol{x}_{jm}-\boldsymbol{x}_{im}\right\| \leq R\right)} \tag{3}$$

Taking the natural logarithm of the above equation

$$\Phi^{m+1}(R)-\Phi^{m}(R) \tag{4}$$

where

$$\Phi^{m}(R)=\ln\left(P\left(\left\|\boldsymbol{x}_{jm}-\boldsymbol{x}_{im}\right\| \leq R\right)\right) \tag{5}$$

The probabilities can be obtained by simple kernel based probability density function estimation methods by defining the correlation sum as $C_i^m(R)$, where $\Phi^m(R)=\ln(C_i^m(R))$ and $C_i^m(R)$ is defined as,

$$C_i^m(R)=\frac{1}{N-m}\sum_{j=1}^{N-m}\Theta(R-norm(\boldsymbol{x}_i,\boldsymbol{x}_j)) \tag{6}$$

Θ is the havyside function,

$$\Theta(s)=\begin{cases}0 & s<0\\ 1 & s\geq 0\end{cases} \tag{7}$$

and the norm can be defined as euclidean distance,

$$norm(\boldsymbol{x}_i,\boldsymbol{x}_j)=\sqrt{\sum_{k=1}^{m}\left(x_{ik}-x_{jk}\right)^2} \tag{8}$$

The value of R determines the range within which neighbouring points in the phase space must lie. Pincus has used the complexity measure termed Approximate Entropy (ApEn) and defined as,

$$\begin{aligned}ApEn(m,R,N)&=\Phi^{m}(R)-\Phi^{m+1}(R)\\ &=\frac{1}{N-m+1}\sum_{j=1}^{N-m+1}\ln C_j^m-\frac{1}{N-m}\sum_{j=1}^{N-m}\ln C_j^{m+1}\end{aligned} \tag{9}$$

For N>>1, ApEn approximate to,

$$ApEn(m,R,N)=\frac{1}{N-m}\sum_{j=1}^{N-m}\ln\left(\frac{C_j^m}{C_j^{m+1}}\right) \tag{10}$$

Hence approximate entropy is the difference between the frequency that all patterns having m dimension are close to each other and the frequency that all the patterns having $(m+1)$dimension lies close to each other [9]. Pincus et. al [7] suggests , $J = 1$ and $R = rSD_x$, where SD_x is the standard deviation of the original data,

$$SD_x = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left[x(n) - \frac{1}{N}\sum_{n=1}^{N}x(n)\right]^2} \tag{11}$$

and r is a user defined parameter which can reduce the influence of noise. Embedding dimension m is related the dynamics of the underlying process in the time series and can vary according to the complexity of the dynamics.

3. Experimental setup

Twenty six Subjects have participated in the experimental study and are divided into two groups. Group YNG consists of nine young healthy subjects having ages between 21 to 30 years (mean 24.7±6 years), body weight distribution is 63.1±7 kgs and height distribution is 156.6±4 cms. Group OLD consists of seventeen elderly healthy subjects with no major disease having ages between 60 to 80 years (mean 69±6 years), body weight distribution is 56±8 kgs and height distribution is 154±7 cms. All subjects were asked to give signed informed consent. Most of the elderly subjects have good walking habit and some of the elderly subjects are doing one hour exercise classes, once or twice a week in Sendai city silver centre, Sendai, Japan. All subjects were asked to walk with their self selected walking speed on a 50m straight walking track. In the next trial, they were asked to follow the tempo of a metronome (sound signal) which was set to different walking speeds in terms of walking steps/minute. Four walking speeds, 80, 100, 120 and 140 steps/minute were selected for the experiment. Sound signal of metronome was sufficiently loud and can be heard easily while walking on the track. Acceleration of the COG during walking was measured by a portable 3D acceleration measurement system made by ITR Co. Ltd.(Japan), shown in Figure 1. The 3D acceleration measurement system was placed on the trunk at about 55% of the subject's height as shown in the Figure 2. It is widely accepted that the COG of adult humans has been found to be slightly anterior to the second sacral vertebra [14] or approximately 55% of a person's height [15]. Although it is very difficult to measure the acceleration at the exact location of the COG, but we assumed that the acceleration of the trunk of subject at 55% height will represent the same changes of acceleration as of COG. Acceleration of the COG was recorded in lateral, vertical and anterior/ posterior directions. In Figure 2, x direction refers to lateral direction, y direction refers to vertical direction and z direction refers to anterior/ posterior direction. The data from the accelerometer was sampled at the frequency of 100Hz.

4. Experimental results

Acceleration data in lateral, vertical and anterior/ posterior directions are plotted in Figure 3 for a young and an old subject along with the step events. Comparing the acceleration data of young and elderly subject, a clear difference between the acceleration in lateral direction is visible in the Figure 3. In the case of elderly subject, the acceleration in lateral direction is more irregular as compared to young subject. While walking on the straight path, the COG of the subject's body accelerates and de-accelerates in all three directions. Changes of acceleration in the lateral direction are most critical in terms of walking stability. A human can easily compensate any sudden change of acceleration or deceleration in the anterior/ posterior and vertical directions by changing the speed of walking or by changing the stride length or both. But it is difficult to compensate any sudden change in the acceleration in lateral direction and can easily cause a fall on the sideways while walking. Elderly people having lesser muscle strength than young people are more prone to fall on sideways when subjected to sudden change in acceleration in lateral

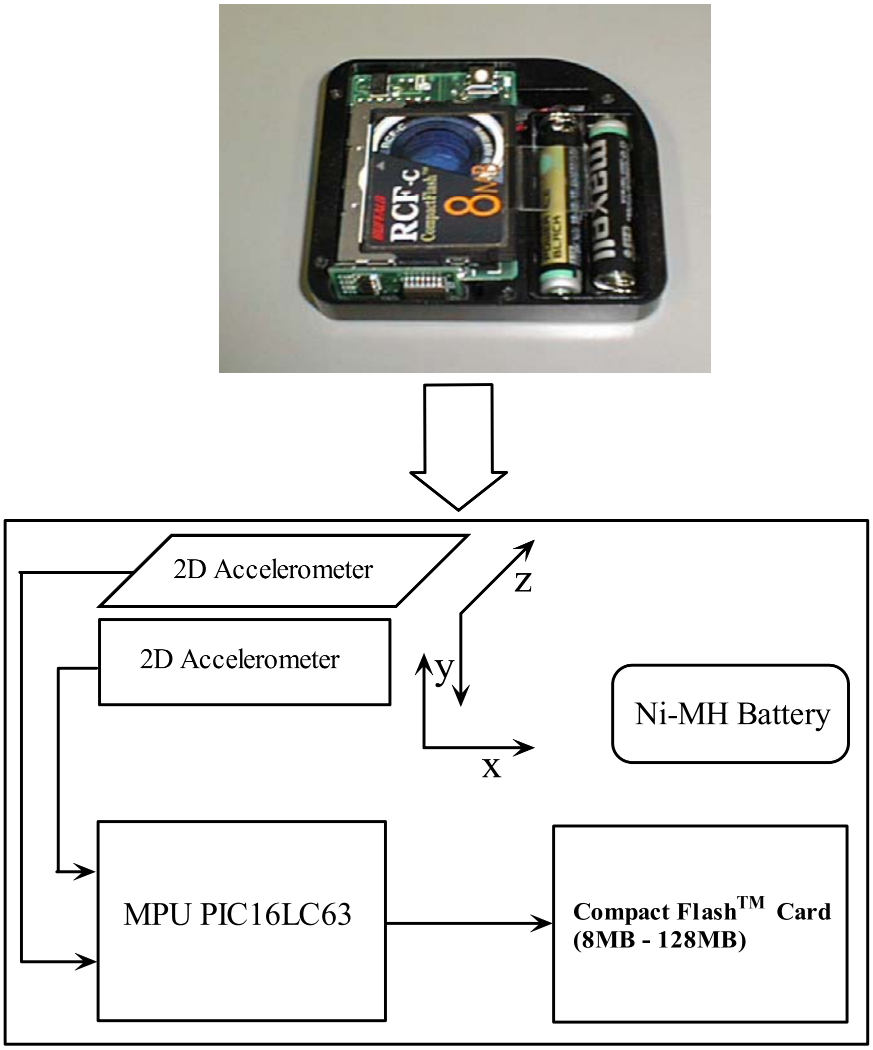

Figure 1: Portable 3D acceleration measurement system

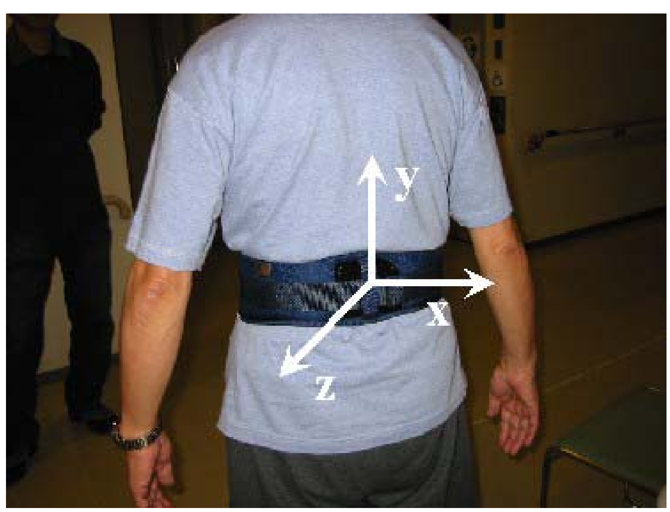

Figure 2: Position of Sensor Unit

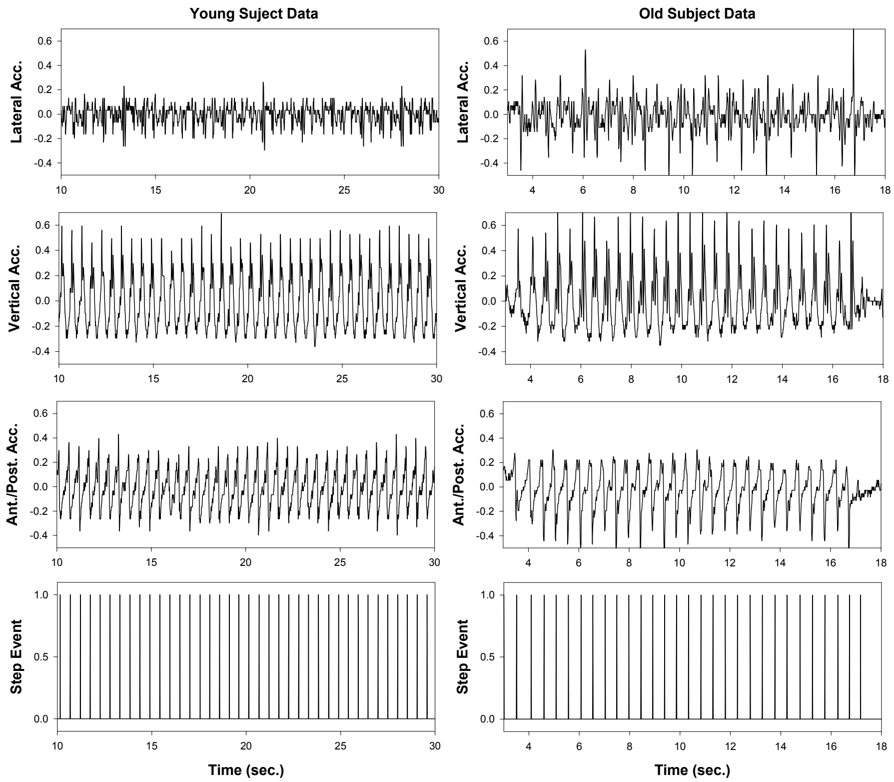

Figure 3: 3D Acceleration data of young and old subjects

direction. The irregularity in the acceleration data shows an increase probability of fall in the elderly people as visible in Figure 3. We have applied the technique of approximate entropy to estimate the irregularity or complexity in the time series signal of the acceleration of COG in lateral, vertical and anterior/ posterior directions for young and elderly subjects for different walking speeds. Approximate entropy technique usually applied to the time series of a finite length and represents the irregularity of the whole time series. Approximate entropy shows the variability or complexity of the walking pattern. This variability reflects the response of dynamic systems involved in walking against internal as well as external perturbations. For example, any deformation of joints or weakness of leg muscles will effect the quality of control during walking and will produce more variability in the walking pattern of the subject which in our case is the acceleration of the COG. More variability in the acceleration data of COG means less walking stability. Moreover neurological disorder associated with age may cause poor motion generation during walking and may induce more variability in the walking patterns of the patient. In our experiments, we are interested in calculating the approximate entropy on various time instants and the calculations are required to be fast such that it can be applied to the online monitoring of the approximate entropy of walking data of a subject. In our analysis, a window of constant size is defined and whole data of each subject is divided into many data segments. The size of window is not time but a certain number of steps taken during walking. Hence the window size can be varied in the time domain according to the time taken by the subject per step of walking but will be fixed in terms of the number of walking steps. Let the acceleration data a having length of N is recorded, in which a subject has taken M number of walking steps, given as,

$$\boldsymbol{a} \triangleq \left[a(1), a(2), ..., a(N)\right] \tag{12}$$

Let $\boldsymbol{a}$ be converted into number of walking steps domain as under,

$$\boldsymbol{\alpha} \triangleq \left[\alpha(1), \alpha(2), ..., \alpha(N)\right] \tag{13}$$

Here $\boldsymbol{\alpha}(1) = \left[a(1), a(2), ..., a(k_1)\right]$, $\boldsymbol{\alpha}(2) = \left[a(1), a(2), ..., a(k_2)\right]$ and vice versa. The variables k_1 and k_2 are the number of time steps per walking step. For instance, recording the data at sampling period of 100 Hz, time taken for the first walking step equals to 0.5 seconds means that k_1 will be equal to 50 data points and time taken for the second walking step equals to 0.52 seconds means that k_2 will be equal to 52 data points and vice versa. Applying a window having size of J walking steps will decompose the acceleration data mentioned in equation (13) into M - J data segments. A data segment $\boldsymbol{a}_w$(i) is defined as,

$$\boldsymbol{\alpha}_w(i) = \left[\alpha(i), \alpha(i+1), ..., \alpha(i+J)\right] \tag{14}$$

for $i = 1, 2, ...M - J$. Approximate entropy of each data segment $\boldsymbol{a}_w$(i) will then be calculated and averaged over all data segments for every subject.
Embedding dimension for all the data analysis is set to be 4 and R is set to be *0.3SD*, *SD* is the standard deviation of the data segment. Window size is selected as 6 walking steps. Four walking speeds are selected for the experiments, which are 80 steps/minute (Slow walking), 100 steps/minute (Normal walking), 120 steps/minute (Normal Walking) and 140 steps/minute (Fast walking). Walking speed is controlled by the sound signals of a metronome and all the subjects are asked to walk on the tempo of metronome.

Figure 4 shows the walking speed of each subject for four pre-set walking speeds. Young subjects can maintain the walking speed by hearing the metronome sound in all the cases except in fast walking mode (140 steps/minute). Whereas, elderly subjects showed some variation in keeping up the desired walking speed in almost all cases. The COG acceleration data of young subjects is analysed first. Approximate entropy of lateral acceleration of COG is plotted in Figure 5 for different walking speeds for all young subjects. The figure suggests that all the young subjects have minimum approximate entropy value near their normal walking speeds (steps/minute). The average normal walking speed of the young subjects is 114±4 steps/minute. Walking on the speed different from their normal walking speed, slower or faster, increases the variability of the lateral acceleration showing more instability which is reflected in the figure as high value of approximate entropy. This behaviour shows that subjects have adjusted their walking speed in a way to optimise their walking stability. Approximate entropy values of the lateral acceleration for elderly subjects are shown in Figure 6 for different walking speeds. It is evident from the figure that elderly subjects make two groups.

One Group exhibits the same behaviour as of young subjects showing minimum value of approximate entropy near their normal walking speed. But subject number 1, 6, 13, and 17 have shown different kind of behaviour, i.e. showing more value of approximate entropy near their normal walking speeds. Normal walking speeds for elderly subjects are plotted in Figure 7 (black circle shows mean value and bar shows the standard deviation of the walking speed). Normal walking speed for these subjects are 127, 121, 123 and 128 (steps/minute) respectively. It suggests that these subjects are unable to optimise their walking stability by choosing proper walking speed. For example, subject number 1 can improve his walking stability by lowering his walking speed. Subject number 6 do not show any significant difference of approximate entropy value for various walking speeds. Hence subject number 6 has lesser walking stability

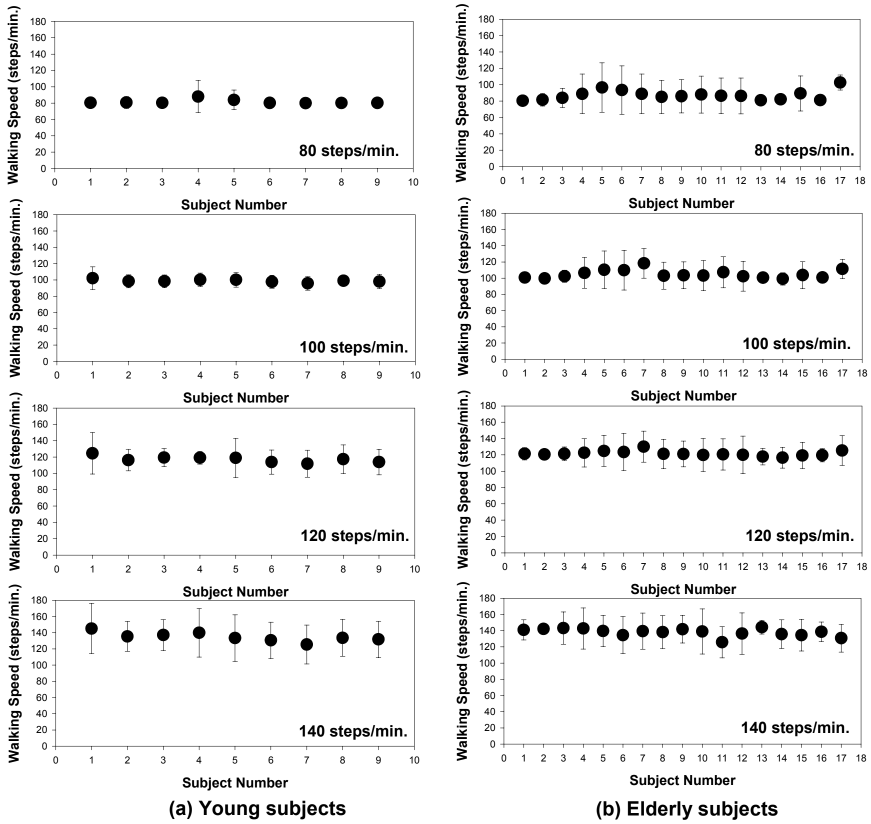

Figure 4: Walking speed of young and elderly subjects when temp is controlled by metronome.

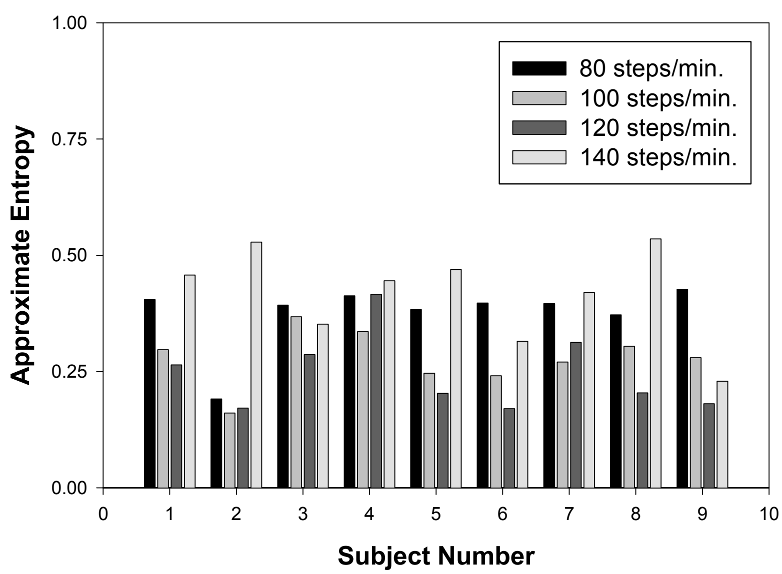

Figure 5: Approximate Entropy of lateral acceleration data of individual young subjects

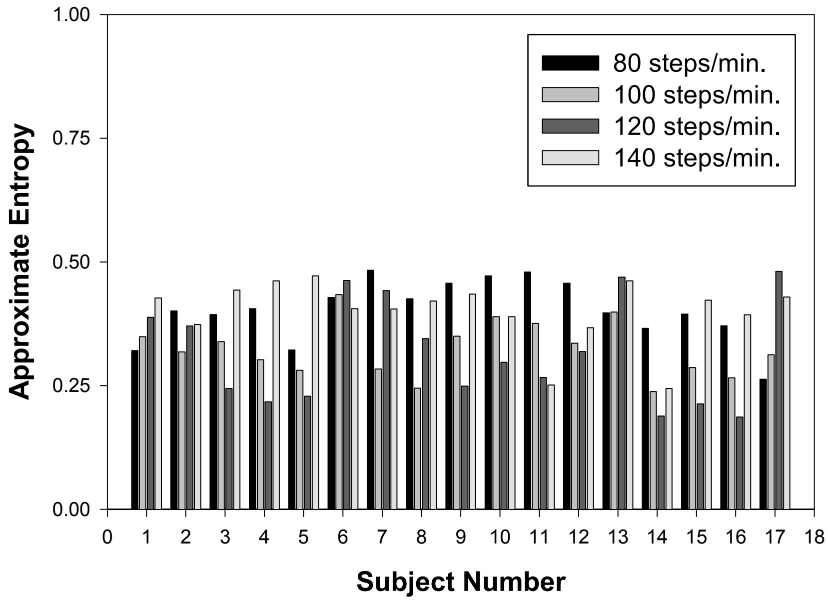

Figure 6: Average approximate entropy values of young and elderly subjects for different walking speeds in lateral direction

independent of his walking speed. Subject number 13, similar to subject 6, also has high values of approximate entropy for all walking speed and shows a little improvement if he decreases his walking speed to 100 steps/minute. Subject number 17 can increase his walking stability significantly if he walks slower than his normal walking speed. Hence by using the above mentioned result, it is possible to suggest the elderly people about their walking speed that can increase their walking stability.

Mean values of approximate entropy for young and elderly subjects walking by different walking speeds are plotted in Figure 8 which showed a U shape curve. In the figure, bar shows the standard deviation of the approximate entropy. Both young and elderly subjects have showed the same trend that is the values of approximate entropy is lower near their normal walking speeds. The approximate entropy value for elderly subjects is higher than young subjects in the walking speed of 100 steps/minute and 120 steps/minute ($p<0.05$) suggesting the fact that young subjects show more lateral walking stability as compared to elderly subjects. The approximate entropy values for young and old are not statistical significant for the walking speed of 80 steps/minute and 140 steps/minute. Experimental results suggest that the effect of age is prominent in the acceleration in lateral direction and the variability or complexity of lateral acceleration increases in the elderly subjects. Hence the walking stability of the elderly subjects decreases in the lateral direction putting the subjects on more risks of lateral falls. Moreover, young subjects always try to adjust their normal walking speed to maximize their walking stability. For other walking speeds, slower or faster, their walking stability decreases. Elderly subjects also try to optimise their walking stability by changing their normal walking speeds. In some cases, it is observed that their normal walking style is less stable and they can improve their walking stability by decreasing their walking speeds.

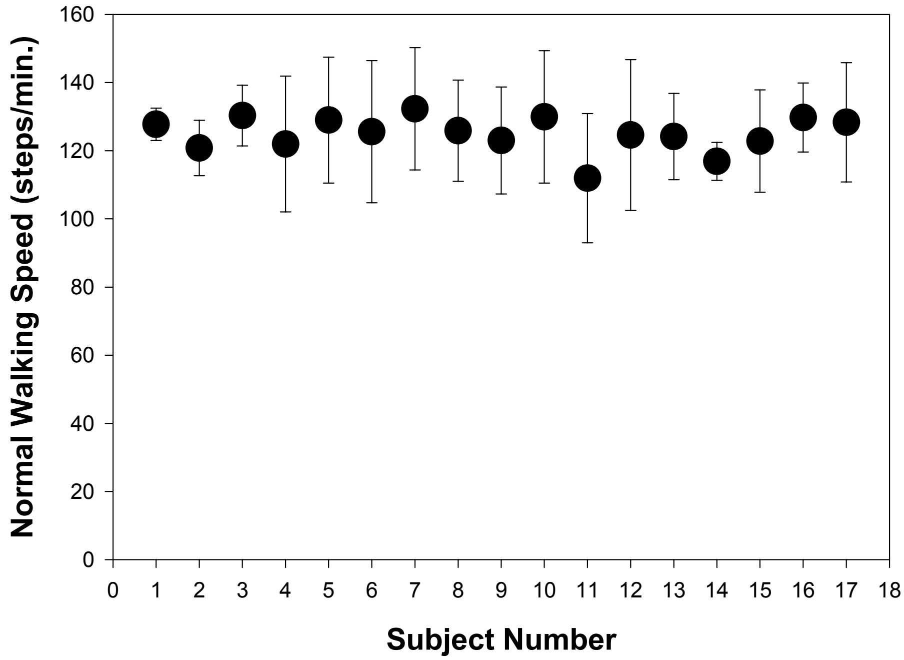

Figure 7: Normal walking speed of elderly subjects

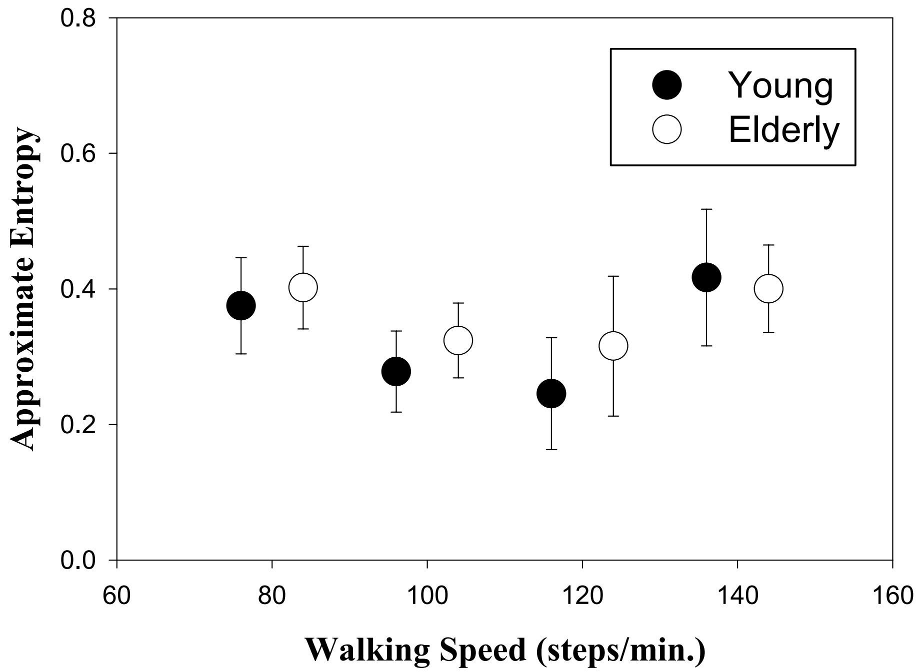

Figure 8: Average approximate entropy values of young and elderly subjects for different walking speeds in lateral direction

5. Discussion

In this paper, we have analysed the walking stability of elderly and young subjects while walking on a controlled pace. At the normal walking speed, the walking stability of elderly subjects has decreased. It is also worth mentioning that the elderly subjects were the participants of the exercise class at Sendai Silver Centre. So they may have better balance as compared to the normal elderly subjects or elderly subjects having some physiological problems. We have also investigated the effect of the walking speed in steps/minute on their walking stability. The most important finding is that young subjects inherently optimise their walking speed to maximize the walking stability. As persons grew old, they try to adjust their walking speed to achieve the maximum walking stability achievable. We have not found any study relating the walking speed with walking stability. Though, in the literature, it is mentioned that elderly people reduce their walking speed to improve their walking stability. Elderly subjects exhibits gait pattern characterized by reduced velocity, shorter step length and increased step timing variability [16]. But the perception of correct walking speed by elderly people may not be correct. In this paper, we have presented a methodology that can be used to suggest the optimal walking speed for the elderly subjects to be more stable during walking.

6. Conclusion

In this paper, we have investigated the walking stability of young and elderly subjects in normal walking and when their walking speed is controlled. The results suggest that the variability in the walking pattern increases with age showing lesser walking stability. Young and elderly subjects try to optimise their walking stability by selecting a proper walking speed in the normal walking. But in some cases, elderly subjects shows less walking stability at their normal walking speed and can improve their walking stability by lowering their walking speed. Age related effects on walking stability in vertical and anterior/ posterior directions are not significant between young and elderly subjects.

Acknowledgements: The authors acknowledge the help of Sendai city silver centre for providing assistance in arranging the subjects to participate in our experiments.

References

[1] D.A. Winter, A.E. Patla, J.S. Frank and S.E. Walt,"Biomechanical walking pattern changes in the fit and healthy elderly persons", Phy. Ther., vol. 70, pp. 340-347, 1990.

[2] J.O. Judge, R.B. Davis and S. Ounpuu, "Step length reductions in advanced age: the role of ankle and hip kinetics", J. Gerontol., vol. 51, pp. 303-312, 1996.

[3] B.M. Nigg, V. Fisher and J.L. Rousky, "Gait characteristics as a function of age and gender", Gait and Posture, vol. 2, pp. 213-220, 1994.

[4] K.M. Ostrosky, J.M. Vanswearingen, R.G. Burdett and Z. Gee, "Comparison of gait characteristics in young and old subjects", Phys. Ther., vol. 74, pp. 634-646, 1994.

[5] D.C. Kerrigen, M.K. Todd, U.D. Crose, L.A. Lipstiz and J.J. Collins, "Biomechanical gait alterations independent of speed in the healthy elderly: Evidence for specific limiting impairments", Arch. Phys. Med. Rehabil., vol. 79, pp. 317-322, 1998.

[6] W.E. McIlory, B.E. Maki, "Age related changes in compensatory stepping in response to unpredictable perturbation", J. Gerontol Med Sci, 51A, M289-296, 1996.

[7] M.W. Rogers, "Disorder of posture, balance and gait in Parkinson's disease", In: Studenski S.A. ed. Clinics in Geriatic Medicine: Gait and balance disorders, Philadelphia PA: W.B. Saunders Company, p. 825 -845, 1996.

[8] S. Pincus, ”Approximate Entropy (ApEn) as a complexity measure”, Chaos, vol.5, pp. 110-117, 1995.
[9] M. Akay, ”Nonlinear biomedical signal processing Volume II: Dynamic analysis and modeling”, IEEE Press, 2001.
[10] D. Sapoznikov, et al., ”Detection of regularities in heart rate variations by linear and nonlinear analysis: power spectrum versus approximate entropy”, Comput. Methods Programs Biomed., vol. 48, p. 201-209, 1995.
[11] S.M. Pincus, ”Older males secrete luteinizing hormone and testosterone more irregularly and joint more asynchronously, than younger males”, Proc. Natl. Acad. Sci. USA, vol. 93, pp. 14100-14105, 1996.
[12] I. Rezek, ”Information Dynamics in Physiological Control Systems”, PhD thesis, Imperial College of Science, Technology and Medicine, 1997.
[13] Ohtaki, K. Sagawa, and H. Inooka, ”A Method for Gait Analysis in A Daily Living Environment Using Body-mounted Instruments”, JSME International Journal, Series C, Vol. 44, No. 4, pp. 1125-1132, 2001.
[14] W. Braune, O. Fischer, ”On the Centre of Gravity of the Human Body” Translated (from 1889 original) by PGJ Maquet and R Furong. Berlin: Springer-Verlag 1984.
[15] FA Hellebrandt, RH Tepper, GLBraun, ”Location of the cardinal anatomical orientation planes passing through the center of weight in young adult women” American Journal of Physiology, 1pp. 21: 465, 1938.
[16] HB Menz, SR Lord, RC Fitzpatrick, ”Age-related differences in walking stability” Age and Ageing Vol. 32 No. 2, pp. 137-142, 2003.