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Gait parameters in school going children using a marker-less approach

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The burden of course work in Indian schools has exposed the school children to various postural/gait disorders due to heavy backpack. Therefore, it is paramount to develop a low cost, non-intrusive and reliable method for calculation of gait parameters. This study assessed the spatiotemporal parameters such as height of earlobe (HoE), stride length (SL) and stride width (SW) using the markerless sensor Kinect v2 and conventional techniques pursued in Indian clinics. Sixty school children (aged 11 to 15 years) were monitored through both the techniques while performing walking trials. To assess the agreement between the techniques Bland–Altman 95% bias, percentage error (PE), Pearson's correlation coefficients (r_1) and concordance correlation coefficients (r_2) were determined. Each parameter obtained from both techniques possessed strong correlation ($r_{1 \text{ and } 2} > 0.90$). Gait analysis using the Kinect V2 sensor is an acceptable, unobtrusive and economical method. The effect of relative backpack weight (RBW), i.e. (bag weight to body weight percentage) and strategies of backpack packing recommended by the American Occupational Therapy Association on the selected parameters was studied. The effect of RBW on the variation in parameters was evaluated using the regression curve whereas the effect of proper packing was evaluated by paired sample T test. RBW has positive correlation with SW ($r_1 = 0.631$), negative correlation with HoE ($r_1 = -0.387$) but shows no correlation with SL. Recommended packing strategy of schoolbag by AOTA shows results to reduce the unwanted variation in gait parameters.

Keywords: Packing, heavy backpack, spatiotemporal parameters, Kinect V2, school children.

BACKPACKS are the most common form of load carriage used in the world since ages, especially by school-going students. According to the data released by the Ministry of Human Resource Development in 2013 approximately 180 million students in India need a backpack to take away items to and from school every day[1]. School-going children are the invaluable resources of the nation. Hence there has been a growing concern among health practitioners, parents and educators to reduce the increasing load of school backpack that may cause serious effects on the gait of the students[2]. Obesity and stair decent may

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enhance the effects[3]. The average load carried by a student over a span of a week ranged from 22% to 27.5% of body weight and one of the students also carried 46.2% of body weight[4]. Many researchers found that the average bag weight carried by the school children should not exceed 10% of the body weight[2,3,5,6]. There were 12,688 acute injuries associated with backpacks in the US[7]. The daily changes/adaptions in posture with the varying load may cause pain and musculoskeletal disorders (MSDs) among school children[8,9]. The forward lean of the head and trunk has a very significant association with the load carried by school children on their backs[10,11]. Researches of human locomotion indicate that there is a requirement of an efficient method to examine the human gait parameters. There have been various approaches to establish an efficient method for gait recognition. In 1975 a model was generated by capturing the human motion by tracking the movement of the light bulbs attached to the contour of human subjects[12]. Another model-based approach generates a stick model from human silhouette[13]. These methods are known as model-based approaches.

Now-a-days, binary silhouette information is used for gait recognition as a model-free approach. In this technique the presence of human motion is extracted by the subtraction of background from the video sequence. An algorithm was designed in 1989 using character recognition techniques on two dimensional 'Eigenspace' for gesture recognition[14]. On the other hand, the use of marker-based motion capture systems for gait assessment has grown very fast in clinical field as well as for research tool. The impact of a backpack load of 15% body weight on the gait parameters of school children was studied using marker and force plate system[15]. It was found that there was significant association of backpack load with double leg support time. However the load did not affect the proportionate time of the stance phase, swing phase and anterior/posterior ground reaction force parameters. Despite their advantages, marker-based systems have a number of drawbacks that prevent their use for conducting experiments in actual field situations. These systems contain multi cameras and markers and it is difficult to setup the workstation everywhere. Moreover, it is expensive. A possible solution to this problem involves the use of markerless motion capture system[16–20]. Wearable sensors are also becoming one of the alternate means to record the gait parameters. Such systems are more suitable when the subject is in dynamic state. Insole pressure sensors for measuring gait properties have also been used[16,21]. For the measurement of comprehensive gait properties, an array of sensors is required because the sensitivity of a single sensor is usually limited to measuring only few gait properties. In spite of its reliability, there are some drawbacks of wearable sensors. The sensors must be placed correctly, securely and the measurements of wearable sensors could be affected by interference due to external uncontrolled noise.

Due to the tedious nature of the problem, complex setups such as model-based systems using superior silhouette information/high quality video system using multi cameras or complicate mesh of wearable sensors are possibly required for gait recognition. Due to these requirements, gait recognition, in an unrestricted surrounding, is difficult to carry out. With advancement of camera and video technology it is possible to capture the depth of image from which it is easy to extract the accurate contour of the subject. The Kinect V2 sensor possesses this capability. It also has the capability to identify the important anatomical landmarks in the human body by using image and depth sensor data combined with artificial intelligence algorithms in real time without the requirement of any sensors/markers[18–20]. The Kinect V2 model used in our study has higher sensitivity and stability as compared to its previous model, as claimed by the manufacturer[23]. The gait variability index has been used as a measure of assessment of risk of fall[24]. However in the current work the correlation of relative backpack weight with various spatiotemporal parameters have been studied. The variations in mean value of these parameters with and without backpack and pre- and post-packing intervention have been used. In a recent study, an algorithm has been developed to identify the human body posture using the Kinect for Xbox, Hausdorff distance theory and joint angle measurement method[25]. Studies of gait parameters such as stride length (SL), stride width (SW) and height of earlobe (HoE) of school children carrying backpack load may be carried out with a Kinect V2. Hence, the purpose of this study was to carry out the following experiments: (1) To examine the validation of the gait features acquired through Kinect by comparing it with features extracted from clinical gait analysis; (2) To find out the variation in the magnitude of walking gait parameters of school children studied in the different group of schools with respect to relative backpack weight (RBW), i.e. bag weight to body weight percentage; (3) To study how proper packing and wearing of school bag will improve the gait parameters.

The study was performed in three schools located in Chandigarh and Punjab, India. Sixty male school students studying in different group of schools (boarding school/ day school (public)/day school (private)) were randomly selected and participated in the study. Permission was sought from Principal of each school and voluntary consent form was signed by each of the students and their parent/local guardian prior to the study. Detailed procedure about the study was explained to them. The study had approval from the Institutional Human Ethical Committee, Department of Industrial and Product Engineering, PEC University of Technology, Chandigarh, India.

The first phase of study consisted of validation of gait parameters acquired using the Kinect V2 markerless system. Unrestricted indoor space at the school was used for the study. A 7 m walkway was marked with 3 m for test

Table 1. Calculation of gait parameters using the Microsoft Kinect V2 skeleton tracking algorithm and conventional techniques used in Indian clinics

Variable	Kinect	Conventional
Stride width	Distance between the ankle joints at initial contact perpendicular to the direction of walking	Distance between heel to heel during the gait cycle
Stride length	Distance between ankle joint between one initial contact and the next for the same limb in the direction of walking	Distance between intra mid-point of the foot
Height of earlobe	Distance between head joint and left/right ankle joint	Distance between earlobe joint and the left/right ankle of foot

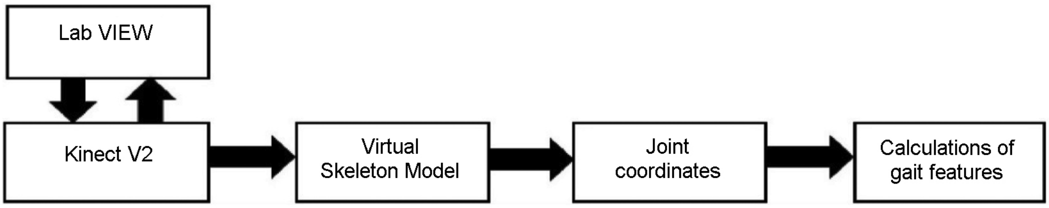

Figure 1. Data acquisition and calculation of gait features.

measurement and an allowance of 2 m of initial and final walk (for acceleration and deceleration of motion). This was covered with a layer of plaster of paris (PoP) to obtain the gait parameters by using conventional technique. The gait parameters were also evaluated using the Haro3D library in LabVIEW (National Instruments, USA) for Kinect V2. During system setup each subject was instructed to walk back and forth at a normal pace; this was done to choose the best gait cycle for the detection phase. The same procedure was carried out with backpack and without backpack. Motion in sagittal plane was recorded with the Kinect. The motion was also recorded in the frontal plane to calculate the stride width (SW) with and without backpack. Six sessions (both sides of body with/without backpack load in the sagittal plane and with/without backpack load in the frontal plane) were recorded using Kinect V2 for each subject. Data from Kinect and conventional techniques were collected simultaneously. Agreement between the conventional technique and Kinect was determined using Bland-Altman 95% bias and limits of agreement[25], Pearson's correlation coefficients (r_1), concordance correlation coefficients (r_2), mean difference and percentage error. The regression curves were used to check the association between RBW and the gait parameters of school children studying in different group of schools.

The automated virtual skeleton produced by the Kinect V2 was obtained using the artificial intelligence algorithms supported in SDK 2.0. The skeleton information is converted into a large set of features which were fed into a customized program written in a LabVIEW using the Haro3D library for the evaluation of the values of interest. Kinect was placed at an angle of 90° with the perpendicular to centre line of the walkway, at a height of 1 m above the floor to capture the virtual skeleton of a walking subject along the path at a frequency of 30 Hz. The Kinect has low capture volume capability and only records motion within 3–4 m of distance in its x-axis. Gait parameters associated with length are constantly related with overall physical function in clinical populations, but can be difficult, time consuming and obtrusive to measure. Heavy load carriage results in bad posture which can be measured through forward lean of the head and trunk. This is reflected in HoE. It may also be reflected in gait parameters like SL and SW. Hence these spatiotemporal parameters were taken as dependent variable for this study. The ease of measuring these parameters using a non-intrusive and economical method was also a deciding factor. The outcomes were calculated from the recorded coordinates using Euclidean distance formula[26].

$$d(i,j) = \sqrt{(xi - xj)^2 + (yi - yj)^2 + (zi - zj)^2}. \quad (1)$$

Table 1 shows the definition of the gait parameters using Kinect V2 and conventional technique.

The gait event time like heel strike and toe off of the subjects was obtained by mapping the position of the ankle joint from a pixel on the screen to its corresponding location on the ground. The virtual skeleton shows the position of 25 joints in the body (such as the wrists, knees, head and torso). The coordinates were acquired from the joints of virtual skeleton read in LabVIEW software and the program written in it gave the measurements of the values of our interest. Figure 1 shows the steps involved in calculation of joint coordinates using the Kinect V2.

Table 2. Mean (±SD) values for each gait parameter with and without backpack measured using the conventional gait analysis technique and Kinect V2 gait analysis system

Gait parameters	Technique Kinect (cm)	Technique conventional (cm)
SL (with backpack)	144.03 (±25.55)	142.63 (±25.75)
SL (without backpack)	136.01 (±25.85)	136.73 (±26.31)
HoE (with backpack)	126.11 (±12.27)	125.89 (±12.14)
HoE (without backpack)	127.98 (±12.27)	127.92 (±12.24)
SW (with backpack)	18.04 (±2.11)	19.03 (±2.05)
SW (without backpack)	16.96 (±1.93)	17.04 (±1.69)

Table 3. Mean difference in gait parameters derived from Kinect and conventional analysis system, 95% limit of agreement (LoA), percentage error (PE), Pearson's correlation coefficient (r_1) and concordance correlation coefficient (r_2)

Gait parameters	Mean Diff. (cm)	95% LOA (cm)[a]	PE (%)[b]	r_1	P-value	r_2 (95% Ci)
SL (with backpack)	–1.41	–2.66 to –0.16	4.12	0.97	<0.001	0.95 (0.95 to 0.98)
SL (without backpack)	–0.73	–0.42 to 1.88	4.07	0.98	<0.001	0.97 (0.96 to 0.98)
HoE (with backpack)	–0.22	–0.55 to 0.11	4.7	0.99	<0.001	0.97 (0.96 to 0.98)
HoE (without backpack)	–0.09	–0.65 to 0.47	7.7	0.99	<0.001	0.97 (0.96 to 0.98)
SW (with backpack)	0.082	–0.1 to 0.256	7.73	0.86	<0.001	0.93 (0.89 to 0.96)
SW (without backpack)	–0.09	–0.17 to 0.01	4.02	0.84	<0.001	0.90 (0.85 to 0.94)

[a]The 95% limits of agreement estimates were obtained from a Bland-Altman analysis which accounted for repeated (right and left limbs) measurements within each participant.
[b]Percentage error was calculated as 100 × (2 SD of bias)/[(Mean kinect + Mean conventional)/2].

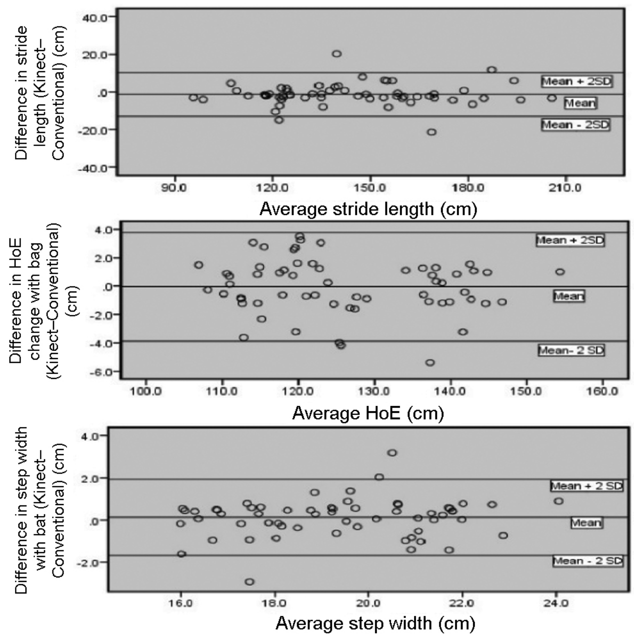

Figure 2. Bland–Altman plot with limits of agreement for gait parameters of students carrying backpack. (The difference of reading between two techniques is plotted on the y-axis and the mean score using both techniques on the x-axis.)

In the conventional gait analysis technique, SL and SW were calculated using the footprints of the subjects on PoP spread on the walkway. The subjects were made to walk with and without backpack and SL and SW were measured using a centimeter scale. HoE in both cases (with and without backpack) was calculated using the manual stadiometer. It was measured during the first two seconds of the walk and the last two seconds of walk in a single complete gait cycle to ensure that, variability effects while walking are taken care of. This process was performed both with and without backpack.

A presentation on basic strategies for packing and wearing of school backpack recommended by the American Occupational Therapy Association (AOTA)[27] was given to the students and their parent/guardian. The gait data was again collected using both the techniques to see the variation in gait parameters. To minimize disruption to classes, gait analysis was conducted in their physical education class. The parameters were measured after a week on the same subjects on the same day to ensure the same load of backpack. Paired-sample T test was used to see the significant association of the backpack packing before and after ergonomic intervention and percentage variation in the gait parameters.

The study consisted of 60 randomly selected school going male students (20 from each school and 5 from each of class 5, 6, 7, 8). On the basis of questionnaire, only those students who had no history of orthopaedic, neuromuscular or cognitive disorder were selected. None of them had practiced any physical activity for more than 12 h per week. The average age, height and the weight of students was 11.77 (±1.52) years; 1.44 (±0.12) m; 37.97 (±8.51) kg respectively.

The weight of school bag ranged from 3.9 to 10.4 kg for CBSE-affiliated schools. The mean bag weight for school children studying in the public, private and boarding schools was 5.84 (±1.22) kg, 7.75 (±1.19) kg, 4.89

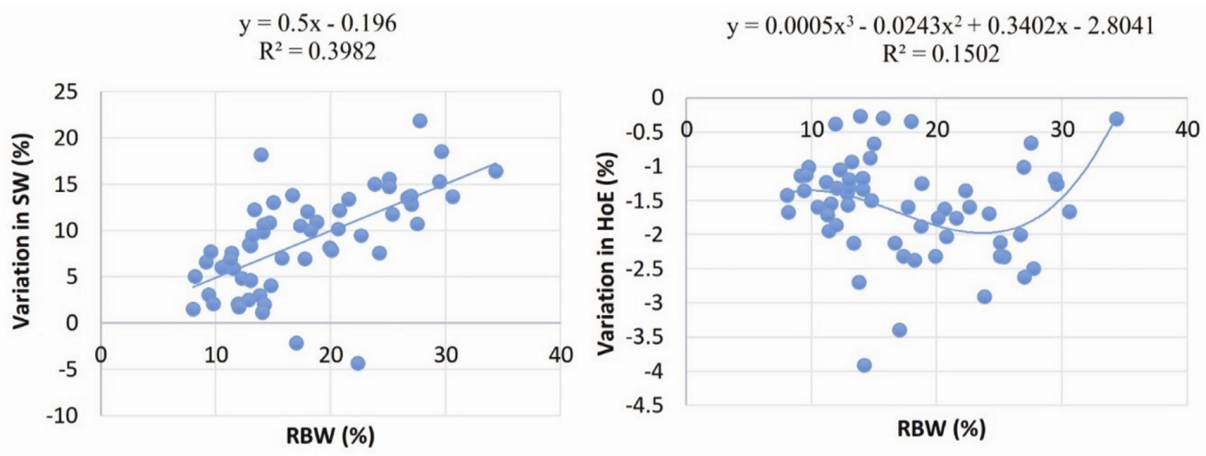

Figure 3. Regression curves for the variation in stride width and height of earlobe with RBW.

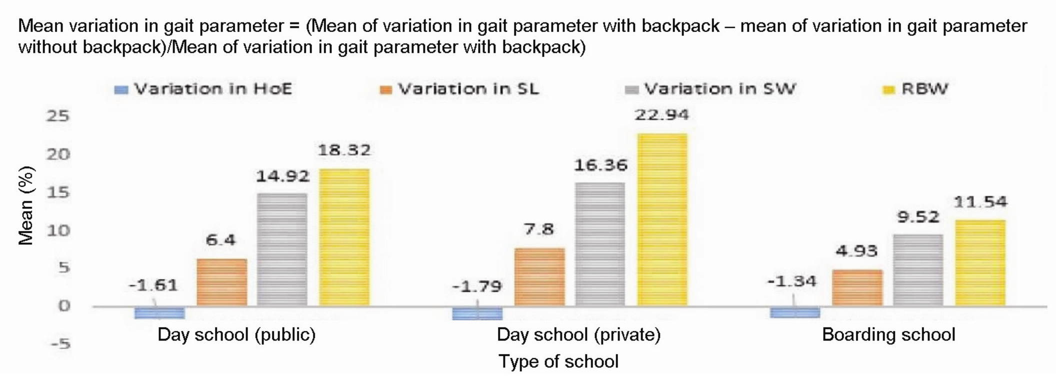

Figure 4. Mean RBW and the mean variation in gait parameters of the students studied in different groups of schools.

Table 4. Significance, correlation, F value and R^2 change of variation in gait parameters with RBW

Variation in gait parameter	r_1	R^2	R^2 change for different regressions	F	P-value
SW	0.631	0.39	–	38.374	0.001
HoE_linear	–0.146	0.021	–	1.527	0.267
HoE_squared	–0.307	0.095	0.073	2.975	0.059
HoE_cube	–0.390	0.15	0.057	3.341	0.026
SL	0.014	0.00019	–	0.104	0.748

(±0.43) kg respectively, and their mean body weight was 32.97 (±6.37) kg, 35.32 (±9.02) kg, 42.83 (±6.83) kg respectively. Now-a-days backpacks with hip belt and chest belt are available. These belts evenly distribute the weight around hip and trunk areas and reduce the load on shoulders. This prevents hunched back problems among school children because of heavy load carriage. Fifty-six students were found to be using normal backpacks with two straps and did not possess ergonomic features such as hip and chest belt. Rest of the students were using backpack with only hip belt feature.

In this work, three type of studies were conducted. The first study was carried out to validate the assessment of the gait parameters using Kinect. The second was carried out to analyse the variation in gait parameters of school children studying in different types of schools on carrying a backpack compared to the parameters when walking without a backpack. The third study was carried out to evaluate the effect of proper packing and wearing of school bags on variation in gait parameters.

To validate the data obtained from Kinect, the measured data was cross-validated with those collected through conventional techniques. The values obtained from Kinect were close to those obtained using conventional gait analysis technique. Table 2 shows mean (±SD) for each parameter. Table 3 gives percentage error,

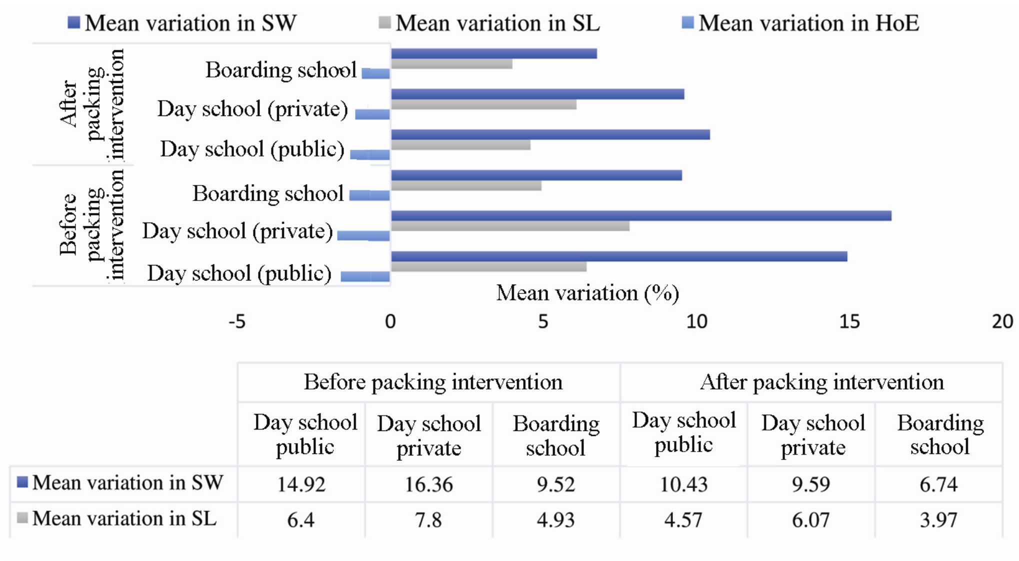

Figure 5. Mean variation of the gait parameters before and after ergonomic intervention (packing and wearing).

Table 5. Paired sample *T* test to check the significant effect of packing on the variation of gait parameters

% Variation in gait parameters_ (pre packing–post packing)	Paired differences: Mean (%)	SD	Std. error of mean	95% confidence interval of the difference: Lower (%)	Upper (%)	*t*	*dof*	Sig. (2-tailed)
Variation in HoE_ (pre packing–post packing)	0.66	0.913	0.118	0.430	0.902	5.64	59	0.001
Variation in SL_ (pre packing–post packing)	–2.40	4.52	0.583	–3.57	–1.23	–4.11	59	0.001
Variation in SW_ (pre packing–post packing)	–4.89	3.96	0.511	–5.914	–3.86	–9.56	59	0.001

mean-difference and correlation coefficients and limits of agreement for gait parameters. SL, SW and HoE possessed strong agreement obtained from both techniques, with low percentage errors (r_1 and r_2 values >0.90 and percentage error <8%) and the points on the Bland–Altman plot were uniformly and closely scattered around the horizontal axis when school children carried backpack as shown in Figure 2.

The relative backpack weight (RBW) was calculated for each student from the percentage ratio of the bag weight to the body weight of school children. The mean (±SD) values of RBW in private, public and boarding school were obtained as 18.32 (±5.13)%, 22.94 (±5.89)% and 11.7 (±2.17)% respectively. The effect of RBW on SL, SW and HoE of each student of different schools was studied using the results of the experiments. Figure 3 illustrates the linear and cubical regression between RBW and the variation in SW and HoE respectively. Table 4 gives the Pearson's correlation (r_1), R^2, R^2 change, *F*-value and *P*-value of RBW with variation in gait parameters. From the table it is clear that there is significant effect of RBW with variation in SW. In case of HoE, the RBW shows better correlation, statistically significant effect and increase in R^2 value when considered the cubical regression model of RBW with HoE. The change in R^2 illustrates that 13% of the variability in HoE is being accounted for by the addition of the nonlinear effect whereas linear and quadratic model of RBW and HoE shows insignificant effect. Results also demonstrated the statistically insignificant effect of RBW on variation in SL. Mean variation in the gait parameters and RBW in different types of schools is shown in Figure 4.

Paired-sample *T* test shows that there is a significant effect of packing and wearing intervention on gait parameters. The variation in gait parameters for proper packing and wearing, before and after an ergonomic intervention was significantly different and the results obtained from the statistical test are given in Table 5. The values given in the column of mean (%) demonstrate that mean difference of variation in HoE for packing before and after intervention was increased whereas mean difference of variation in SL and SW is decreased after the packing intervention. The mean variation in gait parameters before and after proper packing and wearing of school bags is given in Figure 5. It can be seen that after proper packing and wearing, mean variation of combined gait parameters in day school (public), day school (private) and boarding school was reduced by 30.64%, 34.76% and 25.4% respectively.

The Microsoft Kinect V2 has coincidental validity with conventional clinical analysis technique for some spatio-temporal parameters. Irrespective of its validation with conventional technique, it possesses some limitations such as difficulty in measuring those parameters which are heavily dependent upon the precise identification of an event timing and the inability of the sensor to locate multiple important anatomical landmarks of foot such as calcaneous and metacarpophalangeals which would help detect more precise gait parameters. Further, the range of the skeleton tracking with the Kinect was only limited to 3–4 m. This capture volume restricts its use when compared to wearable sensors which have a potentially greater range. Accuracy of the Kinect depends upon the distance from the place where it is installed. As the distance increases, resolution decreases and error in depth measurement also increases. Despite its limitations, Kinect has several advantages over other devices because of its low cost, non-intrusive nature and absence of any sensors or markers which improves its feasibility to detect the gait parameters in different surroundings or terrain. At present researchers are trying to develop algorithms by using the portable gait analysis approach based on Microsoft Kinect[28,29]. In this study all trials were conducted on school children using the Kinect. This assumes importance in view of the fact that the backpack load and its daily carriage may be a major cause of MSDs in school children. Gait parameters of subjects without backpack were considered as baseline readings. Variation of gait parameters means variation in selected gait parameters from the baseline. According to the results obtained from Kinect V2, there is increase of SW and decrease of HoE. This is an instant biomechanical coordination for maintaining body posture and balance during dynamic condition. The same has been reflected with a correlation coefficient of 0.631 for SW and –0.39 for HoE. Although there is increase in SL during carrying of backpacks in all schools with the increase in RBW, SL assessed in the study shows no significant correlation with RBW. This may be due to the consideration of less number of subjects or considering single gait cycle. The study also reveals that variation of gait parameters is lesser in the boarding school students compared to students studying in other schools. This may be due to the fact that boarding school students carry lower backpack weight compared to students of other schools. Hence there are fewer changes in posture adaptions in boarding school students.

Data was collected for the same set of students when subjects properly packed and carried their backpack as per the recommendations of AOTA. There was an improvement in the gait parameters. The paired sample *T* test also shows significant effect of packing and wearing interventions on the mean variation of gait parameters. The maximum variation in gait parameters was observed in the case of day school (private), in which children need to carry more load than the students of other schools because of various curricular activities happened in these types of school. Thus simple ergonomic interventions may help reduce the musculoskeletal disorders caused due to the sagittal flexion because of backpack usage[8].

Awareness regarding packing and appropriate wearing of backpack should be created among healthcare professionals, teachers and parents. The backpack load should be restricted to 10–12% of the body weight as suggested in the literature.

School bag carriage is an integral part for school-going children. There are important biomechanical changes in the body associated with it. An efficient gait evaluation technique is required that can measure gait parameters in an unobtrusive manner. This study represented a comparison between two different techniques for measuring gait parameters – a highly intrusive, conventional technique used to calculate gait parameters in Indian clinics and a markerless, easy to use, economical technique based on Kinect V2 sensor. Proper packing and wearing of school backpack intervention helps reduce unwanted variation in gait parameters. Hence, proper packaging and wearing of school backpack should be encouraged to minimize the effect of backpack load.

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Molecular genetic diversity of landraces, cultivars and wild relatives of rice of Goa

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We studied 51 rice varieties to understand their genetic diversity. Out of 19 ISSR primers, 15 primers produced reproducible bands. Out of 110 ISSR bands, 104 were polymorphic bands with an average of 6.93 bands per primer. The amount of polymorphism varied from 50% to 100%, with an average of 92%. Genetic identity value ranged from 0.5091 to 0.9727, with an average of 0.740. Dendrogram revealed the formation of four major clusters. Wild rice *Oryza rufipogon* formed a separate clade, indicating its uniqueness. Our study opens up avenues for use of traditional rice varieties for rice breeding, genome-wide association mapping and conservation of rice germplasm.

Keywords: Genetic diversity, ISSR markers, landraces, *Oryza sativa*, *Oryza rufipogon*.

MOLECULAR genetic diversity of rice germplasm has been evaluated intensively on a large scale using molecular markers[1–3]. Consequently, the global studies present an outstanding overview of the cultivated rice population structure. However, an in-depth knowledge on local germplasm of rice could not be provided. Hence, various local rice germplasm studies have been taken up at the national or state level to understand the genetic diversity of rice in a particular area[4–8]. Molecular markers have been used as an important tool for assessing the genetic relations, identification and for the desirable genotype selection in breeding programmes and germplasm conservation[9]. In this communication, we present the molecular genetic diversity among landraces, cultivars and wild rice in Goa.

During the field survey, we collected a total of 50 varieties of rice from different talukas of Goa (28 landraces, 22 high yielding rice varieties), India. We also included wild rice *Oryza rufipogon* from Goa, and a salt-tolerant rice variety Pokkali from Kerala (Tables 1 and 2). The seeds were germinated in laboratory conditions and allowed to grow for 20 days. Genomic DNA was extracted from the fresh/frozen rice leaf material using standard protocol[9]. The universal random oligonulceotide primers, specifically inter-simple sequence repeat (ISSR), were obtained from Metabion International AG (Martinsried, Germany). The primers used during this analysis of molecular genetic diversity of rice are listed in Table 3.

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