Title: Temporal Correlations in Center of Body Mass Fluctuation during Standing and Walking

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Abstract

It has been reported that body fluctuations during both quiet standing and walking have temporal correlations that reflect the mechanism for balance control. However, little is known about the relation between the temporal correlations in standing and walking. The purposes of this study were 1) to investigate temporal correlations in the fluctuations of the center of body mass acceleration (ACC) in standing and walking, and 2) to test the hypothesis that the degree of the temporal correlation for the two tasks are similar and correlated across subjects. Seventeen young, healthy subjects were asked to stand and walk for ten minutes on a treadmill equipped with two force platforms. The temporal correlations of the ACC in the anteroposterior (ACC_{AP}), mediolateral (ACC_{ML}), and two-dimensional (ACC_{2D}) directions were evaluated using the scaling index (α) calculated with Detrended Fluctuation Analysis. The scaling indices of ACC fluctuations while standing and walking were categorized as stationary signals which are temporally correlated ($0.5 < \alpha < 1.0$). Further, there were significant, positive correlations for ACC_{AP} and ACC_{2D} between the scaling indices during standing and walking. The results suggest that there are common characteristics in the balance control system for standing and walking, which may be associated with temporal correlations in COM acceleration.

Key words: Balance, Walking, Standing, Center of Body Mass, Temporal Correlation

Introduction

Much attention has focused on the control mechanisms for standing and walking, which are fundamental behaviors in daily life. Studies of these activities are motivated by scientific interest and the need to find solutions to the problem of motor disabilities that develop because of diseases and aging. One possible approach to finding a solution is to analyze the characteristics of body fluctuations in standing and walking. The control systems of standing and walking consist of various sensory-motor integrations at multiple levels of the nervous system, and the dynamic interaction between the nervous system and the musculoskeletal system. Therefore, the study of changes in movement, such as body fluctuation, can be useful in the detection of characteristics of the underlying system.

Many studies have focused on center of pressure (COP) fluctuations during quiet standing, in order to investigate the upright postural control. The COP is proportional to the resultant ankle torque, which primarily controls the center of body mass (COM) during quiet standing and is partly regulated by the neural system (Loram, Maganaris, & Lakie, 2005a, 2005b; Masani, Popovic, Nakazawa, Kouzaki, & Nozaki, 2003; Masani, Vette, & Popovic, 2006; Peterka, 2000, 2002). Thus, by investigating COP dynamics, one may gain insight into the neural control of balance. Previous studies have reported that COP fluctuations are not random in time; but have temporal correlations (Collins & De Luca, 1993, 1994, 1995; Collins, De Luca, Burrows, & Lipsitz, 1995; Duarte & Zatsiorsky, 2000, 2001). Collins and colleagues (Collins & De Luca, 1993, 1994, 1995; Collins et al., 1995) believe that such temporal correlations reflect open-loop control in the short-time scale (within one second) and closed-loop control in the long time scale (over one second). Peterka (2000) suggested that this characteristic could be produced by appropriate selection of control parameters in a very simple feedback model that represents body dynamics as an inverted pendulum. Although these studies suggest different mechanisms for the emergence of temporal correlations, the common understanding between these studies is that the neural controller that maintains the COM over the base of support can modulate the temporal correlation. In fact, the degree of the correlation is influenced by aging and disease, which degrade the neural system for balance control (Collins et al., 1995; Laughton et al., 2003; Maurer, Mergner, & Peterka, 2004; Priplata, Niemi, Harry, Lipsitz, & Collins, 2003; Priplata et al., 2006).

Inter-stride fluctuations during walking have been used to investigate the control system of walking, with particular focus on falling in the elderly (Gabell & Nayak, 1984; Hausdorff, Rios, & Edelberg, 2001; Maki, 1997; Masani, Kouzaki, & Fukunaga, 2002; Pailhouse & Bonnard, 1992; Yamanishi, Sasaki, & Torii, 1991). Hausdorff and colleagues (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Hausdorff et al., 1996) demonstrated that the fluctuation of stride intervals shows temporal correlations, and that such time dependent dynamics are influenced by aging and disease (Hausdorff et al., 1997). There are some debates about the emerging process of the temporal correlation in stride intervals; Hausdorff et al. (1995) showed that the central pattern generator (CPG) model with memory function could generate a persistent temporal structure across stride intervals. West and Scafetta (2003) developed the super CPG (SCPG) model to explain the changes in stride interval temporal correlations in fast and slow walking speeds, as well as walking paced by a metronome. While these researchers focused on the neural mechanism that generates a given rhythm, Gates, Su, and Dingwell (2007) demonstrated that interaction among simple neural controllers, the musculo-skeletal system, and noise input could generate temporal correlations. It is unknown, however, if balance control in walking relates to the emergence of the temporal correlation observed in stride interval fluctuation. Furthermore, it has not been determined if the body fluctuations during walking show the temporal correlations that have been reported in body fluctuations while standing.

As a logical development, the next question would be whether body fluctuations in walking have temporal correlations similar to those in standing, and if so, how the structure in the body fluctuation during standing and walking are related. While the COM dynamics and CNS control strategies used in walking are generally considered to be different from that of standing (Winter, 1995), the control of posture and gait share the same neural (Mori, 1987, 1989; Mori, Nakajima, Mori, & Matsuyama., 2004; Morton & Bastian, 2003, 2004) and musculoskeletal systems. In addition, both tasks have a common goal; the COM position must be controlled to prevent falling. We hypothesize that the temporal correlations in body fluctuations during standing and walking could be similar and correlate with each other among a group of people, i.e., those who have a strong correlation in walking would have a similarly strong correlation in standing.

A few studies have compared the stability between standing and walking. Shimada et al. (2003) investigated the response to a perturbation applied to the body during standing and walking, and demonstrated that the responses between the motor tasks were unrelated. Kang and Dingwell (2006) investigated the trunk motion during standing and walking, and analyzed its stability using local dynamic stability analysis. They measured the trajectory of the trunk in state space in standing and walking. They then estimated the rate of the divergence of the trajectory to the neighboring one, which describes local dynamic stability, i.e., faster divergence indicates greater instability. They found that the parameters of the divergence curves between standing and walking had no correlation, suggesting that the mechanisms governing standing and walking stability are different. Since temporal correlations during standing and walking may be affected by the stability of the control system of each task, their results could provide evidence against the above-mentioned hypothesis. However, as far as we know, no study has directly compared temporal correlations of body fluctuations among strides during walking with body fluctuations during standing.

In order to directly compare temporal correlations in body fluctuations during standing and walking, we used ‘COM acceleration’ (ACC) as a measure of body fluctuation since ACC is one of the representative and commonly measurable parameters of body behavior during the motor tasks. Therefore, the purposes of this study were to 1) investigate the temporal correlations for ACC in standing and walking, and to 2) test the hypothesis that the degree of temporal correlation in ACC time-series during standing and walking are related. A preliminary account of the results was published in abstract form (Abe, Nakazawa, Masani, & Akai, 2004).

Methods

Subjects

Seventeen healthy subjects (9 males and 8 females), aged 21-34 years, participated in this study. The mean (±Standard Deviation: SD) height and weight of all subjects was 1.72 ± 0.07 m and 64.5 ± 8.4 kg, respectively. None of the subjects had a history of motor disorder. Informed consent was obtained from all subjects prior to their participation in this study. The experimental procedure used in this study was approved by the local ethics committee.

Apparatus

To obtain ACC during standing and walking, we recorded ground reaction forces (GRF) using a treadmill equipped with two force platforms (ADAL3D, Techmachine, Andr´ezieux-Bouth´eon France). GRF data in mediolateral (ML), anteroposterior (AP), and vertical (VL) directions from each force platform were recorded. The natural frequency of this apparatus was over 120 Hz and the linearity was ensured by the manufacturer to range from 0 to 3000 N for the vertical components and 500 N for the horizontal components. Belli, Bui, Berger, Geyssant, & Lacour (2001) examined the same type of treadmill in detail and concluded that the treadmill would be accurate for analyzing human gait behavior.

Protocol

Subjects performed two tasks: a standing task and a walking task. In the standing task, subjects were asked to stand still without moving their arms or feet for 10 minutes on the treadmill. The heel-to-heel distance between feet was about 6 cm. In the walking task, the subjects were asked to walk for 12 minutes on the treadmill with the belt speed set at 1.1 m/s. All subjects reported that the speed was natural, and that they performed the task easily without feeling excessive effort and fatigue. Before the recording session, subjects performed a five-minute practice session. There were five-minute breaks between the pre-training and the experimental trials in walking tasks, and ten-minute breaks between the standing and walking tasks. The length of each break was decided based on the subjects' objective comments. They were able to execute the next task comfortably after the break.

Data Analysis

The GRF data was recorded at 100 Hz using a 16-bit AD converter (WE7000, Yokogawa, Tokyo, Japan) and stored on a personal computer. All data were digitally low-pass filtered with a zero-phase-lag 10th order FIR filter with a Blackman window at a cut-off frequency of 20 Hz. This filtering removed noise artifacts during push-off, and enabled the moment of heel contact to be accurately identified. For the walking task, the last 10 min of data (out of 12 min) were used in the subsequent analysis. The standing and walking data in the AP and ML directions for 10 minutes were used to calculate COM acceleration in AP (A_{AP}) and ML (A_{ML}) directions as follows:

$$A_{AP}(t) = F_{AP}(t)/m$$

$$A_{ML}(t) = F_{ML}(t)/m \quad \ldots(1)$$

where *m* is the mass of the body, and F_{AP} and F_{ML} are GRF data in AP and ML directions, respectively. Note that we only focused on balance control in horizontal plane and therefore did not analyze the vertical force in the present study, since vertical movement during standing is not prominent. The ACC absolute value in each direction (ACC_{AP} and ACC_{ML} for AP and ML directions, respectively) and the magnitude of the two-dimensional ACC vector (ACC_{2D}) were calculated for each trial as follows:

$$ACC_{AP}(t) = \sqrt{A_{AP}(t)^2}$$

$$ACC_{ML}(t) = \sqrt{A_{ML}(t)^2}$$

$$ACC_{2D}(t) = \sqrt{A_{AP}(t)^2 + A_{ML}(t)^2} \quad \ldots(2)$$

First, we assessed stride-to-stride fluctuations in the walking data by partitioning the time-series into individual strides. The stride interval was defined as the moment from one heel contact to the next ipsilateral heel contact. Heel contact was identified as the time when the vertical GRF reached 10% of subjects' body mass. For all subjects, the stride interval was about 1 sec. (1.09 ± 0.04 sec., mean ± SD) and contained roughly 500-600 data points. For each stride interval, the average magnitudes of ACC_{AP}, ACC_{ML}, and ACC_{2D} were calculated as in Equation (2). This created new a time-series for each variable that consisted of these average ACC magnitudes, in which the number of data points was equal to the number of stride intervals. Then based on these stride intervals, the entire sequence of ACCs in the standing task was divided into bins in which the data length was defined by the average stride interval for each subject. Figure 1 represents typical examples of the ACC series for standing and walking. The number of data points was equal in the standing and walking tasks. Table 1 shows a summary of average and standard deviations for the ACC time-series.

To investigate temporal correlations in ACC, we used Detrended Fluctuation Analysis (DFA) (Peng et al., 1993; Peng, Havlin, Stanley, & Goldberger, 1995). DFA evaluates degree of correlation in a time-series by a parameter referred to as the scaling index (α). The scaling index is quantified by calculating the slope of the line relating log $F(n)$ to log n, where n and $F(n)$ represent the window size and the variance of the time-series within each window (of size n), respectively (Figure 2). In DFA, the data was normalized with mean = 0 and SD = 50, and integrated for the calculation of slope. If the scaling index (α) is less than 1, the time-series is categorized as a stationary signal (Eke, Herman, Kocsis, & Kozak, 2002). In addition, if there are no correlations between past and future fluctuations in the time-series, as in *white noise*, the scaling index will be $\alpha = 0.5$. When the signal is temporally correlated, the scaling index ranges from 0.5 to 1.0 (Eke et al., 2002). Note that $\alpha > 0.5$ in DFA does not necessarily indicate 'long-range' correlations, as time-series having short-range correlations also can show $\alpha > 0.5$ in DFA (Maraun, Rust, & Timmer, 2004; Wagenmakers, Farrell, & Ratcliff, 2004, 2005). In this study, we used the scaling index simply as an estimation of the degree of time correlation. In stationary signal ($0.5 < \alpha < 1.0$), the scaling index is statistically equivalent to degree of the decay of autocorrelation and power spectrum. Peng et al. (1993) demonstrated that the measurement of scaling index could dramatically reduce the influence of artifact noise compared to the other analyses.

The range of the slope calculation was from the 8th step to the 28th step ($8 < n < 28$) in which the slopes were straight. To validate our method for calculating the scaling index, we created twenty time-series with $\alpha = 0.5, 0.6, 0.7, 0.8, 0.9, 1.0$ (data length of 512) by using a previously validated method (Peng et al., 1993), and calculated the scaling indices using the above-mentioned method. The mean of the scaling indices for the simulated time-series was within 5 % of the theoretical value as a result.

Although we recorded 10 minutes of data in standing and walking in order to compare their scaling index by the same time-scale and same data number, these tasks might be affected by boredom and fatigue. In particular, the standing task might be unnaturally long compared to standing in daily life. To check the influence of time effects over the scaling indices, the 10 minutes of data were divided into two bins (2 × 5 minute) and scaling indices for these bins were compared in each direction by using a paired t-test. The test showed no significant difference between scaling indices in the two time bins for both tasks in three directions ($p > 0.05$ in all cases), suggesting that the effect of physical/mental fatigue on the scaling index of body fluctuation in standing and walking was not particularly critical in this study. Thus, we used the ACC series for 10 minutes in the subsequent analysis.

We performed a ‘shuffled’ surrogate test (Scheinkman & LeBaron, 1989) for the scaling indices. While this test cannot distinguish white noise from linear-filtered white noise, we used it in order to confirm that the scaling index was generated from the temporal order of the ACC series and not merely from the amplitude distribution (Theiler, Eubank, Longtin, Galdrikian, & Farmer, 1992). Twenty shuffled data sets from each of the ACC data were made by randomly shuffling the temporal order of the original data, and the averaged scaling index for the shuffled data set was compared with that of the original data by a paired t-test at each task and direction.

A comparison of the scaling indices of ACC in each condition was done by repeated measures two-way (direction × task) ANOVA with a Bonferroni post-hoc test. The cross correlation between the scaling indices in standing and walking tasks in each direction was tested using Pearson’s correlation coefficient. The significant levels of all statistical tests including the above analyses were set to $p < .05$.

Insert Figure 1 and Table 1 around here

Results

Figure 2 shows the averaged DFA results for the original ACC_{2D} data and the shuffled data in standing and walking tasks for all subjects. As shown in this figure, the scaling index of the original data was much larger than 0.5 in both the standing and walking tasks, while the shuffled data set showed the scaling indices close to 0.5. Table 2 summarizes the results of the scaling indices of each ACC component for the standing and walking tasks. The scaling indices for the standing and walking tasks ranged from 0.524 to 0.915 and from 0.602 to 1.006, respectively. The ANOVA showed a significant interaction between conditions ($F_{2.32} = 5.267$, $p = .011$). The post-hoc test for each direction showed a significant difference in the scaling indices for ACC_{ML} between standing and walking tasks ($p = .037$). There were no significant differences for ACC_{AP} and ACC_{2D} between the tasks ($p > .05$). Table 2 also shows the scaling indices for shuffled data. Paired t-tests between scaling indices in the original and shuffled data showed that the scaling indices of the original data were significantly larger than that of shuffled data for both tasks in all directions ($p < .05$).

Figure 3 shows the relationships of the scaling indices for each ACC parameter between the standing and walking tasks across all subjects. In all figures, the horizontal axis represents the scaling indices of the standing task and the vertical axis represents the scaling index of the walking task. There were strongly significant correlations between the scaling indices from the standing and walking tasks for ACC_{AP} ($r = .593$, $p = .012$) and ACC_{2D} ($r = .612$, $p = .009$). For ACC_{ML}, there was no significant correlation between the scaling indices during standing and walking ($r = -0.081$, $p = .758$).

Previous studies for walking focused on the long-time correlation of the stride interval. Thus, we also compared scaling indices of ACC in walking with scaling indices of stride interval in walking. The averaged scaling index of the stride interval was 0.780 ± 0.112. There were no significant correlations between the scaling indices for stride interval and for ACC during the walking task in each direction ($r = .358$, $p = .159$ in ACC_{AP}, $r = -.128$, $p = .624$ in ACC_{ML}, and $r = .335$, $p = .189$ in ACC_{2D}).

Insert Figure 2 and 3 around here

Insert Table 2 around here

Discussion

Temporal correlations in ACC fluctuations during standing and walking

The scaling indices of ACC for each direction ranged from 0.60 to 1.01 for walking and 0.52 to 0.92 for standing (Table 2 and Figure 3). Except for one scaling index for $\mathrm{ACC}_{\mathrm{ML}}$ in walking, these values were less than one, meaning that the fluctuations of these signals were stationary (Eke et al., 2002). This suggests that subjects in this study controlled the center of body mass in both standing and walking so that the amplitude of the acceleration was maintained at a certain level. In addition, all parameters of $\mathrm{ACC}_{\mathrm{AP}}$, $\mathrm{ACC}_{\mathrm{ML}}$, and $\mathrm{ACC}_{\mathrm{2D}}$ were significantly larger from the values of the surrogate data, i.e., ≈ 0.5, which indicates that the ACC signals were temporally correlated. The results of the surrogate testing indicate that the time correlations were due to the temporal ordering of the ACC fluctuations, and were not related to the amplitude distribution.

Temporal correlations in the body fluctuation during standing have been analyzed using COP (Collins & De Luca, 1993, 1994, 1995; Collins et al., 1995; Duarte & Zatsiorsky, 2000, 2001) and body displacement (Priplata et al., 2003; Priplata et al., 2006). Duarte and Zatsiorsky (2001) examined COP using DFA and found that the scaling index of COP fluctuation during standing was $\alpha = 0.98 \pm 0.17$ and $\alpha = 1.01 \pm 0.03$ in AP and ML directions, respectively. Since their measurements were different from ACC, it is impossible to compare the values in their research directly to the results in the present study. It is true, however, that temporal correlations are commonly observed in body fluctuations measured using ACC as well as COP.

Temporal correlations in the body fluctuation during walking have been shown using the stride time interval of gait (Hausdorff, Ashkenazy, et al., 2001; Hausdorff et al., 1997; Hausdorff et al., 1995; Hausdorff et al., 1996; Hausdorff, Zemany, Peng, & Goldberger, 1999). Hausdorff et al. (1995) reported the scaling exponent as $\alpha = 0.76 \pm 0.11$ for young subjects. This value is close to the value for ACC in this study. In fact, the scaling index for the stride interval in this study also showed a similar value (0.78 ± 0.11). The scaling indices of both ACC and stride interval during walking, however, were not significantly correlated across subjects. This suggests that temporal correlations of ACCs during walking were not simply a by-product of fluctuations in stride intervals.

Two possible causes of the temporal correlations are considered: neural effects related to balance control and mechanical effects of musculo-skeletal system. The temporal correlations can reflect neural processes for balance control in which the equilibrium of the body during standing and walking is maintained by referring to past states of the body. In this context, the degree of temporal correlation reflects the underlying neural mechanism for maintaining postural stability. On the other hand, the temporal correlations may be caused by the filtering properties of the musculo-skeletal system during standing and walking (Gates et al., 2007; Peterka, 2000). Even if motor commands generated by the neural system have no temporal correlations, these outputs can be low-pass filtered by the musculo-skeletal system, based on its visco-elastic and inertial properties. Such neuro-mechanical influences, and the interaction between them, can affect the degree of correlation in ACC, although this study cannot identify the relative contributions.

Temporal correlations in ACC fluctuations during walking might be influenced by the use of a treadmill. While the treadmill with twin force platforms afforded us a precise and stable recordings of ACC in walking, the constant belt speed might decrease variability compared to overground walking (Dingwell, Cusumano, Cavanagh, & Sternad, 2001). Although the scaling indices for stride interval in walking, as described above, showed similar levels with those of previous studies that recorded overground walking, further tests would be needed to determine the relationship between ACCs in treadmill and overground walking.

Comparison of the degree of temporal correlation between standing and walking

While scaling indices of ACC in standing and walking showed inter-subject variability, they were related for ACC_{AP} and ACC_{2D} measures (Figure 3). This result indicates that an individual, who shows strong temporal correlations when standing, also shows strong temporal correlations when walking, and *vice versa*. This result is interesting because, in general, balance control and body segmental dynamics in standing and walking are considered different (Winter, 1995). The positive relationship between the temporal correlations in standing and walking has two potential explanations. First, the temporal characteristics of balance control in standing and walking might be similar across subjects. Second, the intrinsic properties of the subjects' musculo-skeletal systems may have similar effects on the temporal correlations of ACC during standing and walking.

Previous studies suggested that there is little relation between balance controls in standing and walking (Kang & Dingwell, 2006; Shimada et al, 2003). The difference between previous investigations and this study might be due to the adopted methods. In the present study, periodic components of walking data were removed by using the averaged data at each stride, and the temporal correlation among strides was compared with that of standing data in the same time scale. Focusing on the body fluctuation among strides in walking allowed a direct comparison between time-dependent characteristics of standing and walking in the same time scales.

In contrast to ACC_{AP} and ACC_{2D}, the scaling index for ACC_{ML} in walking was significantly larger than that in standing. In addition, there was no significant correlation between the scaling indices in standing and walking for ML direction. Compared to the AP direction, ACC in the ML direction may be more sensitive to the mechanics of the musculo-skeletal system. Lateral dynamics in walking is more unstable than in standing, as it takes more time to recover after a lateral perturbation. This could induce large temporal correlations in ACC during walking. The relatively larger difference between standing and walking in this direction might hide the similarity seen in AP and 2D direction. In fact, previous studies demonstrated that the body fluctuations in the ML direction during standing are not sensitive enough to reflect changes induced by aging (Collins and De Luca, 1995; Prietro, Myklebust, Hoffmann, Lovett, & Myklebust, 1996), although the body fluctuations in the ML direction during walking are more sensitive (Dean, Alexander, & Kuo, 2007; Owings & Grabiner, 2003).

Conclusions

In summary, we demonstrated that the fluctuations of COM acceleration during standing and walking had a similar degree of temporal correlation ($0.5 < \alpha < 1.0$). There was a positive relationship between the standing and walking ACC temporal correlations in the anteroposterior direction and also in the horizontal plane, but not in the mediolateral direction. This suggests common characteristics in the balance control system in standing and walking, which may be related to the fluctuations in COM acceleration. While neural effects related to balance control and the mechanics of the musculo-skeletal system are presumed to be the causes of the temporal correlation, further studies are needed to identify the relative contribution of the neural and mechanical components in the AP and ML directions.

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Table

Table 1: Mean and standard deviation of ACC.

	Mean (cm/s^2)		Standard Deviation (cm/s^2)	
	Standing	Walking	Standing	Walking
ACC_{AP}	0.576±0.126	75.7±9.6	0.235±0.070	4.09±0.67
ACC_{ML}	0.330±0.077	58.0±7.7	0.161±0.048	2.87±0.58
ACC_{2D}	0.752±0.136	99.7±10.1	0.261±0.071	3.51±0.59

Table 2: Scaling indices of ACC in standing and walking for all subjects. The right column 'Mean (shuffled)' shows the result of shuffled surrogate test.

	Max - Min		Mean		Mean (shuffled)	
	Standing	Walking	Standing	Walking	Standing	Walking
ACC_{AP}	0.87 - 0.52	0.80 - 0.60	0.67±0.09	0.69±0.05	0.51±0.01	0.52±0.01
ACC_{ML}	0.90 - 0.62	1.01 - 0.74	0.74±0.08	0.84±0.07	0.52±0.01	0.52±0.01
ACC_{2D}	0.92 - 0.52	0.89 - 0.69	0.72±0.10	0.77±0.05	0.52±0.01	0.52±0.01

Figure Legends

Figure 1: Typical examples of the fluctuations of ACC_{2D} in standing (top) and walking (bottom).

Figure 2: Ensemble plots of detrended fluctuation analysis for ACC_{2D}. Black lines show the results of original data and gray lines show the results of shuffled surrogate data. The dotted lines represent the range for the slope calculation. The slopes, i.e., the scaling indices (α) are shown for each plot.

Figure 3: Relations between scaling indices of ACC in standing (horizontal axis) and walking (vertical axis). The top, middle, and bottom figures show the results for ACC_{AP}, ACC_{ML}, and ACC_{2D}, respectively.