Use of Nonlinear Measures to Compare Athlete Postural Sway Dynamics

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The purpose of this study was to examine the use of nonlinear analysis as a tool to evaluate postural sway patterns in athletes and physically active non-athletes. Balance is an integral part of many sports but seems to be task specific. Data collection occurred for 30 seconds during eyes open condition on double leg and single left and right leg trials. Analysis of the data using Transfer Entropy (TE) and Fractal Dimension (FD) yielded Ice Hockey and Football players having distinctly different postural dynamic control from each other and physically active non-players in only a couple conditions for TE and multiple conditions for FD. These balance measures support the idea of sports requiring different postural sway dynamics.

KEY WORDS: Postural Sway, Balance, Fractal Dimension, Transfer Entropy

INTRODUCTION: Ice hockey (IH) players have a different set of conditions on which to balance compared to most other sports. The blade on the skate foot produces a fulcrum for rotation around the longitudinal axis of the foot with a point of rotation well below the plantar surface of the foot. Additionally, the blade has very low surface area and is in unstable equilibrium, meaning an athlete will have to correct for the slightest deviations of the blade medially or laterally to maintain balance. In contrast, the point of rotation for most land based sports is either the inside or outside edge of the players shoe, with a much larger surface area. IH players do not typically have a flight phase when skating, as opposed to running/jogging in other land sports. Hence, IH players spend more time in contact with the ground and must maintain their balance, either single or double leg, much differently when compared to running where ~60% of time is airborne. Schmit, Regis & Riley (2005) found that Track athletes and Ballet Dancers displayed different postural sway patterns.
Considering IH players are under different requirements for stabilization, we hypothesize IH players will have devised different balance dynamics as compared to football players or physically active college-aged students. The purpose of this study was to determine if IH players, football players, and physically active college-aged students exhibit uniquely different postural sway dynamics due to their unique balance demands.

METHODS: We recruited 16 NCAA Division 1 IH players, 65 Division 1 football players, and 43 physically active college-aged students. Table 1 below contains descriptive data of our sample data by group.

Table 1. Descriptive data of Subjects

Group	Age (years)	Height (cm)	Mass (kg)
Football	19.3 (1.0)	184.4 (6.3)	97.8 (15)
Ice Hockey	21.4 (1.3)	184.6 (5.4)	86.8 (10)
Physically Active	21.6 (1.0)	180.5 (7.0)	81.8 (13)

Subjects reported to the biomechanics lab where, after fulfillment of informed consent, they completed three counterbalanced order balance tasks: a double leg stand, single left leg, and single right leg stands; with eyes open. We asked subjects to stand still, barefoot on a 60 x 90 cm in-ground Bertec force plate with feet approximately shoulder width apart and arms crossed over the chest. While in this position, we recorded Center of Pressure (COP) in the Anterior-Posterior (AP) and Medial-Lateral (ML) directions at a sampling rate of 1000 Hz for trials lasting 30s.

During all trials, participants directed their visual attention towards a 5 x 5 cm piece of cardboard fixed to a tripod at eye level 1m in front of the participant. If balance was lost during a trial, subjects repeated that trial until successful completion. Analysis of the data included Transfer Entropy (TE), & Fractal Dimension (FD). TE examines the asymmetrical flow of information between two variables (AP→ML; ML→AP) accomplished by time-shifting one variable; whereby more information being exchanged results in a decrease in uncertainty of the time-shifted variable. More information is generated when a signal is more complex; i.e. less periodic in movement. Since TE is asymmetrical, you must calculate it in both directions to measure the information exchanged between two variables. The FD (box-counting) is a measure of geometrical complexity by looking at the length changes as function of the scale, the higher the number, the higher the complexity of sway movement in the balance task. Peng et al. (1993) determined that the particular mathematical scaling of statistical fractals in biological systems is adaptive for 2 reasons: 1) long-term correlations establish a self-organization of a highly nonlinear chaotic system across multiple time scales, and 2) the lack of a singular scale aids in the prevention of excessive mode locking that would inhibit the functional responsiveness of the organism to changes within its systems. We utilized Analysis of Variance with post-hoc Tukey Honest Significant Difference in R Statistical Programming (R Core Team, 2017), Fractaldim (Sevcikova, Percival, & Gneiting, 2014) package, and custom TE code (Tankanen, 2008) to determine differences among the groups for each measure under the difference conditions. Null hypothesis significance testing was set to $\alpha = 0.05$.

RESULTS AND DISCUSSION: We utilized unfiltered data for Fractal analyses and later statistical analyses as filtering/smoothing can destroy the inherent nonlinearities of the data, tending to make the FD closer to one (that of a simple line segment), and TE closer to 0. We utilized a time-shift of 1ms for all TE analysis. We detected significant differences for TE in the AP→ML direction for double leg and left leg condition. Table 2 contains TE results. Example, AP→ML double leg for Physically Active reads as: AP movement adds 0.10 digits of predictability to ML movement.

Table 2. Results for Double and Single Leg TE. [1,2,3] denote significance with other groups. Natural units are reported.

Condition	Physically Active[1]	Ice Hockey[2]	Football[3]
AP→ML – double leg	0.10(0.10)	0.21(0.21)[1,3]	0.13(0.08)
AP→ML – left leg	0.16(0.14)	0.12(0.12)	0.08(0.10)[1]
AP→ML – right leg	0.14(0.14)	0.19(0.14)	0.15(0.13)
ML→AP – double leg	0.07(0.06)	0.07(0.04)	0.07(0.06)
ML→AP – left leg	0.05(0.06)	0.04(0.06)	0.04(0.04)
ML→AP – right leg	0.04(0.05)	0.03(0.01)	0.04(0.04)

IH players had higher TE from AP→ML Double Leg compared to both Football and physically active. These results partially agree with our hypothesis that IH players would have a uniquely different postural sway dynamics per their sport specific conditions (e.g. standing on low surface area thin blade) and having to make quick adjustments to maintain balance in the ML direction. Football players also had a significantly lower TE than Physically Active group, but only for the left leg in the AP→ML condition. ML→AP influence was not significantly different among all groups and conditions, though it was lower than all AP→ML. This suggests that ML movement is periodic and changing little over 30 seconds, even with less surface area in the Single Leg conditions. Even though IH players spend more time on one leg than Football or physically active when performing in their sport/exercise, their single leg conditions were not significantly different from the other groups. As TE is not a widely utilized measure in assessing balance dynamics, different time-shift measures have not been explored that would be match up well with known physiological delays that may give us more information about balance changes than the 1ms used in the present study.

While each directional movement (AP and ML) is topologically one-dimensional, the movement in those directions is not so straightforward that it produces a simple line segment, more comparable to a statistically self-similar non-rectifiable curve with a FD existing between one (line segment) & 2 (surface). IH players had significantly lower FD values than both Football and physically active groups in almost every condition, particularly both single leg conditions and directions. Football players had significantly higher FD than Physically Active in all ML conditions, but similar FD in all AP conditions. Table 3 contains FD Results.

Table 3. Results for Double and Single Leg FD. [1,2,3] denote significance with other groups

Condition	Physically Active[1]	Ice Hockey[2]	Football[3]
AP – Double Leg	1.59(0.04)	1.56(0.04)[3]	1.59(0.06)
AP – Left Leg	1.52(0.04)	1.47(0.03)[1,3]	1.54(0.04)
AP – Right Leg	1.53(0.04)	1.48(0.03)[1,3]	1.54(0.04)
ML – Double Leg	1.61(0.06)	1.61(0.05)	1.67(0.08)[1,2]
ML – Left Leg	1.52(0.04)	1.48(0.03)[1,3]	1.59(0.03)[1]
ML – Right Leg	1.53(0.05)	1.49(0.02)[1,3]	1.59(0.04)[1]

A higher FD indicates more complex postural sway dynamics. Schmit et al. (2005) found more complex and chaotic postural sway patterns were associated with better balance using Sample Entropy, a measure similar to FD. Interestingly, Football players produced the highest FDs, Physically active either matching one of the groups or somewhere in-between IH and Football, and IH having the lowest FDs. however, we are not fully aware why IH players would exhibit a less complex sway pattern. One possibility is that IH skates restrict AP and ML motion possible at the ankle, and although the muscles that operate those movements are still active during IH tasks, it is more isometric than isotonic. By cause of this ankle restriction, utilization of the hips and knees is imperative for changing direction and stopping to maintain balance during IH tasks. Another possibility is that IH players, due to performing sports related tasks on a thin blade, will tend to return to a centerline on their skate in order to maintain balance, limiting their degrees of freedom in the ML directions and indicating more periodic movement. This also runs counter at first thought to some of the TE results, as a more complex movement would result in higher entropy; however, FD is a geometrical (shape) complexity measure whereas TE measures information transfer between two variables (predictability) in a system. This is also similar to how ML→AP generated very little information, but FD was much higher for ML conditions; again, they measure different types of complexity. A possible explanation for Football players having a higher FD in the three ML conditions than Physically Active is because Football players train in cutting maneuvers, which occur in a ML direction, and failure to be very good at cutting motions would limit someone's performance in Football related tasks. As these are college level Football players, we would expect them to have a better level of performance in maintaining balance in the ML direction. Although the cutting maneuvers and other training associated with the ML directions involves dynamic balance, we would expect some transference to static balance; however, how much would be difficult to quantify.

CONCLUSION: We confirmed our hypothesis that IH and Football players developed uniquely different balance strategies compared to physically active individuals, most of which can be attributed to their sports-specific tasks and maneuvers. Further research should investigate how specific training programs alter these postural sway measures to optimize balance for athletes in their respective sport. Further investigating of TE time delay for different physiological feedback timing with respect to balance tasks and if this changes with specific training.

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