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## The Effect of Virtual Reality on Gait Variability

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**Abstract:** Optic Flow (OF) plays an important role in human locomotion and manipulation of OF characteristics can cause changes in locomotion patterns. The purpose of the study was to investigate the effect of the velocity of optic flow on the amount and structure of gait variability. Each subject underwent four conditions of treadmill walking at their self-selected pace. In three conditions the subjects walked in an endless virtual corridor, while a fourth control condition was also included. The three virtual conditions differed in the speed of the optic flow displayed as follows – same speed (OF<sub>n</sub>), faster (OF<sub>f</sub>), and slower (OF<sub>s</sub>) than that of the treadmill. Gait kinematics were tracked with an optical motion capture system. Gait variability measures of the hip, knee and ankle range of motion and stride interval were analyzed. Amount of variability was evaluated with linear measures of variability - coefficient of variation, while structure of variability i.e., its organization over time, were measured with nonlinear measures - approximate entropy and detrended fluctuation analysis. The linear measures of variability, CV, did not show significant differences between Non-VR and VR conditions while nonlinear measures of variability identified significant differences at the hip, ankle, and in stride interval. In response to manipulation of the optic flow, significant differences were observed between the three virtual conditions in the following order: OF<sub>n</sub> > OF<sub>f</sub> > OF<sub>s</sub>. Measures of structure of variability are more sensitive to changes in gait due to manipulation of visual cues, whereas measures of the amount of variability may be concealed by adaptive mechanisms. Visual cues increase the complexity of gait variability and may increase the degrees of freedom available to the subject. Further exploration of the effects of optic flow manipulation on locomotion may provide us with an effective tool for rehabilitation of subjects with sensorimotor issues.

**Key Words:** virtual reality, detrended fluctuation analysis, locomotion, vision, optic flow, approximate entropy.

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## INRODUCTION

The importance of Optic Flow (OF) on locomotion has received considerable attention in the last fifty years. It began with Gibson's (1958) pioneering work when the ecological theory of visual perception was proposed. According to the theory, visual perception is a direct and non-inferential process. The pattern of the visual motion perceived at the moving eye, i.e., the OF, provides important information about the speed and direction of self-motion. This information is important during goal-directed locomotion to control the heading direction (van den Berg, 1992; Warren, Young, & Lee, 2001) and the speed of locomotion (Pailhaus, Ferrandez, Fluckinger, & Baumberger, 1990; Prokop, Schubert, & Berger, 1997).

Manipulation of OF has been shown to alter both kinematic gait parameters which are descriptors of motion as well as the gait kinetics, which are the descriptors of the causes of the motion. In a recent study, it was shown that gait kinematics like walking speed, stride length, stride frequency and drift were affected in both healthy young and older subjects when OF was manipulated (Chou et al., 2009). Walking trajectory was shown to be affected when healthy young subjects were exposed to rotational, translational or a combination of the two types of OF, demonstrating the importance of OF on steering behavior during locomotion (Sarre, Berard, Fung, & Lagmontage, 2008). During treadmill walking, OF was shown to impact kinematic parameters like step time (Warren, Kay, Zosh, Duchon, & Sahuc, 1986). In a study investigating the interaction between somatosensory and optic input for controlling locomotion, OF was shown to regulate the kinematic parameters of locomotion whereas somatosensory input, although regulated by vision, was involved mainly in the control of gait kinetics (Varraine, Bonnard, & Pailhaus, 2002).

Since OF plays an important role in human locomotion and manipulation of OF characteristics causes changes in locomotion patterns, it is intuitive to expect that manipulating the velocity of the OF would also cause a change in locomotion patterns. Indeed when healthy human subjects, while walking on a treadmill at self selected pace, were exposed to different directions and velocities of optical flow, characteristic locomotion patterns were observed (Prokop et al., 1997). Particularly, it was shown that kinematic parameters of locomotion like walking velocity and stride length had negative correlations with OF such that faster OF induced slower walking velocity and reduced stride length while slower OF induced the opposite effect. Similar observations have also been made in other studies with healthy subjects (Prokop et al., 1997; Verraine, Bonnard & Pailhaus, 2002) and patients with stroke (Lamontagne, Fung, McFadyen, & Faubert, 2007). These effects have also been attenuated over time due to adaptation (Prokop et al., 1997). Therefore, locomotion patterns demonstrate different characteristics when the OF is manipulated for longer periods of time.

The variability of the locomotor pattern can also be impacted when the OF is manipulated. Indeed, in comparison to the study by Prokop et al. (1997), much lower stride cycle variability was observed when treadmill walking was

performed at comparable walking velocities without OF input (Zijlstra & Dietz, 1995). Variability of both kinetic (Hollman, Brey, Bang, & Kaufman, 2007) and kinematic (Hollman, Brey, Robb, Bang, & Kaufman, 2006) locomotion patterns was reduced when healthy subjects were exposed to different velocities of the OF while walking on a treadmill. However in these studies by Hollman and colleagues, the treadmill speed always matched the OF velocity and therefore the true effect of OF on the locomotion patterns of the subject's comfortable walking speed could not be gauged. Specifically, gait variability measurements are speed-dependent (Jordan, Challis, & Newell, 2007). In other words, variations in walking velocity affect the amount of variability present in the locomotion patterns. Thus, the application of a constant-driven treadmill can facilitate the measure of movement variability by controlling for speed variations. In addition, the variability measures in all these studies were restricted to linear measures like standard deviation and coefficient of variation which at best can only provide information on the amount of variability and not its organization over time, i.e., structure (Herman et al., 2005; Sosnoff et al., 2005). Nonlinear measures like approximate entropy (ApEn) and detrended fluctuation analysis (DFA) may provide such answers and reveal hidden structures like the presence of long range correlations (Hausdorff et al., 1996; Herman et al., 2005; Jordan et al., 2007; Slifkin & Newell, 2000; Sosnoff et al., 2005; Stergiou, Buzzi, Kurz, & Heidel, 2004).

Therefore, the purpose of this study was to investigate the effect of the velocity of OF on gait variability using both linear and nonlinear measures. This two-pronged approach would clarify not only changes in the amount of variability of the locomotor patterns but also changes in the structure of variability that occur as a result of manipulation of the OF. This approach may lead to more conclusive results. In this study OF was induced by means of a virtual reality (VR) system, and healthy human subjects were exposed to it while walking on a treadmill at a self-selected pace. In contrast to past studies, this study incorporated longer durations of walking trials (15 minutes) to get a more accurate effect of the OF manipulation on locomotor patterns. It was hypothesized that gait variability during treadmill walking for VR and Non-VR conditions would be significantly different. The second hypothesis was that as the velocity of the OF becomes asynchronous with respect to the speed of the treadmill, gait variability would be significantly affected.

## **METHOD**

### **Subjects**

Ten healthy adults (6 males, 4 females) participated in the study (age,  $28.4 \pm 7$  yr; height,  $171.8 \pm 9$  cm; weight,  $68.1 \pm 11$  kg). Subjects were free from any musculoskeletal problems and had no recent or remote history of significant lower extremity injuries that might have affected their gait. In addition, subjects were excluded from the study in case of any type of visual or vestibular

deficiency. Prior to testing, each subject signed an informed consent approved by the Institutional Review Board of the university's Medical Center.



**Fig. 1.** Experimental set up consisting of the treadmill and the body weight support system and the six-camera motion capture system. The projector was located right behind and above the subject's head and three meters away from the screen to ensure a wide field of view for the subject. On the right side, the virtual reality (VR) environment is shown as it appeared to the subject without the red-blue stereo glasses. The use of a stereo graphics card (nVidia Corporation, Santa Clara, CA) renders not one but two separate images on the screen. On viewing them with the stereo glasses, the two scenes merge and there is a feeling of depth of the rendered scene.

### **Instrumentation**

A custom VR environment, written in C++ using the open graphics library (OpenGL; Silicon Graphics Inc., Sunnyvale, CA) and the graphics library utility toolkit was created and was projected by a commercial projection system (NEC Display Solutions, Itasca, IL) on an 80-inch (diagonal) flat screen that was positioned 3 meters away from the plane of motion. This created a vertical and horizontal field of view of 51.28 degrees. For the VR conditions, an endless virtual corridor with realistic side walls was projected onto the screen to create the VR environment (Fig. 1). The virtual walls of the VR environment extended about 10 meters in front of the subject and did not extend behind the subject. The velocity of motion of the projected environment was synchronized to match the treadmill speed. Once the subject determined the preferred walking speed (the subject's average and not instantaneous speed), the speed of the VR environment was synchronized to the treadmill manually by entering it into the program using a keyboard function. Thus, the OF of the corridor was perceptually equivalent to the speed of the treadmill. The VR environment consisted of two separate images projected on the screen. By viewing them through red-blue stereo glasses that the subjects wore throughout the experiment, the two images merged into a single scene providing the subject

with a feeling of depth of the rendered scene. Based on preliminary data from the lab, subjective measures show that the subjects were immersed in the VR environment.

A Motion Analysis (Motion Analysis Corp, Santa Rosa, CA) camera system was used to capture kinematics at 60 Hz, while subjects walked on a motorized treadmill (312-C, Bodyguard, Canada; Fig. 1). Six optoelectric cameras were positioned around the treadmill to collect the three-dimensional trajectories from the markers that were placed on the subjects prior to data collection. Reflective markers were placed on specific anatomical landmarks to track the motion of the hip, knee and ankle joints (Nigg, Cole, & Nachbauer, 1993). To ensure safety, each subject wore a safety vest suspended overhead throughout the course of the experiment (Fig. 1).

### **Experimental Design**

Each subject underwent four conditions of treadmill walking at their self-selected pace, with each condition being 15 minutes long. Prior to testing, all subjects were given enough time to warm up and familiarize themselves with treadmill walking. For this purpose all subjects were instructed to walk at a comfortable pace that could be easily maintained for a long time. When the subject informed the investigator who had identified such a speed, the value was recorded. This value of the velocity was used for all testing conditions. By using a self-selected pace, any variability changes detected were due to the independent variable and not due to probable discomfort that may be associated with using a pre-determined speed for all subjects (Jordan et al., 2007). The familiarization period was approximately six minutes, which was considered sufficient for the achievement of reliable kinematic measurements during treadmill locomotion (Matsas, Taylor & McBurney, 2000).

All subjects performed the control condition (Non-VR) before walking for fifteen minutes at each of the following VR conditions that were presented in a random order: OF that matched the speed of the treadmill (OFn); OF that was 50% faster than the self-selected pace (OFf); and OF that was 50% slower than the self-selected pace (OFs). Since the subjects were healthy young adults walking at their self selected speeds, the effect of fatigue was minimal. However, all the conditions were randomized and a rest period was provided between conditions which was kept constant for all subjects.

### **Data Analysis**

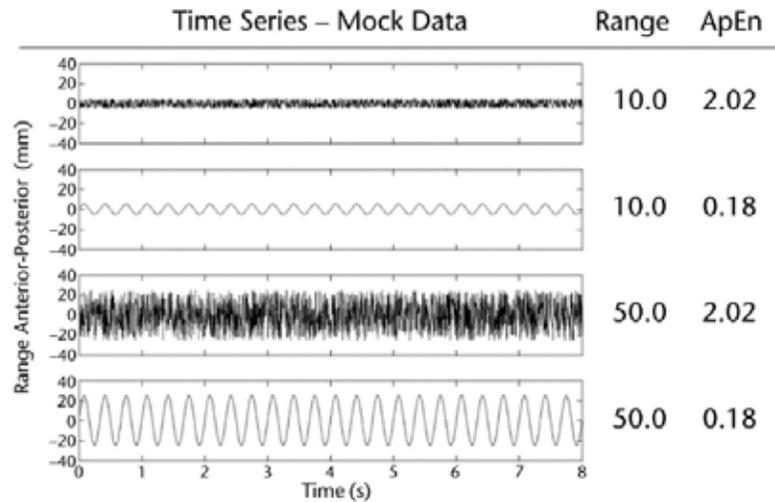
Fifteen minutes of continuous unfiltered data were analyzed so as to get a more accurate representation of the variations within the system (Mees & Judd, 1993; Rapp, 1994). Furthermore, since the same instrumentation was used for all subjects, it was assumed that the level of measurement noise would be consistent for all subjects and that any differences could be attributed to changes within the system itself. Filtering the data might have eliminated important information and provided a skewed view of the system's inherent variability.

The unfiltered time series of the marker position data were acquired by EVART software (Motion Analysis Corp., Santa Rosa, CA). The three dimensional angular displacements of the hip, knee and ankle joints were calculated using laboratory software developed in Matlab (Mathworks Inc., MA, USA) and according to the algorithms described by Vaughn, Davis, & O'Connor (1999). However, we only examined the sagittal angular displacement because data from the other planes collected via skin markers are associated with increased error (Capozzo, Catani, Leardini, Benedetti, & Della Croce, 1996). We collected three-dimensional data instead of two-dimensional to increase accuracy by minimizing perspective error. After identifying the minimum and maximum joint angles for each gait cycle and for each condition, the range of motion (ROM) was calculated by subtracting the maximum and minimum values for each gait cycle. Joint kinematic variability was examined in addition to variability of the stride interval, because it has been shown that variability of joint kinematics offers a more sensitive measure of differences between groups than the variability of the stride characteristics (Barrett, Noordegraaf, & Morrison, 2008). However, it has also been shown that the distribution of the stride interval may be a fractal process (Goldberger, Peng, & Lipsitz, 2002; Griffin & West, 2000; Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Hausdorff et al., 1996; Terrier, Turner, & Schutz, 2005; West & Griffin, 1998, 1999). Therefore, variability of joint kinematics was analyzed in addition to variability of the stride interval.

Stride interval was defined as the time duration between two consecutive maximum angular positions of the knee joint. All variables were unidimensional, since they were measured once per gait cycle. Subsequently, means and the coefficients of variation (CV) were calculated from 704 consecutive gait cycles for each dependent variable in each testing condition and from each subject. The CV was calculated as standard deviation divided by the mean value. Fifteen minutes of continuous walking in each condition allowed the examination of an average of 800 data points, which corresponded to an equal number of gait cycles. However, the final number of all the data series was truncated to 704, which was the least number of gait cycles performed in any of the tested conditions by a subject. This process ensured that all time series were of the same length.

A measure of quantifying the predictability or regularity of a time series is ApEn (Pincus & Goldberger, 1994; Ryan, Goldberger, Pincus, Mietus, & Lipsitz, 1994). A time series that is predictable and regular is also less complex. If there is a change in complexity of the time series, it may indicate reorganization of the available degrees of freedom (Newell, 1997; Vaillancourt & Newell, 2000). ApEn is a measure of the logarithmic probability that a series of data points a certain distance apart exhibit similar relative characteristics on the next incremental comparison within the state space (Pincus & Goldberger, 1994). A time series with similar distances between data points results in lower ApEn values, while large differences in distances between data points results in higher ApEn values. The ApEn algorithm was implemented in MatLab

(Mathworks, Inc., Natick, MA). All time series were analyzed using ApEn with  $m$ , the number of observation windows to be compared = 2 and  $r$ , the tolerance factor = 0.2).



**Fig. 2.** Comparison of linear and nonlinear measures of several signals. Four signals are displayed, with the respective values for range and approximate entropy (ApEn).

Figure 2 illustrates the concept of ApEn in comparison to a linear measure of variability. Four different time series are shown in the figure with the linear measure of range and the nonlinear measure of ApEn. The signals in the first and third rows seem to be random, with one signal larger in amplitude than the other which is reflected in their range values. However, the ApEn values of these two signals are equivalent. This shows that in these two time series only the amplitude varies but not the structure of the time series. The second and fourth rows also depict time series that differ in amplitude (range differences) but not in structure (same ApEn value). However, comparison of the first signal with the second signal (and the third signal with the fourth signal) shows that the amplitude, quantified by the range, is the same (and the standard deviation, a linear measure of variability, would also be the same) but that the structure of the series, described by ApEn, is different. Therefore, the characteristics of variability measured by linear and nonlinear measures are different. These different measures of variability can reveal important information about normal and abnormal human movements that can significantly impact clinical decisions (Harbourne & Stergiou, 2009) and improve upon the current knowledge about the motor control of human movements.

Lastly, to determine the extent of long-range correlations in the time series, DFA was used (Hausdorff et al., 1996; Jordan et al., 2007; Peng et al.,

1995). One of the main advantages of using this method over other analytical methods is that it is robust with respect to non-stationarities in the time series (Chen, Ivanov, Hu, & Stanley, 2002). Briefly, this method first forms an accumulated sum of the time series sectioning it into windows ranging in length from 4 to  $N/4$  data points (where  $N$  is the total number of data points in the time series). The log of the average size of fluctuation for a given window size is plotted against the log of the window size and  $\alpha$ , the slope of this line, is the value returned by the DFA algorithm. The DFA algorithm was also implemented in MatLab. For an example of how DFA is sensitive to gait biomechanics, it was shown that young healthy human subjects walking at different speeds demonstrated long range correlations of their stride intervals (Hausdorff et al., 2007). The  $\alpha$  values were 0.9 for slow walking, 0.84 for normal walking and 1.0 for fast walking. Such fractal-like fluctuations have also been demonstrated for running (Jordan et al., 2006).

### Statistical Analysis

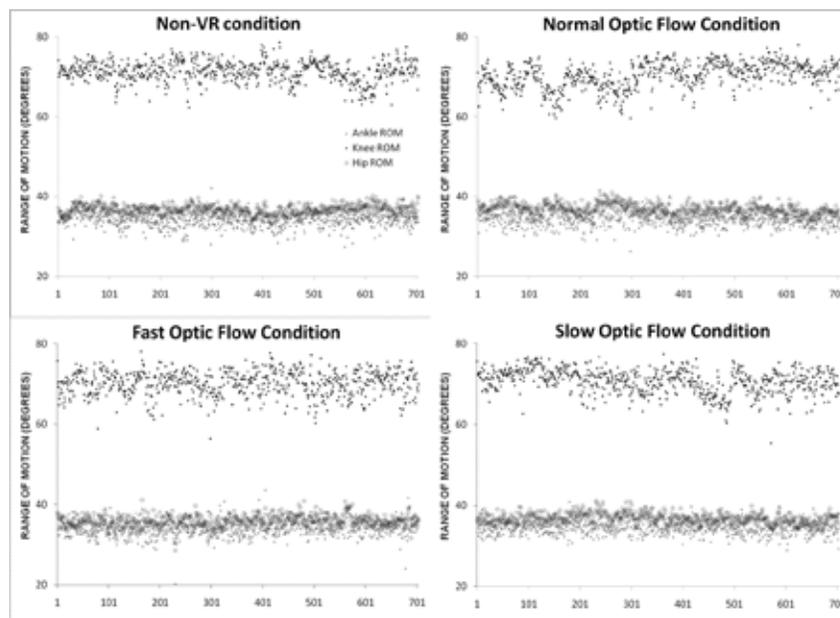
Group means for all dependent variables were calculated for each condition. A three way repeated measures ANOVA was performed using SPSS (14.0, Chicago, IL, USA) to determine significant overall effects of the following factors: VR condition (4 levels: Non-VR, OFn, OFF, and OFs), type of measurement (4 levels: Mean, CV, ApEn, and DFA) and biomechanical variable (4 levels: ROM of the hip, knee and ankle joints and stride interval). Pairwise comparisons with least squared differences were performed to determine specific differences between the four VR conditions. However since very different types of measurements (mean and variability, linear and non-linear variables) formed part of the analysis, separate repeated measures ANOVAs were performed on the group means for each of the four biomechanical variables (ROM of the hip, knee and ankle joints and stride interval) and for each of the four measurements (Mean, CV, ApEn, and DFA) to determine the effect of the repeated factor – VR condition (4 levels: Non-VR, OFn, OFF, and OFs). Post-hoc analysis using least square differences was performed to identify significant differences among groups. The level of significance was set at  $\alpha = 0.05$ .

### RESULTS

The effect of the four different conditions (nonVR, OFn, OFF and OFs) on the range of motion of the ankle, knee and hip joints in one subject are shown in one subject in Fig. 3. As is evident, it is very difficult to discern the properties of the data structure with a simple viewing of the raw data.

The three-way repeated measures ANOVA revealed an overall effect of the VR condition ( $F_{3,27} = 15.465$ ,  $p = 0.000$ ). This means that the different VR conditions brought about a significant change in the biomechanical variables tested. There was a significant interaction between the VR condition and the type of measurement ( $F_{9,81} = 7.361$ ,  $p = 0.000$ ). This means that the VR effect was different for different types of measurements. The interaction between the

VR condition with type of biomechanical variable – ROM of the hip, knee, ankle joint and stride interval was also significant ( $F_{9,81} = 5.772$ ,  $p = 0.000$ ). This means that effect of the VR conditions was different across the biomechanical variables tested. Pair wise comparisons to determine which VR conditions were significantly different overall revealed the following: Non-VR and OFn was not significantly different ( $p = 0.097$ ); OFn was significantly different from both OFf ( $p = 0.030$ ) and OFs ( $p = 0.000$ ), and OFf was significantly different from OFs ( $p = 0.000$ ). Specifically the overall trend was OFn > OFf > OFs.

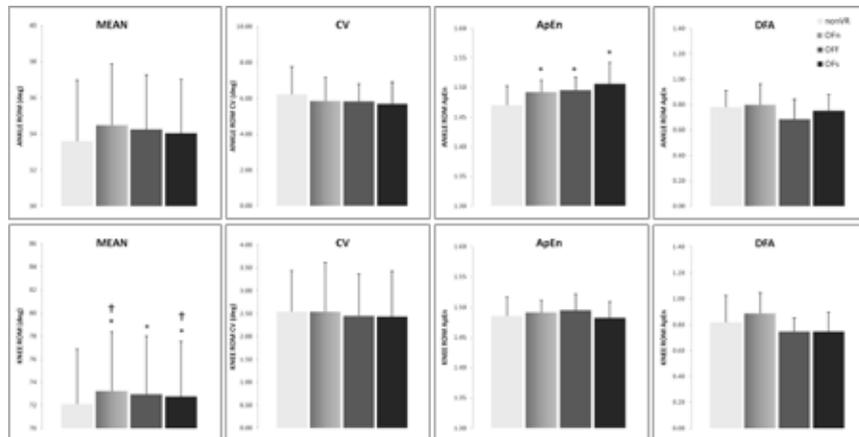


**Fig. 3.** Raw time series from one subject for the effect of the four different conditions on the range of motion of the ankle, knee and hip joints.

To determine the specific locations of the differences in the VR conditions, separate repeated measures ANOVAs followed by post-hoc analysis were carried out for each type of biomechanical variable (ROM of the hip, knee, ankle joint and stride interval) across the types of measurements (Mean, CV, ApEn and DFA). The significant differences are shown in Figs. 4 and 5.

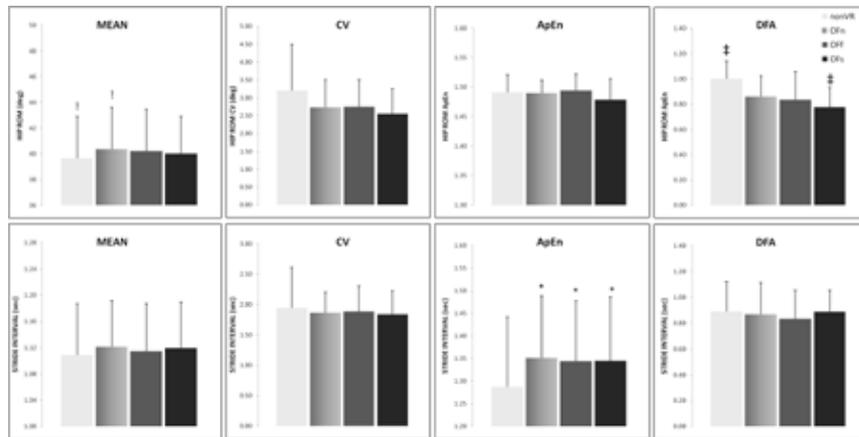
#### **Differences Between Non-VR and VR Conditions**

Significant differences were obtained between the Non-VR and VR conditions for each biomechanical variable albeit through different measurements. At the ankle, the Non-VR condition was different from each of the three VR conditions as measured by ApEn ( $F_{3,27} = 3.9$ ,  $p = 0.019$ ).



**Fig. 4.** Group means from 704 consecutive strides for mean, coefficient of variation (CV), ApEn, and DFA values for ROM of the ankle and the knee at each condition (nonVR = walking on a treadmill; OFn = walking in VR environment with normal optic flow; OFf = walking in VR environment with fast optic flow; and OFs: walking in VR environment with slow optic flow). \*indicates significant differences in comparison to nonVR at  $p < 0.05$ . † indicates significant differences between the OFn and OFs conditions at  $p < 0.05$ .

Specifically, the Non-VR condition elicited significantly lower ApEn values than all three VR conditions ( $p = 0.026$  between Non-VR and OFn,  $p = 0.049$  between Non-VR and OFf, and  $p = 0.016$  between Non-VR and OFs). At the knee, the mean results showed significant differences between the Non-VR and all three VR conditions ( $F_{3,27} = 6.698$ ,  $p = 0.002$ ). Specifically, the Non-VR condition elicited significantly lower mean values than all three VR conditions ( $p = 0.003$  between Non-VR and OFn,  $p = 0.044$  between Non-VR and OFf, and  $p = 0.024$  between Non-VR and OFs). At the hip joint, the Non-VR and VR conditions were significantly different as elicited by the mean values ( $F_{3,27} = 3.383$ ,  $p = 0.033$ ) and also by DFA values ( $F_{3,27} = 3.252$ ,  $p = 0.037$ ). Specifically the mean hip joint ROM was significantly lower for the Non-VR than the OFn ( $p = 0.003$ ), while the DFA value for the hip joint ROM was significantly higher for the Non-VR than the OFs ( $p = 0.015$ ). Finally, for the stride interval, the Non-VR condition exhibited significantly lower values for the ApEn when compared to all the VR conditions ( $F_{3,27} = 9.609$ ,  $p = 0.000$ ). Specifically the values for Non-VR were lower than OFn ( $p = 0.015$ ), OFf ( $p = 0.013$ ) and OFs ( $p = 0.016$ ). All other comparisons between Non-VR and VR conditions were not significant. Regarding the amount of variability, the linear measure (CV) did not reveal significant differences between the Non-VR and the VR conditions for any of the parameters investigated. Regarding the structure of variability and as indicated above, the nonlinear measures identified significant differences for the hip (DFA), ankle (ApEn) and the stride interval (ApEn).



**Fig. 5.** Group means from 704 consecutive strides for mean, coefficient of variation (CV), ApEn, and DFA values for the ROM of the hip joint and for stride interval at each condition (nonVR = walking on a treadmill; OFn = walking in VR environment with normal optic flow; OFf = walking in VR environment with fast optic flow; and OFs: walking in VR environment with slow optic flow). \* Indicates significant differences in comparison to nonVR at  $p < 0.05$ . † indicates significant differences between the nonVR and OFn conditions at  $p < 0.05$ . ‡ Indicates significant differences between the nonVR and OFs conditions at  $p < 0.05$ .

### Effect of Asynchronous OF on Locomotion Patterns

Mean values of the knee joint ROM was significantly different between OFn and OFs. Specifically, the OFn condition produced higher values when compared to OFs ( $p = 0.038$ ). Regarding the amount and the structure of variability, neither linear nor nonlinear measures revealed any significant differences. Since there was an overall significant difference between OFn and both OFF and OFs as mentioned before, we examined our analysis more closely to identify comparisons that might have influenced the overall result. Hip ROM mean between OFn and OFs was not significant but was a borderline case ( $p = 0.051$ ). The repeated measures ANOVA for Hip ROM CV revealed a similar case ( $F_{3,27} = 2.908$ ,  $p = 0.053$ ) with there being significant differences between OFn and OFs ( $p = 0.009$ ), and between OFF and OFs ( $p = 0.018$ ). Moreover the overall direction of OFn values being the largest followed by OFF and OFs in that order was reflected through individual comparisons where OFn was largest in 10 of the 16 comparisons and OFs was the smallest in 10 of the 16 comparisons.

## DISCUSSION

The aims of this study were twofold: first, to determine if there were differences in gait variability between the Non-VR and the VR conditions

during walking at a preferred walking pace and second, to determine if gait variability was affected when OF became asynchronous with gait velocity.

### **Differences Between Non-VR and VR Conditions**

It was hypothesized that gait variability during treadmill walking for Non-VR and VR conditions would be significantly different. The linear measures of variability, CV, did not show significant differences between Non-VR and VR conditions while nonlinear measures of variability identified significant differences at the hip, ankle, and in stride interval.

Variability as measured by CV was not significantly different across the OFn and the Non-VR conditions. Young healthy adults who walked on a treadmill at a self-selected pace elicited increased variability in stride velocity and step width (Hollman et al., 2006), and increased variability in weight acceptance rates and peak forces in a VR environment when compared with a Non-VR condition (Hollman et al., 2007). Although our findings are different from these studies, there may be several explanations for this result. First, lack of significant findings of the linear measures in the present study can be attributed to the longer duration of the walking trial. In a previous study, variability changes in walking velocity and stride length due to OF was shown to be attenuated over a period of 600 strides (Prokop et al., 1997). As mentioned before, our study had more strides and therefore the effect of attenuation was presumably more. Since the subjects of the present study were healthy individuals, the adaptation time to external visual stimuli was much shorter. It might be interesting to test how gait parameters are affected during the first minute of each condition. However, this analysis cannot be carried out with nonlinear measures due to the small number of data points. A second explanation of our findings was that they were a true measure of the quantitative nature of the locomotor variability. Studies in the past which have shown variability in stride length and step width (Hollman et al., 2006; Hollman et al., 2007) were expressed by a linear analysis of only 20-30 data points (strides), which is considered insufficient even for traditional measures of stride-to-stride variability (Owings & Grabiner, 2003). Experimental trials in this study were considerably longer and generated over 700 strides in each trial. Moreover, the measures of interest in this study (variability of joint ROM and stride interval) were different from the other studies (variability of step width and step velocity; Hollman et al., 2006; Hollman et al., 2007). A third explanation for the findings could be that the level of complexity across the two conditions (as evidenced by the closeness of the variability values between the Non-VR and VR conditions) was quite low and therefore there were no significant differences among conditions. Indeed, walking at self-selected pace is considered a low energy-cost activity. These explanations, however, are limited to the amount of variability because when we consider the structure of variability, the findings are quite different.

To our knowledge, this is the first time that nonlinear measures of variability have been used to identify significant effects on the structure of the

variability of the gait pattern as a result of VR although the importance of such measures in normal and pathological locomotion has been revealed in the past (Dingwell & Casumano, 2000; Hausdorff et al., 1996; Slifkin & Newell, 2000; Stergiou et al., 2004). These differences between the Non-VR and VR conditions were identified at the hip, ankle, and in the stride interval and were the result of utilizing specific nonlinear techniques. The different techniques revealed the unique abilities of the nonlinear measures to extract pertinent information from the same data set.

Approximate Entropy demonstrated significant differences between Non-VR and VR conditions in stride interval and in ROM at the ankle although linear measure of variability did not show significant differences. Several human movement studies have demonstrated the differences between ApEn and linear measures of variability (Slifkin & Newell, 2000; Vaillancourt, Slifkin & Newell, 2001). These studies showed that linear measures of variability do not follow the same patterns of nonlinear measures to the extent that they may not be sensitive in measuring variability differences between healthy and pathological populations (Vaillancourt et al., 2001) or they may show differing trends than non-linear measures of variability (Slifkin & Newell, 2000).

The ApEn values were lower for the Non-VR condition than the VR condition. This means that introduction of VR introduced irregularity into the system. However this increase in irregularity does not necessarily demonstrate an abnormal status. In fact several studies have shown that abnormal human physiology is associated with regularity and periodicity in the time series while the opposite is true for normal human physiology - greater irregularity and complexity (Fleisher, Pincus & Rosenbaum, 1993; Pincus, 2000; Vaillancourt & Newell, 2000; Veldhuis & Pincus, 1998).

Lower values for DFA were revealed for the hip joint ROM during OFs in comparison to the Non-VR condition. DFA for OFn and OFf also showed lower values for the hip joint ROM than the Non-VR condition but they did not reach statistical significance. Values closer to 0.5 are indicative of uncorrelated randomness while values closer to 1 are characterized by strong long range correlation (Jordan et al., 2007). Thus, DFA revealed that introduction of VR might reduce long range correlations that are observed at the hip joint during normal treadmill locomotion. Reduced long range correlations are not indicative of instability. This has been shown in the past with preferred walking speeds having low DFA values while higher and lower walking speeds resulting in higher DFA values (Jordan et al., 2007). Reduced long range correlations may be considered to be indicative of large numbers of independently controllable systems or degrees of freedom that are available to the subject in the novel environment (Slifkin & Newell, 1999). The subject might be making use of these available degrees of freedom to get better at the walking task with novel sensory cues. Alternatively strong long range correlations while walking without visual cues may indicate a constriction on locomotion patterns due to the unavailability of the visual feedback. This may be happening when we walk on a

treadmill in closed surroundings without OF and therefore, we prefer to walk outside where the OF gives us a perception of self-motion.

In general, the DFA values in this study were found to hover around 0.8 to 1. This region has been associated with Pink noise or  $1/f$  noise in several studies (Lauk, Chow, Pavlik, & Collins, 1998; Gilden, Thornton & Mallon, 1995; White, Rubinstein & Kay, 2000). Pink noise makes its appearance in both living and non-living systems and it is believed to provide a sort of “connecting link” between the two systems (Ward, 2001).

Regarding the mean values of ROM, significant differences were obtained for the hip and knee joints. Although stride interval and ankle ROM were not different between the Non-VR and VR conditions, all four parameters (stride interval and ROM of hip, knee, and ankle) had a common characteristic: Non-VR mean values were lower than VR values. The lack of OF during treadmill walking in the Non-VR condition might have made the task more constricted in terms of joint ROMs and stride intervals. These differences, being small, may not mean much for the healthy young adults who were the subjects of this study, however if we consider patient populations with gait abnormalities, these differences may be magnified to the point that walking on a treadmill without some form of OF maybe a stressful situation. Increase in these measures in the VR condition may also be attributed to the increased stride interval during the OFn condition. Longer stride intervals may have resulted from longer stride lengths since speed was held constant, causing the higher ROM values. These findings may be considered different from those reported in the past (Hollman et al., 2006) where VR environment caused a decrease in stride length and step width in comparison to the Non-VR condition. However, such a conclusion should be made with caution. First, the dependent variables of the two studies were different, stride intervals and joint ROM in this study versus stride length and step width in the study by Hollman et al. (2006). Second, the gait velocity in this study was the subject’s self selected pace or their preferred walking velocity unlike Hollman et al., where the gait velocities were fixed at 0.9, 1.1 and 1.3m/s. Third, the duration of the experimental trials was different (8 min in this study versus 3 min in Hollman et al.).

### **Effect of Asynchronous OF on Locomotion Patterns**

The second hypothesis was that as the velocity of the OF became asynchronous with respect to the subject’s preferred walking speed, the variability of gait would become significantly different. There was an overall significant difference between OFn and both OFf and OFs. The overall direction was  $OFn > OFf > OFs$  and although the only significant difference was at the knee joint ROM, most comparisons exhibited the same direction as in the overall comparisons.

Changes in the velocity of OF has been known to cause deviations in gait patterns. Walking velocity and stride length have been shown to have negative correlations with OF causing slower walking velocity and shorter stride length when OF was faster and vice versa (Prokop et al., 1997). Similar

observations have also been made in other studies in healthy subjects (Verraine et al., 2002) and also in patients with stroke (Lamontagne et al., 2007). However in these studies kinematic parameters measured were the walking velocity, stride length and step width and not the joint angular changes during the VR conditions that caused these changes.

Variability of gait was not significantly impacted by the OF. These findings are comparable to those of Prokop and colleagues (2007) who reported that stride cycle variability did not have a relation to the velocity of OF. However in that study the direction of VR variability values being higher than Non-VR conditions was opposite to the findings of this study. There may be several reasons for this. First, Prokop et al. used a paradigm where the velocity of the treadmill was related to the subjects walking velocity. Since velocity was not held constant, making inferences about stride cycle variability is difficult since gait variability measurements are known to be speed-dependent (Jordan et al., 2007). To reduce the effect of variations in walking velocity affecting the amount of variability present in the locomotion patterns, a constant-driven treadmill was used in this study to hold the velocity constant. Second, conclusions about stride cycle variability were made by Prokop and colleagues using data from another study (Zijlstra & Dietz, 1995). It is not clear whether the same subject pool was used for both studies. Last but not the least, the dependent variables for both studies were different.

In summary, differences were observed using both linear and nonlinear tools, in the locomotor patterns of healthy human subjects while walking at constant velocity with the OF being manipulated at higher and lower velocities to the preferred walking speed. The findings demonstrate the sensitive nature of the analytical tools to specific anatomical areas and sensorimotor conditions. In addition, changes in the flow of these optical cues caused changes in both the amount of variability of the locomotor patterns and changes in the temporal organization of variability. Further exploration of the effects of OF manipulations is warranted to determine the specific combination of parameters that could eventually be most beneficial in the rehabilitation of subjects with sensorimotor issues.

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