COMPARING DETERMINISTIC AND STOCHASTIC PROPERTIES OF FRONTO-NORMAL GAIT USING DELAY VECTOR VARIANCE

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ABSTRACT

Human gait is a useful biometric which has been used in many fields such as human identification, motion synthesis and clinical diagnosis. The derivation of features used to describe gait depends very much on the temporal nature of the movement signal. We focus on the fronto-normal view of gait which provides more dynamic information. Newer features based on nonlinear analyses require the establishment of nonlinear behaviour. The level of determinism of a signal also indicates what kind of auxiliary analyses may be needed. The confounding of deterministic and nonlinear properties motivates us to perform an original analysis on gait data using the recently introduced method of Delay Vector Variance. This method shows promise as it will easily indicate the level of deterministic and nonlinear behaviour of a signal separately. We look into and compare various approaches of doing this on human gait derived from video signal.

1. INTRODUCTION

There are many applications of human gait as a measure of a person's characteristics. It can be used as a biometric, to help identify a person in a security application. Also, it is used in motion capture, to synthesize animation and physiologically, to assess a person's psychomotor functions. However, human gait captured from video is mainly used in security applications because there is no need for high precision analysis of motion. Today's heightened security atmosphere has made video capture devices affordable and versatile. Also, consumer demand for higher quality image capture and display facilities has fuelled the increase in resolution of these cameras. So the amount of multimedia data available can increasingly be used to derive new signal features for automatic identification of people, motion capture and assessment of medical conditions. Collecting video data is especially useful as it does not require the cooperation of the subject and is therefore non-intrusive and non-invasive. It can also be used at a distance, and with the use of optical or digital zoom and therefore is able to observe the subject for a longer period without going out of the field of view.

Current video gait analyses do so mainly in an image plane parallel to a camera, the so-called fronto-parallel (FP) view. This gives the largest variation in silhouette from which the time series data is obtained for analysis. Motion from a plane perpendicular to this, the fronto-normal view (FN), is considered as a special case. But very commonly, people are made to queue up to access a facility. Also, the video capture system is in an enclosed space. Most analyses of a FP walk need at least two cycles or four steps. For more robust estimation of the period of walking, twice that distance is needed. This translates to the need to adequately capture enough walking cycles. For example, if a person were to walk about 0.7 m per step, to capture a movement of 8 steps would require a distance of about 5.6 m. However because of the focal length of the camera, the camera distance required to capture this movement is about 8.5 m. Practically, it is difficult to have such a wide uncluttered space, when we desire to measure a person's gait as many people and objects will be present.

In a FN walk, we can still use the 8.5 meters, but this time, twelve steps are covered and we only need a corridor-like structure, the width being about that of a human body. A considerable amount of space is saved. This is illustrated in Fig. 1.

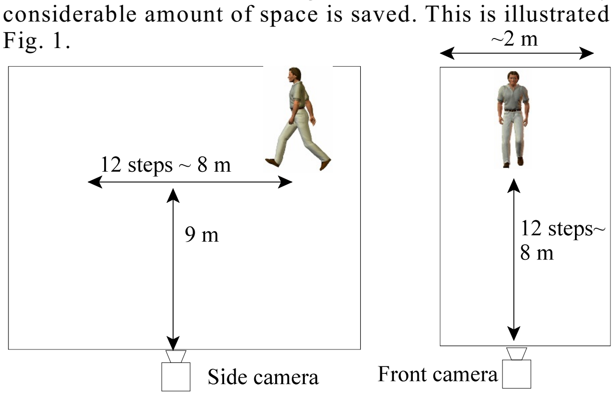

Figure 1. FP vs FN gait - physical dimensions for video capture

In order to derive useful features, the fundamental temporal nature of the signal has to be ascertained which are its stationarity and linearity. The stationarity of a signal can be decomposed into its *deterministic* part that can be expressed by equations and its *stochastic* or random part, as described by Wold's [1] theorem. These will lead to the appropriate type of signal processing as shown in Fig. 2. This is a sketch showing the areas of knowledge in signal processing, for signal types ranging from nonlinear to stochastic ones. This figure is inspired by similar ones in [2] and [3] where areas of available knowledge and technology for the analysis of time series are outlined. Besides analysing (possibly noisy) periodic signals, there are also the deterministic chaotic parts. Linear stochastic areas are marked by ARMA analyses and its nonlinear (NARMA) variants. Various types of hidden Markov models (HMM) represent areas of research with varying degrees of nonlinearity and stochasticity.

For all the ways to analyse data linearly, there are much more ways to do so nonlinearly as described by Tong [4], which gives rise to a rich source of features. Nonperiodic analyses are capable of giving new insights into temporal data and this is the motivation for the search for nonlinear features in FP gait. In summary, the advantages of the monocular FN non-silhouette approach are:

i) Smaller physical space needed,

ii) Ease of combining other biometrics,
iii) Non-periodic motion analysis

In the search for features in a time series or signal, nonlinearity has often been confounded with determinism. The Delay Vector Variance (DVV) method was devised to address this problem by providing a simple, graphical way to highlight the level of determinism and nonlinearity of a signal. In Section 2 we discuss prior work related to nonlinear FN gait analyses and the use of DVV. Section 3 describes our experimental setup. The theory behind various nonlinear analyses is covered in Section 4. Then the results of our experiments will be covered in Section 5 before concluding in Section 6.

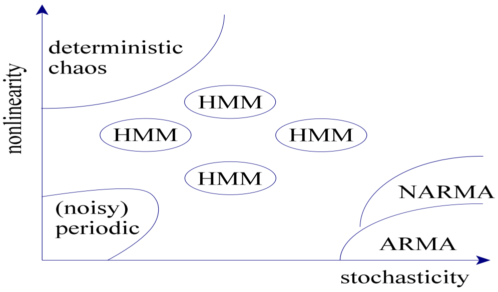

Figure 2. Analytical systems covering the range of nonlinear and stochastic properties of a signal.

2. ANALYTICAL REVIEW OF PRIOR WORK

In this section, we present some prior analyses of FN gait and the use of the DVV method which makes use of phase space analysis and delay vector embedding with surrogate data for verification purposes.

2.1 Use of nonlinear analyses for gait

Most analyses of human gait from video signals consider motion of a silhouette from the FP view. These assume the linear nature of the signal and use standard methods like Fourier Transforms to process it. A thorough review has been done by Nixon et al. [5]. The use of nonlinear analyses is fairly new and for example, Lee et al. [9] have shown that the FP view of gait is particularly amenable to linear analysis in contrast to FN gait. Here they show the stationary nature of FN gait signals and thereby use features derived from deterministic chaos to help identify a person.

2.2 Phase space characterization of time series

In using phase space methods to test for nonlinear behaviour, a *scalar* time series is subjected to dynamical analysis which assumes that the time series data X is generated by a vector valued process. The actual state vectors describing this process may never be known but we can create a set of *phase space* vectors which are topographically equivalent, and can be considered to be a reconstruction of them. Takens "method of delays" [6] is an established method for obtaining these vectors. The reconstructed trajectory of X is described in a matrix $\boldsymbol{X}$ made up of several phase space vectors as follows:

$$\boldsymbol{X} = [\mathbf{x}_1\ \mathbf{x}_2 \dots \mathbf{x}_m]^T$$

where $\mathbf{x}_i$ is the state of the system at sample i. Each row of $\boldsymbol{X}$ is a phase-space vector with a length of the embedding dimension m. That is, for each $\mathbf{x}_i$,

$$\mathbf{x}_i = [x_{i-m\tau}\ x_{i-(m-1)\tau} \dots x_{i-\tau}]$$

where τ is the time lag. This is for a time series $x = \{x_1, x_2, \dots, x_N\}$ with N points. So $\boldsymbol{X}$ is a M by m matrix, and the number of phase space vectors M is equal to $N - (m - 1)\tau$. In keeping with the topic, we will now refer to these phase space vectors as Delay Vectors (DV). Every DV has a corresponding *target* which is defined as the next element in the time series which is the *scalar* x_i. Thus targets can be considered to be the predicted values of their respective DVs. The spread of the values of the targets in DV space provides a measurement of the *local predictability* of the time series.

The DVV methodology builds on earlier efforts to characterize a signal's level of determinism and nonlinearity as described in [3]. In much of the literature using DVV, a variety of methods have been described to determine m, but the parameter τ is left at 1 citing simplicity without justification, for example in [3] and [12]. For an infinite amount of noise free data, this parameter is arbitrary but for real world data, too small a value of τ will result in the DVs being highly correlated or in other words, deterministic. The parameter m is needed to capture the dynamics of the system.

In an earlier work, Lee et al. [7] have determined the values of m and τ for an optimal vector embedding. They have also determined that FN gait has a stationary [8] and nonlinear [9] temporal character. The results are reproduced in this paper for the sake of completeness and comparison.

2.3 Surrogate data

When testing for the temporal nature of real life data, statistical tests often are employed. It may not be possible to generate all the data needed to test and verify a hypothesis about the data. However, test data in the form of surrogates can be generated as a statistical resampling bootstrap procedure on existing data. Described originally by Theiler et al. [10], the literature contains various improvements to the algorithm. We use the version provided in [3] for comparison. Importantly, surrogate data can be considered to be produced by a linear process so any nonlinearity in the data is inherent to it. Test statistics on the original and surrogate data can be used to determine the validity of the hypothesis about the data.

3. EXPERIMENTAL SETUP & INITIAL RESULTS

In FN gait recognition, we use feature points that have more motion in the image plane. This would be the hands, feet and knees, for a FP walk. For a FN walk this is also true, although the motions are smaller in magnitude. For the two kinds of walk, the coloured marker set up is shown in Fig. 3. The marker designations are: *lh/rh* - left/right hand, *lf/rf* - left/right foot, and *lk/rk* - left/right knee. Two additional discs of the same colour are attached to the waist and neck are used for distance normalization, due to the looming effect of a FN walk. They are: *tm/bm*, the top/bottom markers. So for the FN walk we have 6 data markers for each subject giving 12 time series, for the x and y motion. Two additional FP walks involving 3 markers were recorded for comparison purposes.

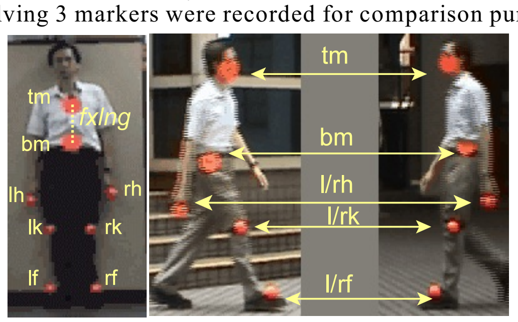

Figure 3. Marker positions - left : FN view and right : FP view

The markers are tracked using the CAMSHIFT [11] algorithm. We take video clips of twelve subjects and a further three for testing. The capture rate was 25 frames/s at 720 by 480 resolution, resulting in time series ranging from 90 to 150 samples. The normalized plots for FP and FN walks are shown in Fig. 4 and Fig. 5 respectively. Note that the large amplitude periodic waveforms are those for the *x-axis* movements which correspond to our natural limb swings.

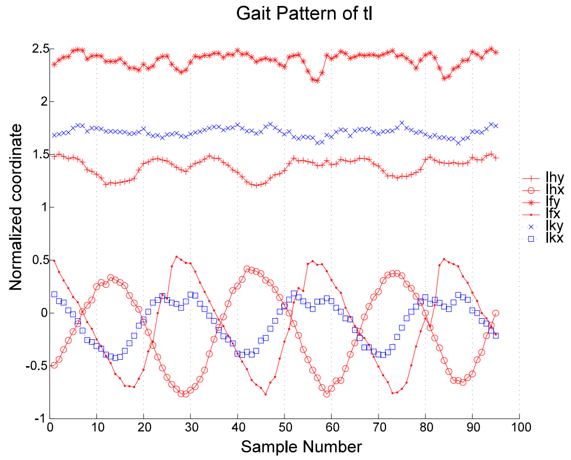

Figure 4. Plots of normalized FP walk

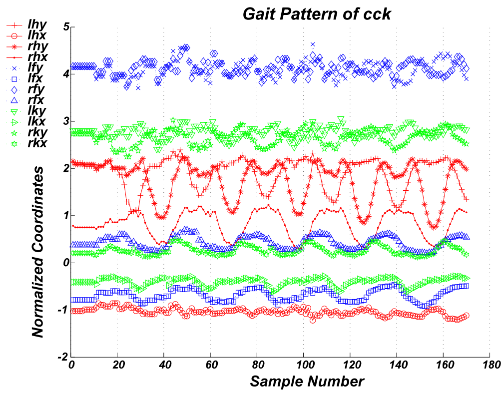

Figure 5. Plots of normalized FN walk

Next, the autocorrelation plot for the FP walk in Fig. 6 shows the strong periodicity in movement, especially in the *x-axis* which swamps out the "non-periodic" signal in the *y-axis*. In our earlier work [9], we have shown that these *x-axis* movements are in fact linear in nature.

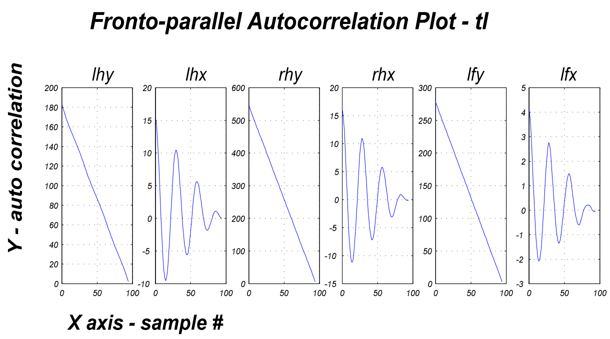

Figure 6. Autocorrelation plots - left marker trajectories - FP Left to Right

In contrast, the autocorrelation plot for FN gait in Fig. 8 does not show any periodicity in *any* of the twelve marker trajectories. This is an indicator of nonlinear dynamics or chaotic behaviour.

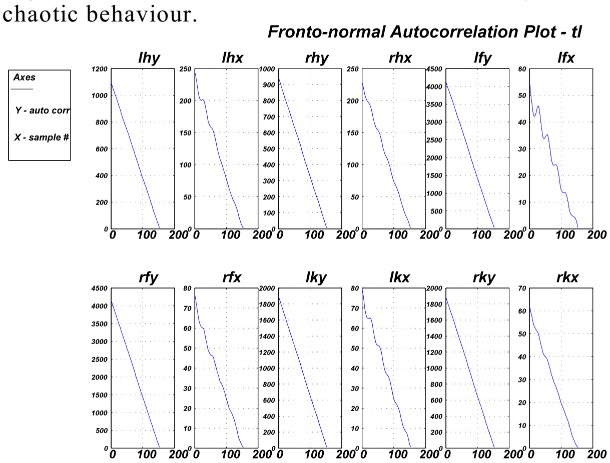

Figure 7. Autocorrelation plots - FN walk

4. Theory of Nonlinear Analysis

In this section, we attempt to extend and apply one of the recent methods in the assessment of nonlinearity and determinism in time series, namely the DVV method.

4.1 Delay Vector Variance

The idea behind DVV lies in measuring the local predictability of a time series. For a given DV **x**, a set of DVs that are geometrically (in a Euclidean sense) near to it are found. Assuming that the vector space described by the DVs is continuous, the targets of the nearby DVs should, in the same way, be geometrically near to each other as well as they are just one time lag away. The presence of noise affects this and thus provides a measure of determinism.

As for nonlinearity, the DVV method relies heavily on the use of surrogate data for detection of the same. As mentioned earlier, surrogate data is formed by a linear process on the time series. If the data is linear, then properly chosen operations on the surrogate data will produce results similar to the original data. The measurement of the local predictability is one such operation and the deviation of results from the original against the surrogate data provides a measure of nonlinearity. More precisely:

i) The mean μ_d, standard deviation σ_d, are computed of the Euclidean distances between *all* pairs of DVs $\|\boldsymbol{x}_i - \boldsymbol{x}_j\|$ $(i \neq j)$.

ii) To compute the local linear distances, a range of inter-vector distances r_d are generated in the interval $[\max\{0, \mu_d - n_d\sigma_d\}; \mu_d + n_d\sigma_d]$. In this interval, the values of r_d are specified for N_{tv} uniformly spaced points, where n_d is the *span* over which computations are performed. Now for every DV $\boldsymbol{x}_k$, a *restricted* list of every other DV $\boldsymbol{x}_i$ which is geometrically closer to it, for every value of r_d is kept in $\Omega_k(r_d)$ so that:

$$\Omega_k(r_d) = \{\boldsymbol{x}_i \mid \|\boldsymbol{x}_k - \boldsymbol{x}_i\| < r_d\}$$

For the list of DVs in every $\Omega_k(r_d)$ the variance of the targets $\sigma_k^2(r_d)$ is calculated. The average over all $\Omega_k(r_d)$ normalized by the variance of the time series σ_x^2 with N samples gives a measure of the unpredictability as the 'target variance':

$$\sigma^{*2}(r_d) = \frac{\frac{1}{N}\sum_{k=1}^{N}\sigma_k^2(r_d)}{\sigma_x^2}$$

By plotting $\sigma^{*2}(r_d)$ against $(r_d - \mu_d) / \sigma_d$, the presence of determinism shows as small values of $\sigma^{*2}(r_d)$ for small spans and the minimum value $\sigma_{min}{}^{*2}(r_d)$ is a measure of stochasticity of the time series. However Gautama et al. [12] noted that the *relative* values of $\sigma_{min}{}^{*2}(r_d)$ should be used for the measure of determinism when the length of the time series $N < 1000$.

By doing the same computation for the surrogates, their target variances should be the same for various values of r_d if the data are linear. By plotting the average values of $\sigma^{*2}(r_d)$ for the surrogates against the original values will show the degree of nonlinearity. A scatterplot of these DVV values will show this, an example being the lower part of Fig. 10.

5. Results of Nonlinear Analyses

Since the determination of the embedding parameters is important, we show the results first.

5.1 Embedding parameters

There are several methods to select suitable parameters m and τ. For the latter, a standard way is to take the instance when the autocorrelation plot first reaches zero. But we see that it never reaches zero until the end of the walk. An alternative is the time delayed mutual information measure as proposed by Fraser and Swinney [13]. A sample plot is shown in Fig. 9 for one person. The point at which the first minimum of the plot is taken to be the best value for τ which is 2 in this case, for all twelve marker trajectories.

For m, we use the method of false nearest neighbours (FNN) as proposed by Kennel et al. [14] and shown in Fig.8, 11. Taking the average of *all* the largest values where the FNN goes to zero, we find the nearest integer value to be six.

5.2 Delay Vector Variance Analyses

To start with, we use the values $n_d = 4$, $N_{tv} = 20$ and 25 surrogates, as these give a good balance between efficiency and undue strange results. The parameter τ is set to 1 as in many of the other DVV analyses discussed in Section 2. The results for the marker movements are similar, so we show just one result in Fig. 10. Here, the DVV plot on the left shows a low variance for small standardized distances indicating high determinism: that is, the local predictability is high. On the right, the scatter plot is generated by using the values of r_d as a parameter and the values of the target variances $\sigma^2(r_d)$ for the original data versus that of the *average* of the surrogates are plotted. Since there is good agreement between these sets of data, they lie on the dashed line denoting equality of values on the axes, which shows linearity in the data.

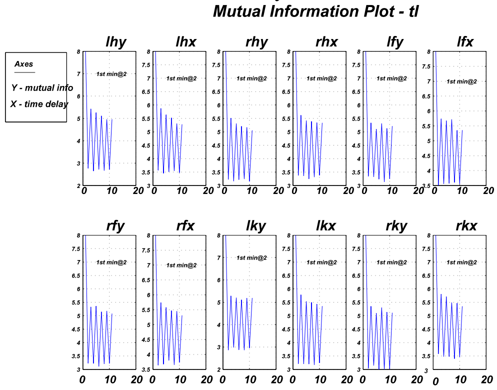

Figure 9. Mutual Information plots: markers of a person in FN walk

Now when we set $m = 6$ as the optimal value for the delay as described in Section 5.1, the results are markedly different.

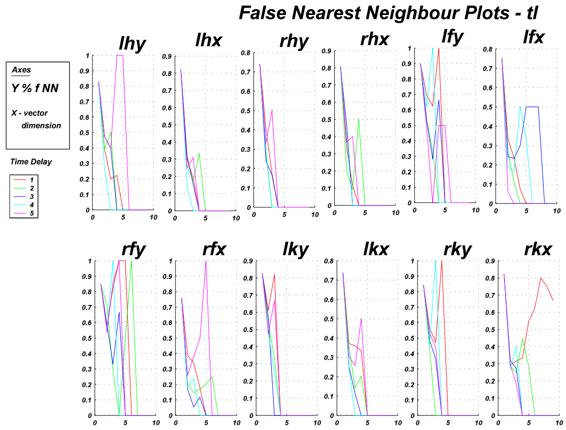

Figure 8. False Nearest Neighbour plots for the markers of one person in a FN walk

This is shown in the FP plot which has linear data in Fig. 12. What is surprising is that the movements of the *rhx*, *rfx* and *rkx* markers which have been shown to be linear, do not demonstrate this as seen in the DVV scatter diagrams. However, the minimum of the DVV plots show values below 1, indicating a low level of stochasticity.

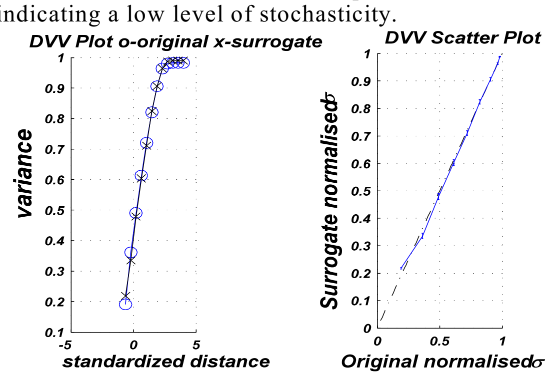

Figure 10. Typical DVV plot and scatter diagram: τ=1

In contrast, we show a plot of a FN walk in Fig. 11 where all the marker data have been shown to be nonlinear in nature, but stationary. The marker movements in the *x-axis* demonstrates low values, showing some determinism, the smallest values all being smaller than 1. However, the *y-axis* values do not seem to show this.

6. CONCLUSIONS

We have performed a novel analysis on FP and FN gait using the DVV method. We have seen some degree of determinism in both sets of gait signals. In earlier work, we established the stationarity of FN gait signals. In establishing the deterministic nature of these signals, we reinforce their properties of stationarity. Thus we have added support for our earlier work where we sought for justification for chaotic analysis of data.

Assessment for nonlinearity however requires a larger set of samples and better choice of parameters to fit the analysed data. This forms the basis for future research which can use nonlinear features to characterise such gait, being applied to medical diagnosis and assessment, biometrics to name a few.

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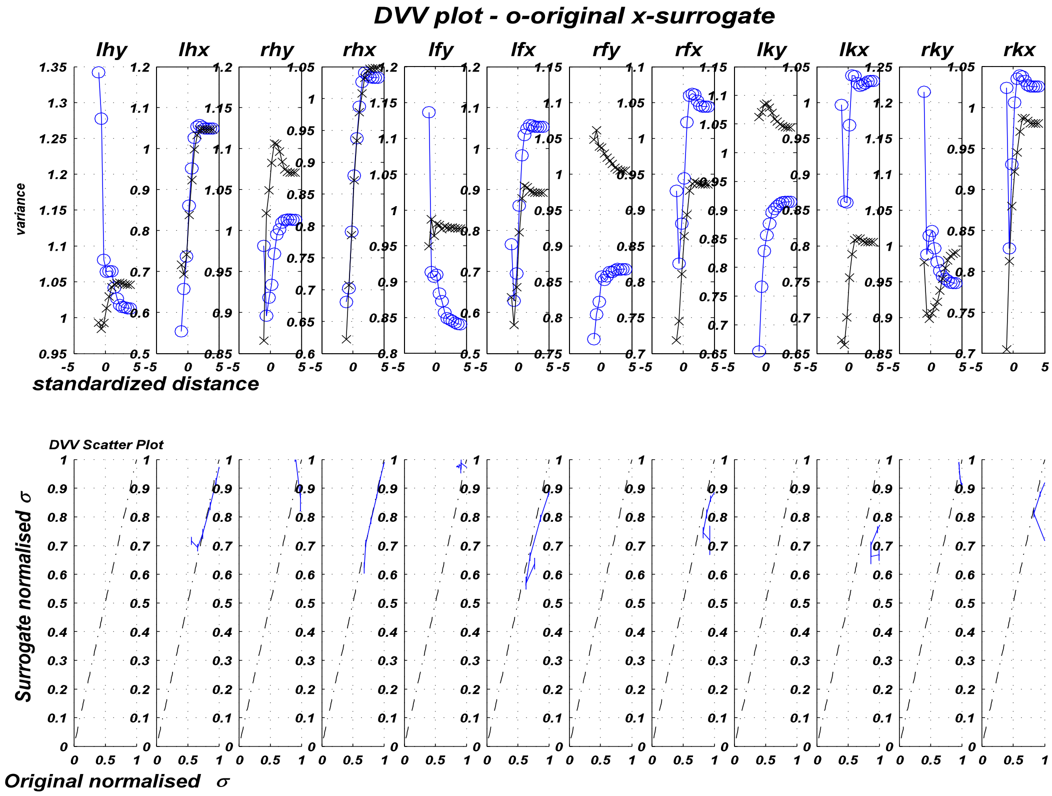

Figure 11. DVV and scatter plot for 12 markers of a FN walk

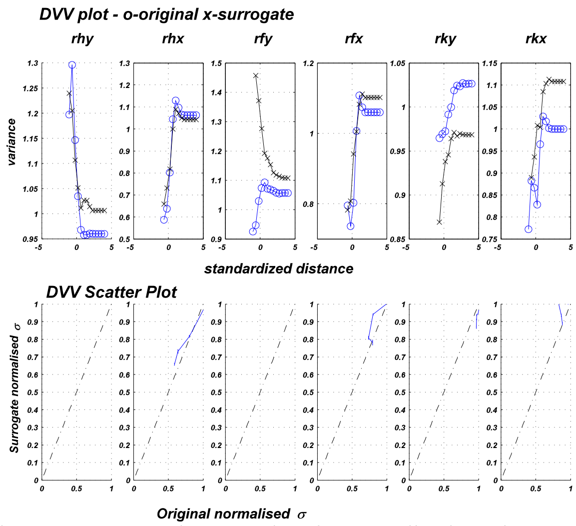

Figure 12. DVV and scatter plots for FP walk where the x-axes data are linear for $\tau = 6$

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