Gait & Posture 55 (2017) 49–54

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Comparison of the Classifier Oriented Gait Score and the Gait Profile Score based on imitated gait impairments

Christian Josef*, Kröll Josef, Schwameder Hermann

Department of Sports Science and Kinesiology, University of Salzburg, Schlossallee 49, 5400 Hallein-Rif, Austria

ARTICLE INFO

Keywords:
Gait
Score
Impairment
Pattern
Imitation

ABSTRACT

Common summary measures of gait quality such as the Gait Profile Score (GPS) are based on the principle of measuring a distance from the mean pattern of a healthy reference group in a gait pattern vector space. The recently introduced Classifier Oriented Gait Score (COGS) is a pathology specific score that measures this distance in a unique direction, which is indicated by a linear classifier. This approach has potentially improved the discriminatory power to detect subtle changes in gait patterns but does not incorporate a profile of interpretable sub-scores like the GPS. The main aims of this study were to extend the COGS by decomposing it into interpretable sub-scores as realized in the GPS and to compare the discriminative power of the GPS and COGS. Two types of gait impairments were imitated to enable a high level of control of the gait patterns. Imitated impairments were realized by restricting knee extension and inducing leg length discrepancy. The results showed increased discriminatory power of the COGS for differentiating diverse levels of impairment. Comparison of the GPS and COGS sub-scores and their ability to indicate changes in specific variables supports the validity of both scores. The COGS is an overall measure of gait quality with increased power to detect subtle changes in gait patterns and might be well suited for tracing the effect of a therapeutic treatment over time. The newly introduced sub-scores improved the interpretability of the COGS, which is helpful for practical applications.

1. Introduction

The abundance of data generated in instrumented gait analysis is an ongoing challenge in clinical applications and has provoked the development of summary measures of gait quality [1]. Such summary measures aim to extract a single number from various gait variables to represent an overall impression of the quality of a person's gait. Cimolin and Galli [1] reviewed the most commonly considered approaches in this domain: the Normalcy Index (NI) [2], the Gait Deviation Index (GDI) [3] and the Gait Profile Score (GPS) [4]. Regardless of the gait variables that constitute the feature space, these measures are based on the principle of measuring a distance of a person's gait pattern from the mean pattern of a healthy reference group. For that purpose various types of Euclidian distance measures have been used. For the NI, the Euclidian distance is squared whilst for the GDI, a logarithmic scaling is applied [2,3]. The GPS uses the root mean square difference, which essentially is a linearly scaled version of the Euclidian distance. The GPS focuses on interpretability and therefore avoids any additional scaling. It also avoids the principal component decomposition used in the NI and GDI to enhance interpretability. Moreover, it incorporates a decomposition of the GPS into sub-scores, which in the original work are referred to as Gait Variable Scores and are each associated with a specific joint angle. This decomposition is highly relevant for practical applications as it makes the GPS more comprehensible for the clinician by indicating the variables that contribute to its value. Therefore, the GPS can be linked to functional aspects of a gait pattern [4].

The recently introduced Classifier Oriented Gait Score (COGS) is an approach that is conceptually different from these summary measures of gait quality [5]. Like the other measures, the COGS quantifies how far a person's gait pattern differs from a healthy reference group. The specificity of this score is that the distance is measured along an axis in a specific direction determined by a linear classifier, which separates a group with a specific gait pathology from a healthy reference group. Therefore, the COGS is a pathology specific measure and a specially built COGS model is necessary for the evaluation of a specific gait pathology. The orientation of the COGS axis represents a weighting of each feature according to its contribution to separate the groups. Features that are less discriminatory are suppressed by assigning low classifier weights, while higher weights are given to stronger discriminatory features. The advantage of this approach is illustrated in Fig. 1,

* Corresponding author.
E-mail addresses: josef.christian@sbg.ac.at (C. Josef), josef.kroell@sbg.ac.at (K. Josef), hermann.schwameder@sbg.ac.at (S. Hermann).

http://dx.doi.org/10.1016/j.gaitpost.2017.04.007
Received 9 September 2016; Received in revised form 13 March 2017; Accepted 3 April 2017

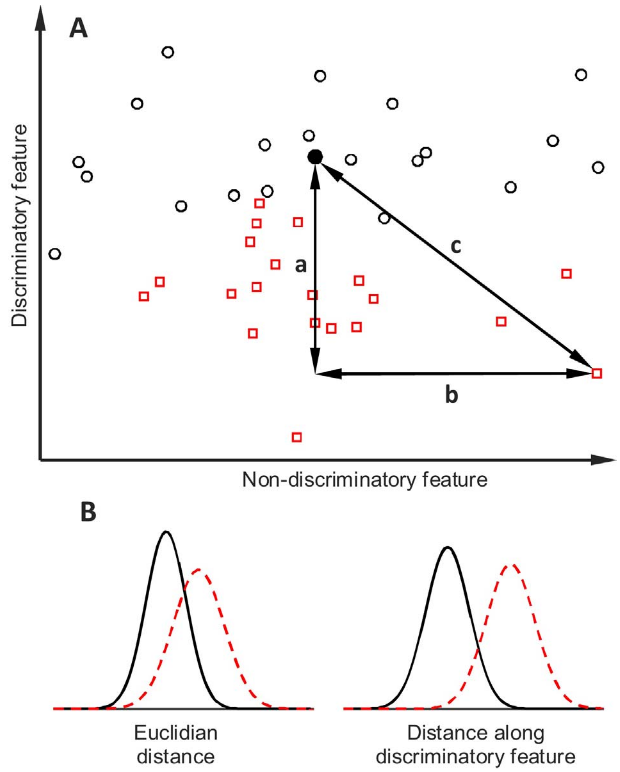

Fig. 1. Schematic example of distance measures in a 2-dimensional gait pattern vector space spanned by a discriminatory feature and non-discriminatory feature. A: The patterns of a healthy group (circles) and a group with gait pathology (squares) are depicted. For one example pattern three distance measures from the mean pattern of the reference group (filled circle) are indicated: distance along the discriminatory feature (a), distance along the non-discriminatory feature (b) and the Euclidian distance (c). B: Probability density functions of the healthy group (solid lines) and the pathologic group (dashed lines) for the Euclidian distance and the distance along the discriminatory feature.

which schematically shows that pathology has impact on the discriminatory feature, but not on the non-discriminatory feature (Fig. 1A). The overlap of the groups is greater with the Euclidian distance measure, while the distance along the discriminatory feature is better suited to differentiate the groups (Fig. 1B). The distance along the non-discriminatory feature is included into the calculation of the Euclidian distance and constitutes an additional source of non-informative variability leading to a reduction in group separation. In this example, the classifier would have a high weight on the discriminatory feature and a low weight on the non-discriminatory feature such that the COGS axis is oriented predominantly in the direction along the discriminatory feature. This makes the COGS a potentially more powerful method for detecting subtle changes in gait patterns compared with other methods that are based on the principle of measuring a Euclidian distance from the mean pattern of a healthy reference group [2–4]. The COGS, however, does not incorporate a profile of sub-scores like the GPS [4,5]. Decomposing the COGS into sub-scores could be useful to clarify its relation with functional aspects of the gait patterns and enhance its interpretability.

Consequently there were three aims in this study. The first aim was to extend the concept of the COGS with a profile of interpretable sub-scores similar to the GPS. The second aim was to compare the GPS and the COGS and their power of discriminating gait patterns associated with a specific type of impairment. The third aim was to validate the sub-scores of the GPS and the COGS and compare their ability to indicate functionally reasonable changes in the gait patterns.

2. Methods

2.1. General definition of the COGS based on [5]

Let $\boldsymbol{x}_v$ be a row vector of preprocessed discrete waveform data of a biomechanical gait variable (e.g. knee flexion angle) with samples x_t at T time points.

$$\boldsymbol{x}_v = [x_1\ x_2 \ldots x_t \ldots x_T] \tag{1}$$

Then $\boldsymbol{f}$ is the vector representation of a gait pattern resulting from concatenating equally sized waveform vectors of M variables with index v.

$$\boldsymbol{f} = [\boldsymbol{x}_1\ \boldsymbol{x}_2 \ldots \boldsymbol{x}_v \ldots \boldsymbol{x}_M] \tag{2}$$

The feature Matrix $\boldsymbol{F}$ is built by arranging the feature vectors of N participants from two gait pattern classes; the healthy class c^h and the pathologic class c^p.

$$\boldsymbol{F} = [\boldsymbol{f}_1^T\ \boldsymbol{f}_2^T \ldots \boldsymbol{f}_i^T \ldots \boldsymbol{f}_N^T]^T \tag{3}$$

Before fitting a classifier to the data, each column of $\boldsymbol{F}$ is z-transformed with the mean μ_j^h and standard deviation σ_j^h over a healthy reference group.

$$Z_{ij} = \frac{F_{ij} - \mu_j^h}{\sigma_j^h} \tag{4}$$

$$\boldsymbol{Z} = [z_1^T\ z_2^T \ldots z_i^T \ldots z_N^T]^T \tag{5}$$

This transformation ensures that the mean of the healthy reference group is the origin of the COGS axis and that each feature is scale independent. Then a weight vector $\boldsymbol{w}$ is computed by training a linear classifier function c to classify the patterns $\boldsymbol{z}$. $\boldsymbol{w}$ is a column vector with unit length ($\boldsymbol{w}_2 = 1$) that is orthogonal to the separating hyperplane with distance b from the origin.

$$c(z) = \begin{cases} c^n & \text{for } z\,\boldsymbol{w} + b \geq 0 \\ c^p & \text{for } z\,\boldsymbol{w} + b < 0 \end{cases} \tag{6}$$

The raw COGS of a gait pattern is computed by projecting its z-transformed feature vector onto $\boldsymbol{w}$.

$$COGS^{raw} = z\,\boldsymbol{w} \tag{7}$$

The raw score is scaled with a factor α to yield values from 0 to 10 between the mean raw score of the healthy reference group $COGS^{raw,h}$ and the mean raw score of the pathologic reference group $COGS^{raw,p}$.

$$COGS = COGS^{raw}\,\alpha \tag{8}$$

$$\alpha = \frac{COGS^{raw,h} - COGS^{raw,p}}{10} \tag{9}$$

2.2. Extension of the COGS by decomposing into sub-scores (Aim 1)

The COGS is decomposed into sub-scores, which are each associated with a specific biomechanical variable. An individual sub-score is calculated by first projecting $\boldsymbol{w}$ onto the subspace spanned by all features corresponding to a specific variable. This can be realized using a diagonal matrix $\boldsymbol{D}_v$ with all entries corresponding to the variable with index v set to one and all other entries set to zero.

$$\boldsymbol{w}_v = \boldsymbol{w}\,\boldsymbol{D}_v \tag{10}$$

$$\boldsymbol{D}_v = diag(\boldsymbol{d}_v) \tag{11}$$

$$\boldsymbol{d}_v = [d_1\ d_2 \ldots d_j \ldots d_{M\,T}] \tag{12}$$

$$d_j = \begin{cases} 1 & \text{for } (v-1)T + 1 \leq j \leq v\,T \\ 0 & \text{for all other } j \end{cases} \tag{13}$$

Projecting the z-transformed feature vector of a gait pattern onto $\boldsymbol{w}_v$ yields the raw sub-score.