A markerless platform for automatic assessment of gait

R. Di Marco [a], M. Boldo [a], S. Aldegheri [a], E. Martini [a], M. Cosma [b], A. Baricich [c], G. Gasperini [d], A. Picelli [e], N. Smania [e], N. Bombieri [a]

[a] Dept. of Engineering for Innovation Medicine, University of Verona, Italy, [b] Physical Medicine Unit, Azienda Ospedaliero-Universitaria di Ferrara, Italy, [c] Dept. of Health Sciences, University of Piemonte Orientale, Italy, [d] Villa Beretta Rehabilitation Center, Italy, [e] Dept. of Neurosciences, Biomedicine and Movement Science, University of Verona, Italy

Introduction

Instrumental gait analysis (iGA) is time-consuming and needs dedicated spaces and personnel. Observational gait analysis (oGA) offers an alternative, relying on clinicians assessing video recordings of walking to identify normal and abnormal patterns. Despite the development of structured instruments, oGA remains strongly operator dependant, with low test-retest and inter-rater reliability, calls for visual gait phases segmentation, introducing more evaluation bias [1]. Markerless presents a promising solution to iGA and oGA limitations, and its efficacy in clinical settings has already been tested [2]. This article presents a Markerless Automatic video-based platform for Gait Analysis (MaGA) as a rightful trade-off between iGA and oGA.

Methods

MaGA, adapted to the Rancho Los Amigos (RLA) [4], consisted of: (i) a video camera and OpenPose [3]; (ii) a joint kinematics estimator; (iii) a gait phases identification algorithm; and (iv) a Support Vector Machine (SVM), with a linear and a non-linear Gaussian kernel, for altered/normal pattern classification for each RLA cell.

Kinematics from ten adults with chronic stroke (7 males, 52.4±9.5 yo) and eight healthy adults (6 males, 28.0±3.7 yo) were segmented over gait cycle sub-phases and manipulated to extract descriptive statistics (average, minimum, maximum, etc), closeness (mean absolute error (MAE) and Linear Fit Method coefficients [5]) and statistical difference (area under the Statistical Parametric Mapping *t*-curve [6]) between test and control datasets.

Three experts evaluated videos of chronic stroke patients, merging their assessments and assigning RLA cell values (0-3) based on raised concerns. These data and the extracted features were used to train and test MaGA with a k-fold cross-validation (k=10). Performances were assessed with accuracy, precision, sensitivity, specificity, F1-score and MAE.

Results

Fig. 1 shows a MaGA-filled RLA sheet against the experts-merged. MaGA generally underestimated severity. Non-linear SVM generally outperformed the linear model (MAE ≤ 0.50 vs. 0.04-0.70), leading to non-ambiguous severity levels. For instance, severity = 2 and MAE > 0.5 could indicate switching between normal/altered states (severity ≤ 1.5 or ≥ 2.5).

		MaGA evaluation								Experts' evaluation							
		IC	LR	MSt	TSt	PSw	ISw	MSw	TSw	IC	LR	MSt	TSt	PSw	ISw	MSw	TSw
Hip	Flexion limited																
	Flexion excess																
	Inadequate extension			1.37	0.98							1	2				
	Past retract																
Knee	Flexion limited		0.32			0.41	0.48				1			1	1		
	Flexion excess																
	Inadequate extension			1.01					0.81			2					1
	Wobbles																
	Hyperextended																

Figure 5. MaGA-filled RLA sheet (left side) and experts' RLA evaluation (right side) obtained for hip and knee sagittal kinematics for an individual with chronic stroke. In black the non-relevant cells, in grey those with least relevance and in white the most relevant cells [4]. Severity is reported in each cell if different from zero.

Discussion

MaGA accurately identified all expert-highlighted items, with only one instance of knee wobbles being missed (marked by one expert). This could potentially be mitigated with higher resolution and capture rate devices.

MaGA has the potential to be customized according to various oGA tools, thereby addressing their limitations. Future plans include MaGA sensitivity analysis to data collection conditions and the establishment of a broader reference dataset, encompassing individuals with diverse disorders and severity levels.

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