Low-Dimensional Individualized Continuous-Task Joint Kinematic Modelling

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I. Introduction

Wearable robots have a great potential to assist their human users in every day locomotion tasks by using predictive models to track and assist their behaviors [2], [4]. Models that predict joint kinematics for the average person as a function of gait phase or stride completion variables are especially useful in this context. Recent models have introduced task variables that model the alterations these kinematics undergo in varying inclines and speeds [1]. However, it has been noted that the biggest source of error in the modelling of joint kinematics is the individuality between people [1]. In this work we approach the problem of modelling the individuality of multi-task gait models using a principle component analysis.

II. Methodology

Our joint kinematic model is defined as a linear combination of basis functions of the phase variable and the task variables (ramp angle and stride length). Given this linear model, we estimate the optimal fit for a person using least squares. We create a set of vectors, one for each individual, that represents their fit minus the average over all fits. And we then perform a weighted principle component analysis (PCA) to obtain the directions of highest variance. We use as many components as needed to reach 95% variance explained, which then define a personalization map for the gait model—a map from the low dimensional space of the personalized components to the high dimensional space of joint kinematic model parameters.

To validate our methodology, we employ a 10 subject dataset of gait kinematics for 3 speed conditions and 10 incline conditions [3]. Using 9 subjects, a personalization map is calculated for foot kinematics using a model with 252 parameters. We test this map's ability at fitting the remaining subject's foot angle against 1) the inter-subject average fit, and 2) the subject-specific fit using RMSE error to quantify differences in fit quality.

III. Results

The first 5 principle components explain 95.8% of the variance. The remaining subject fit resulted in the following RMSE Errors: Subject specific fit, 5.02 degrees; Inter-subject average fit, 5.76 degrees; and our approach, 5.31 degrees. Plots for level ground walking, 10 degree incline and fast walking are presented in Fig. 1. These plots show how our approach approximates the fit of the subject specific model, drastically improving over the naive inter-subject average fit but having only 5 individualization parameters as opposed to 252 in the subject-specific fit.

IV. Conclusion

If we can use such a low-dimensional personalization map to predict the kinematics of a novel subject, then we could potentially learn these personalization parameters as a "gait fingerprint" [5], [6] online. The personalization map could also be applied to clinical scenarios in which a clinician measures gait kinematics for a single task and uses the resulting personalized model to predict all other tasks. However the current model is limited by the inclusion criteria for the original dataset. Future work will look at pathalogical gait.

References

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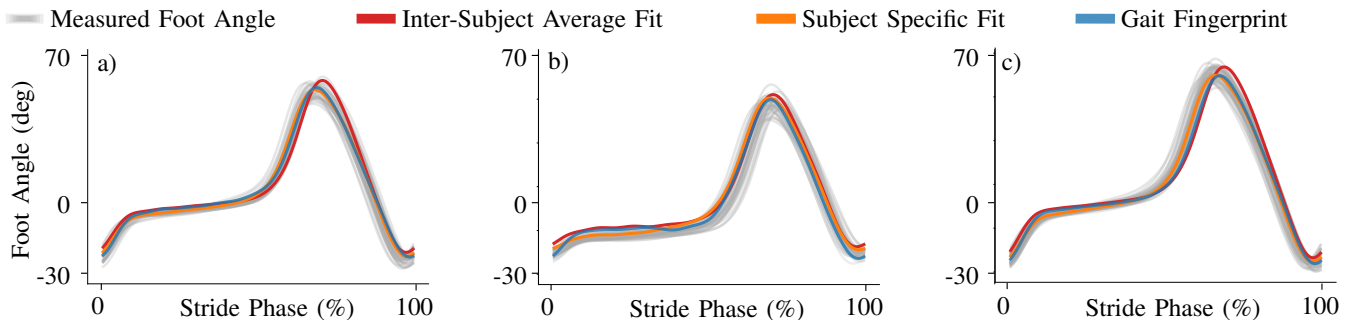[6] M. Derawi, P. Bours *Co&Se* Volume 39, Part B, 2013,Pages 137-144.

Fig. 1. Example model qualities for the global sagittal foot angle: a) 0.8 m/s at zero incline, b) 0.8 m/s at 10 degree incline, and c) 1.2 m/s at zero incline. Every third stride in the experiment is overlaid as the measured foot angle to give a sense of the natural human variability in kinematics.