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Nonlinear Prediction in a Smart Shoe Insole

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Abstract

In our previous work [1], we have investigated different methods to compute the ideal placement of pressure sensors in a smart shoe insole. There, we used a linear model to predict the weight put on the foot/leg. In this work, we investigate how using a quadratic model instead changes the sensor placement and improves prediction performance.

Keywords: Intelligent wearables, model individualization

1. Introduction

Wearable sensors that aid in diagnosis and post-surgery care are becoming more common. One example is a shoe insole equipped with several pressure sensors that can compute the weight put on the foot/leg (e.g. while walking) and warn if it is overstrained. In [1] we have investigated different methods for computing an optimal positioning of the pressure sensors, assuming a customized, linear postprocessing of the sensor readings. In this work, we further investigate how nonlinear postprocessing changes the results. In contrast to a linear model, a nonlinear model allows interactions between sensors. We especially focus on whether the nonlinear model results in different sensor positions, whether the predictions are more accurate, and how the sensors contribute to the prediction over the course of a stance phase.

2. Experiments

In this work we test the global optimization methods differential evolution [2] and simulated annealing [3] as methods for computing the optimal sensor positioning, since these two methods performed best in [1]. We keep the objective with customized, linear postprocessing:

$$\mathbf{s}_1^* = \operatorname*{arg\,min}_{|\mathbf{s}|_1 = \mathbf{n}} \left(\sum_p \min_{\mathbf{w_p}} \|\mathbf{y_p} - \mathbf{X_{s,p}} \mathbf{w_p}\|_2^2 \right)$$

where $\mathbf{s}$ refers to the selected sensor placement, the inner part of the objective constitutes an individual linear least-squares problem mapping sensor values $\mathbf{X_{s,p}}$ of person p at positions $\mathbf{s}$ to the individual target, and the outer part minimizes the residuals, summed over all persons, by adapting the sensor positions $\mathbf{s}$. We now introduce a second objective by replacing the linear model with a nonlinear model f with learnable, per-person parameters $\mathbf{w_p}$:

$$\mathbf{s}_2^* = \operatorname*{arg\,min}_{|\mathbf{s}|_1 = \mathbf{n}} \left(\sum_p \min_{\mathbf{w_p}} \|\mathbf{y_p} - f_{\mathbf{w_p}}\left(\mathbf{X_{s,p}}\right)\|_2^2 \right)$$

Since we assume that the processing happens on hardware with low computational power, we choose f to be a quadratic polynomial, as it is fast to compute. In contrast to [1], we neither use a constant bias for the linear nor for the quadratic model because it seems counterintuitive that the model would give a nonzero prediction with zero pressure sensor readings. The data and other setup is the same as in [1], including the crossvalidation scheme.

3. Results

Figure 1 and 2 show where sensors are placed often. For three sensors (Fig. 1), there are only small differences, namely that with the quadratic model, the sensor cluster on the outer side of the foot is moved up, to the area with higher pressure. For five sensors (Fig. 2), we see that none are placed under the arch of the foot when a quadratic model is used.

Figures 3 exemplifies how the different sensors contribute to the prediction during one step/stance phase. Note that for the quadratic model, some second order components contribute negatively to the prediction. Overall, the prediction of the quadratic model seems to be better.

Median test scores are shown in table 1. It is visible that the quadratic model leads to higher scores compared to the linear model, such that the quadratic model can achieve similar scores as the linear model

(a) Linear (b) Quadratic

Figure 1: Three sensors, differential evolution.

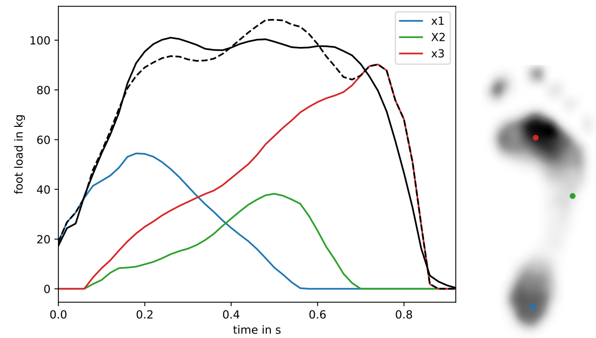
(a) Linear (b) Quadratic

Figure 2: Five sensors, simulated annealing.

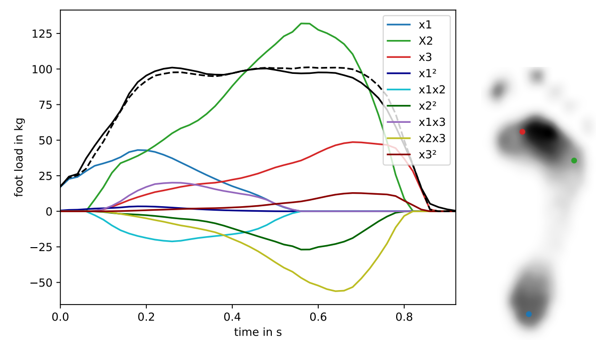
with two to three fewer sensors. However for eight sensors, the quadratic model gives no advantage over the linear model.

4. Conclusion

Using a quadratic model for the prediction seems promising, especially when looking at the test scores.



(a) Linear (b)



(c) Quadratic (d)

Figure 3: Contributions of sensors during one step/stance phase. Solid black line: ground truth, dashed line: prediction.

Table 1: Median R^2 test scores. n is the number of sensors.

	diff. evolution		simulated annealing	
n	linear	quadratic	linear	quadratic
3	0.933	0.966	0.934	0.966
5	0.966	0.985	0.969	0.984
8	0.987	0.986	0.987	0.986

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