Calibration of predictions for a new individual with an application to energy expenditure and smart shorts data

Salme Kärkkäinen[1], **Lauri Mehtätalo**[2], **Olli Tikkanen**[3] & **Taija Finni**[3]

[1] Dept. of Mathematics and Statistics, University of Jyväskylä, Finland
[2] UEF School of Computing, University of Eastern Finland, Finland
[3] Dept. of Biology of Physical Activity, University of Jyväskylä, Finland

Energy expenditure reflects the intensity of physical activity, which plays an important role in sustaining a healthy life. Physical activity has beneficial effects on cardiorespiratory fitness, lipid profiles, blood pressure, weight control, cardiovascular diseases and diabetes (Kesaniemi et al., 2001). It is important to note that exercise for fitness has been reported not to decrease the total daily inactivity time (Finni et al., 2012), whereas low level activities such as standing and breaking up long periods of inactivity/sitting can already bring health benefits (Stephens et al., 2011).

Our goal was to study the prediction of energy expenditure especially at low-to-moderate intensity activities. In Tikkanen et al. (2014) electromyography (EMG) data measured by smart shorts (Finni et al., 2007) was used for the first time in the prediction of energy expenditure. Prediction results based on linear mixed model were quite good at the individual level, especially at low intensity activities. When having unexplained variation between individuals as in our data, an improved individual-level prediction is possible through a calibration approach. For calibration, we need some observations on energy expenditure from the new individual in question and EMG data. Besides presenting the results of Tikkanen et al. (2014), our goal is to perform a similar type of calibration as e.g. Lappi & Bailey (1988) and Mehtätalo (2004) in forest sciences but for the energy expenditure data.

Data includes measurements from 54 volunteers. They performed a treadmill test with several loads each of them lasting 3 minutes: 4 km/h, 5 km/h, 5 km/h (-4 descent), 5 km/h (+4 ascent), 6 km/h, 7 km/h, running load (females 10 km/h; males 12 km/) and if not exhausted, additional loads of 5 km/h (+8) and 7 km/h (+10). For simplicity, measurements for energy expenditure, heart rate, EMG data and accelerometer data were averaged or summarized over the last minute of each load. Energy expenditure was calculated from measured oxygen consumption and respiratory quotient. Using smart shorts with textile electrodes, we obtained EMG data consisting of signals from four muscles, right and left quadriceps, and right and left hamstrings. In the analysis, we used three EMG values: averages of quadriceps, hamstrings, and all measurements. Acceleration value was obtained as a sum vector from 3D accelerometer data. In our analysis, data was categorized such that 1) "all loads"consisted of all measurements and 2) "low loads" consisted of walking loads up to 6 km/h.

In Tikkanen et al. (2014), the predictions of energy expenditure using heart rate, accelerometer or EMG data with age and sex were compared. Considering all loads, heart rate was the best predictor at the population and individual level according to root mean squared errors. However, EMG data based models seem to perform much better at the individual level when compared to the population level. At low loads, acceleration was the best predictor at the population level according to RMSEs, but the fourth at the individual level. Especially, one of the EMG models was superior to heart rate and acceleration at the individual level. As a summary, especially EMG models could benefit from the individual calibration. We study the effect of the number of new measurements on energy expenditure and EMG data, and the effect of chosen load levels to the accuracy of prediction when compared to the case having all measurements as in our data.

Keywords: calibration, EMG data, energy expenditure, mixed model, prediction

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