

Supplementary material

1. Estimation of dynamic component of trunk acceleration, a_D (in gravity units, $1g=9.8m/s^2$):

$a_D = \left| \sqrt{a_x^2 + a_y^2 + a_z^2} - 1 \right|$, where a_x, a_y, a_z are acceleration components at the 3-dimensional axes of sensor frame.

2. Definition of multivariate PA pattern. Information related to *type*, *duration* and *intensity* is combined to define 25 multivariate PA states, as follows:

If *Type=Non-Locomotion*, divide each detected period in epochs of 1second length. For each epoch calculate movement *intensity* as the mean value of dynamic component of trunk acceleration, $mean(a_D)$, then assign to each epoch a PA state according to the value of $mean(a_D)$, as indicated in Table 1S.

If *Type=Locomotion*, assign to each second of the respective period a PA state, according to locomotion *duration* (s) and *intensity* expressed in terms of *cadence* (steps/min), as indicated in Table 1S

Table 1S: Mapping of PA dimensions into multivariate PA states; each PA state has assigned a numerical code and a color for pattern visualization.

Type	Duration	Intensity	Multivariate PA states
If Type=Non-locomotion		& $mean(a_D) \leq 0.1$ (verylow)	1
		& $0.1 < mean(a_D) \leq 0.2$ (low)	2
		& $0.2 < mean(a_D) \leq 0.4$ (medium)	3
		& $0.4 < mean(a_D) \leq 0.6$ (high)	4
		& $mean(a_D) > 0.6$ (very high)	5
If Type=Locomotion	& $duration \leq 30$ (very short)	& $cadence \leq 70$ (very slow)	6
		& $70 < cadence \leq 90$ (slow)	7
		& $90 < cadence \leq 110$ (moderate)	8
		& $110 < cadence \leq 130$ (fast)	9
		& $cadence > 130$ (very fast)	10
	& $30 < duration \leq 120$ (short)	& $cadence \leq 70$ (very slow)	11
		& $70 < cadence \leq 90$ (slow)	12
		& $90 < cadence \leq 110$ (moderate)	13
		& $110 < cadence \leq 130$ (fast)	14
		& $cadence > 130$ (very fast)	15
	& $120 < duration \leq 360$ (medium)	& $cadence \leq 70$ (very slow)	16
		& $70 < cadence \leq 90$ (slow)	17
		& $90 < cadence \leq 110$ (moderate)	18
		& $110 < cadence \leq 130$ (fast)	19
		& $cadence > 130$ (very fast)	20
	& $duration > 360$ (long)	& $cadence \leq 70$ (very slow)	21
		& $70 < cadence \leq 90$ (slow)	22
		& $90 < cadence \leq 110$ (moderate)	23
		& $110 < cadence \leq 130$ (fast)	24
		& $cadence > 130$ (very fast)	25

3. Complexity analysis (Lempel-Ziv and Permutation Lempel-Ziv computation)

- a) Theoretical background for computation of LZC can be found in (1); additional information and Matlab routine for calculation of LZC metric can be found in (2) and downloaded online (accessed 17th Oct 2017)

(http://www.gao.ece.ufl.edu/GCTH_Wileybook/programs/LZ_complexity/LZ_complexity.m)

- b) Theoretical background and Matlab routine for computation of PLZC metric can be found in (3).
c) Principle of LZC and PLZC computation:

LZC is a non-parametric measure of complexity applied directly to analyze the PA pattern represented as a symbolic sequence (i.e., succession of PA states coded with discrete values from 1 to 25).

PLZC(m, t) is a parametric measure of complexity implying two steps:

1. Generate a permutation/ordinal pattern from the original symbolic sequence (PA pattern) by comparison of m consecutive PA states, separated in time by a lag $t > 1$. Detailed description of ordinal patterns generation for different parameters m and t is provided in (4).
2. Apply LZC to the ordinal pattern obtained according to selected parameters (m, t).

Since the parameters of PLZC computation can affect its output, we investigated the results for different values of m and t . The analysis showed relatively stable complexity values for wide range of values chosen for m and t ($m=4$ to 7, $t=10$ to 30), Table 2S. The optimal combination in terms of discriminative properties and computational efficiency appeared $m=4$ and $t=10$.

4. Supplementary results

Table 2S: Comparative values of LZC and PLZC(m, t) obtained with various computational parameters.

Complexity metrics	Fully confident	Less confident	p-value	Effect size (Cliff's delta)
LZC	0.27±0.04	0.23±0.04	0.003	0.56
PLZC(4,10)	0.4±0.07	0.3±0.06	0.001	0.62
PLZC(4,15)	0.43±0.09	0.33±0.05	0.004	0.54
PLZC(4,20)	0.44±0.09	0.34±0.05	0.006	0.52
PLZC(4,30)	0.45±0.09	0.35±0.06	0.005	0.53
PLZC(7,10)	0.3±0.05	0.24±0.04	0.001	0.61
PLZC(7,15)	0.32±0.06	0.26±0.04	0.005	0.53
PLZC(7,20)	0.33±0.07	0.26±0.04	0.007	0.51
PLZC(7,30)	0.34±0.07	0.27±0.04	0.006	0.52

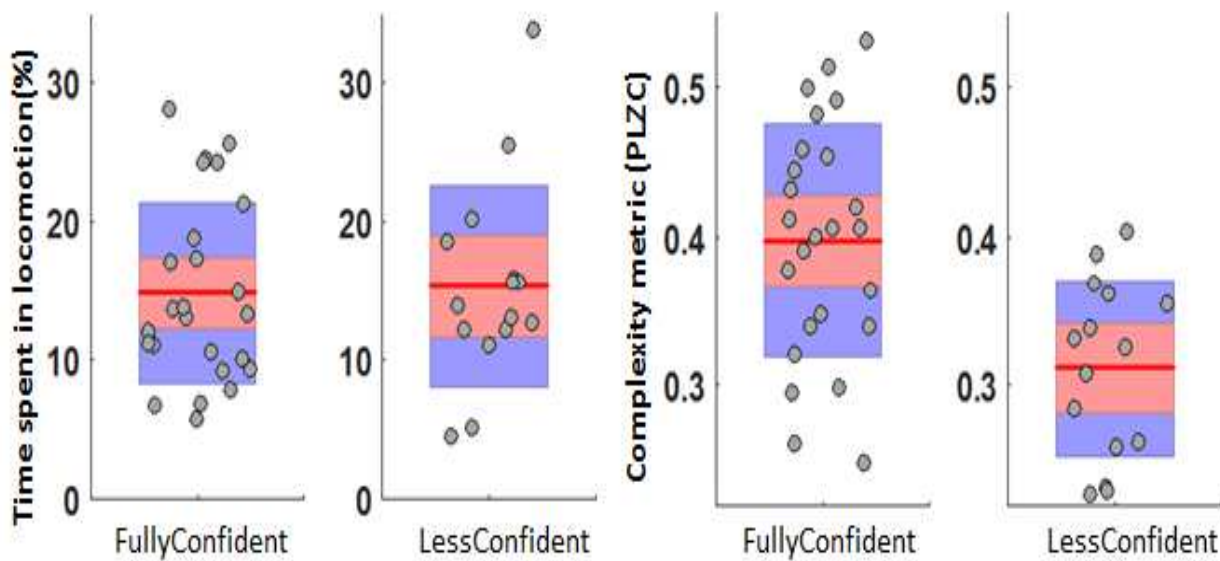


Fig. 1S: Illustration of discriminative properties of *time spent in locomotion* (%) and *complexity* of PA patterns (quantified with *PLZC*). The graphs shows the group mean (red line), standard deviation (blue shadow), as well as the values corresponding to the subjects in each group.

References

- 1 Aboy M, Hornero R, Abásolo D, Álvarez D. Interpretation of the Lempel-Ziv complexity measure in the context of biomedical signal analysis. *IEEE Transactions on biomedical Engineering*. 2006;53(11):2282-8.
- 2 Gao J, Cao Y, Tung W-w, Hu J. Multiscale analysis of complex time series: integration of chaos and random fractal theory, and beyond: John Wiley & Sons; 2007.
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- 4 Parlitz U, Berg S, Luther S, Schirdewan A, Kurths J, Wessel N. Classifying cardiac biosignals using ordinal pattern statistics and symbolic dynamics. *Computers in biology and medicine*. 2012;42(3):319-27.