**Supplementary material**

1. **Estimation of dynamic component of trunk acceleration,** *aD* (in gravity units, **1***g=*9.8m/s2)**:**

**,** where are acceleration components at the 3-dimensional axes of sensor frame.

1. **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(aD)*, then assign to each epoch a PA state according to the value of *mean(aD),* 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 i*ntensity* 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(aD)≤0.1* (verylow) | 1 |
| & 0.1<*mean(aD)≤*0.2 (low) | 2 |
| & 0.2<*mean(aD)≤*0.4 (medium) | 3 |
| & 0.4<*mean(aD)≤*0.6 (high) | 4 |
| & *mean(aD)>*0.6 (very high) | 5 |
| *If* Type=Locomotion | *& duration ≤ 30*  (very short) | *& cadence≤70* (very slow) | 6 |
| & 70<*cadence≤*90 (slow) | 7 |
| & 90<*cadence≤*110 (moderate) | 8 |
| & 110<*cadence≤*130 (fast) | 9 |
| *& cadence>*130 (very fast) | 10 |
| & 30<*duration* *≤ 120*  (short) | *& cadence≤70* (very slow) | 11 |
| & 70<*cadence≤*90 (slow) | 12 |
| & 90<*cadence≤*110 (moderate) | 13 |
| & 110*cadence≤*130 (fast) | 14 |
| *& cadence>*130 (very fast) | 15 |
| & 120<*duration* *≤ 360* (medium) | *& cadence≤70* (very slow) | 16 |
| & 70<*cadence≤*90 (slow) | 17 |
| & 90<*cadence≤*110 (moderate) | 18 |
| & 110<*cadence≤*130 (fast) | 19 |
| *& cadence>*130 (very fast) | 20 |
| & *duration* *> 360* (long) | *& cadence≤70*( very slow) | 21 |
| & 70<*cadence≤*90 (slow) | 22 |
| & 90<*cadence≤*110 (moderate) | 23 |
| & 110*cadence≤*130 (fast) | 24 |
| *& cadence>*130 (very fast) | 25 |

1. **Complexity analysis (Lempel-Ziv and Permutation Lempel-Ziv computation)**
2. Theoretical background for computation of LZC can be found in ([1](#_ENREF_1)); additional information and Matlab routine for calculation of LZC metric can be found in ([2](#_ENREF_2)) and downloaded online (accessed 17th Oct 2017)

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

1. Theoretical background and Matlab routine for computation of PLZC metric can be found in ([3](#_ENREF_3)).
2. 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](#_ENREF_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.

1. **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 |

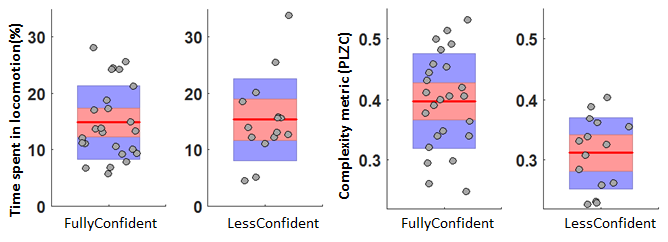


Fig. 1S: Illustration of discriminative properties of *time spent in locomotion* (%) and *complexity* of PA patterns (quantified with *PLZC*). The graphs shows the group mean (red line), standard deviation (blue shadow), as well as the values corresponding to the subjects in each group.

**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.

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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.