Open|Movement

Standard Procedures for (Wrist Worn) Accelerometry

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Analysis of ...	**"Standard" algorithms**	**Description**	**References**
Preprocessing	Calibration	Calibrate accelerometer recording to alleviate sensor specific offset and scaling issues resulting from temperature change	
	Orientation	Rotate accelerometer data to ensure orientation is comparable to other data-sets. Based on overall distribution of accelerometer readings.	
	SVM	Calculate vector magnitude independent of orientation, removing the impact of gravity	
	Interpolation	Interpolate signal to known temporal basis (e.g. 50 Hz)	
	Filtering	Filtering very common, ● 0.5 - 12 Hz Bandpass for voluntary movement ● 0.5 Hz highpass filter on ACC data to remove gravity bias ● 1 Hz low-pass filter for orientation change, posture ● 3 - 8 Hz Bandpass for Tremor in Parkinson's	
	Epochs, Sliding window	Extract characteristic features from epochs (no overlap, e.g. one minute) or using sliding window procedure	
	Feature extraction	Extract statistical descriptors, fourier coefficients, wavelet decomposition or similar from raw data contained in each epoch to apply statistical pattern recognition techniques	
	Wear-time validation	Typical wear-time validation looks at standard deviation with threshold for epochs (e.g. std < 3mg) for each individual accelerometer axis. More recent approaches also consider temperature.	
	Actigraph CPM	Translate recordings to actigraph counts per minute, usually just on one axis (z-axis pointing out of wrist). ● Filter data 0.5 - 12 Hz or similar ● Resolution 0.01664 g / s / count ● Just approximate result as proprietary to Actigraph	

Steps / gait / posture		**Accessible parameters:** - Time spent in gait (stand / walk / run) - Approx. speed - Approx. number of steps - Approx. distance (based on heuristics) - Approx. posture (upright, lying)	Mannini, A. et al., Human gait detection from wrist-worn accelerometer data, Gait & Posture, Volume 37 , S26 - S27 (2013)
	Gait detection	1. Detection of gait (walking / running) 2. Split data into epochs, e.g. 10s 3. Assess self-similarity, e.g. autocorrelation, fourier coefficients, wavelet decomposition to detect gait (repetetive movement) 4. Some work uses statistical classifier to predict type of gait (also: up-stairs, down-stairs) 5. Alternative: Estimate energy to differentiate walking, running 6. Variety of data-sets accessible for calibration (e.g. PAMAP, PAMAP2, Opportunity) 7. Heuristics provide number of steps, distance, speed	

	Posture	1. Low-pass filter acc data
		2. Extract long epochs
		3. Mean orientation gives approx. posture with confidence related to variability in epoch
		    a. Stand -> hands mostly pointing down
		    b. Sit / lie -> hands mostly vertical	

Sleep / Circadian rhythm / Sleep disturbance		**Accessible parameters:** - Total Sleep Time (TST) - Sleep efficiency - Sleep Latency (SL) - Wake After Sleep Onset (WASO) - Number of Awakenings - Number of turns - Sleep phases (to an extent) - Sleep disturbance	Sleep, Automatic. "Technical note automatic sleep/wake identification from wrist activity." *Sleep* 15.5 (1992): 461-469. Marino, Miguel, et al. "Measuring sleep: accuracy, sensitivity, and specificity of wrist actigraphy compared to polysomnography." *Sleep* 36.11 (2013):

	Cole & Kripke	1. Differentiate Sleep / Wake
		    a. 15 second non-overlapping epochs
		    b. “Maximum Movement” per epoch in Actigraph CPM (counts per minute)
		    c. Linear model of 7 subsequent epochs with coefficients in paper
		    d. ~86% agreement to PSG	

	Oakley 97		

		1. Apparently used in Actiwatch
		2. Differentiate Sleep / Wake
		    a. 60 second non-overlapping epochs
		    b. “Total activity count” per epoch in Actigraph CPM (counts per minute)
		    c. Linear model of 5 epochs with coefficients in paper
		    d. “sensitivity” thresholds
			1747.
			
			Tonetti, Lorenzo, et al. "Comparison of two different actigraphs with polysomnography in healthy young subjects." *Chronobiology international* 25.1 (2008): 145-153.

	Chae & Kripke	1. Sleep latency (time until sleep detected) 2. first 5 minutes of no activity (act below threshold, see Oakley)	Chae, Kyu Young, et al. "Evaluation of immobility time for sleep latency in actigraphy." *Sleep medicine* 10.6 (2009): 621-625.

	Sadeh	1. Differentiate Sleep / Wake
		    a. Multi-resolution epochs and different estimates (activity CPM, time above threshold)
		    b. Linear model of 6 minutes to predict “Sleep Probability”
			Sadeh, Avi, Katherine M. Sharkey, and Mary A. Carskadon. "Activity-Based Sleep—Wake Identification: An Empirical Test of Methodological Issues."*Sleep* 17.3 (1994): 201-207.

	Miwa	1. Sleep Stage and Rollovers 2. Accelerometer on upper arm 3. Simple metric for “Posture Difference” with thresholds (included in paper) 4. Sleep “depth” with simple formula based on occurrence of rollovers	Miwa, Hiroyasu, S-I. Sasahara, and Toshihiro Matsui. "Roll-over detection and sleep quality measurement using a wearable sensor." *Engineering in*
	Ortiz-Tudela	1. Estimate TAP variable for epochs of activity (A), temperature (T) and posture (P) 2. TAP predicts sleep/wake	

	Anderson	3. TAP predicts sleep phase
		    a. Temperature crucial to get an idea of sleep "depth"
		
		1. Measure Sleep disturbance
		    a. based on 5 hours of least activity, counts of rest-active transitions, and difference between least and most active 5h period
		    b. Score relative to large study population (337 people)
			Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE. IEEE, 2007.
			
			Ortiz-Tudela, Elisabet, et al. "Ambulatory Circadian Monitoring (ACM) based on Thermometry, motor Activity and body Position (TAP): A comparison with polysomnography." *Physiology & behavior* 126 (2014): 30-38.
			
			Anderson, Kirstie N., et al. "Assessment of sleep and circadian rhythm disorders in the very old: the Newcastle 85+ Cohort Study." *Age and ageing* (2013): aft153.

Physical activities / mostly also applies to energy expenditure, sedentary behaviour	Cut-points	**Accessible parameters** - CPM (counts per minute) - Intesity level of physical activity (sedentary / light / moderate / vigorous / very vigorous) - PAEE physical activity energy expenditure - MET (metabolic equivalent of task) 1. Estimate (mean) activity over epoch, typically one minute in CPM or correlated measure 2. Apply cut-points to classify activity into intensity level (light, moderate, etc) 3. Variety of cut-points have been published for different populations a. infants	**Reviews:** - Atkin, Andrew J., et al. "Methods of measurement in epidemiology: sedentary behaviour." International journal of epidemiology 41.5 (2012): 1460-1471. - Taraldsen, Kristin, et al. "Physical activity monitoring by use of accelerometer-based body-worn sensors in older

	Statistical pattern recognition	b. children c. adults d. older adults e. Specific populations 4. Mostly on Actigraph counts, sensor on waist. MET regression models are accessible to translate those to wrist (approximately), mostly used thresholds: light < 3 MET moderate > 3 MET < 6 MET vigorous > 6 MET 5. Some data-sets are available to fine-tune methods from wrist-data (e.g. PAMAP, PAMAP2) where participants engage in activities with known MET 1. Predict e.g. MET or intensity level 2. Extract epochs (usually short < 10s) 3. Estimate features such as FFT, statistical features, etc 4. Train statistical classifier based on labelled data-set (a large variety is publicly available)	adults: a systematic literature review of current knowledge and applications." Maturitas 71.1 (2012): 13-19. - Kim, Youngwon, Michael W. Beets, and Gregory J. Welk. "Everything you wanted to know about selecting the “right” Actigraph accelerometer cut-points for youth, but…: a systematic review." Journal of Science and Medicine in Sport 15.4 (2012): 311-321. **Specific to wrist:** - Phillips, Lisa RS, Gaynor Parfitt, and Alex V. Rowlands. "Calibration of the GENEA accelerometer for assessment of physical activity intensity in children." Journal of Science and Medicine in Sport 16.2 (2013): 124-128.
Activities of daily living (ADL)		● Time spent performing activities to approx. Katz’ ADL scale for independent living ● Examples: ○ Personal hygiene ○ Housework ○ Eating … ● Without knowledge of context, automatic detection of ADLs is challenging ● Datasets available to train classifiers for activities such as: ○ Housework (vacuum, doing dishes, cleaning) ○ Modes of transport ○ Personal hygiene (shower, brushing teeth) ● Always based on some level of statistical pattern recognition ● No standard approach, many different systems tailored mostly towards home environment	Katz, Sidney. "Assessing self-maintenance: activities of daily living, mobility, and instrumental activities of daily living." Journal of the American Geriatrics Society (1983)
Energy expenditure	see physical activity	1. Data preprocessing (cleaning) 2. Sliding window	[1] E. M. Tapia, “Using machine learning

		3. Per frame: a. ground truth through (indirect) calorimetry b. Usually on treatmills c. regression analysis 4. Wrist-sensor typically imprecise for low-energy activities where trunk is not moving, just arms (compared to sensor on waist). Precision comparable to waist sensor for high-energy activities.	for real-time activity recognition and estimation of energy expenditure," *MIT*, 2008.
Sedentary behaviour	See physical activity	**Accessible parameters:** - time spent in sedentary behaviour - bouts of sedentary behaviour (for comparison between populations) 1. Simple approach based on counts (e.g. CPM in actigraph) 2. Fixed threshold for sedentary behaviour (see physical activity above) 3. Sometimes defined based on MET (metabolic equivalent of task)	
Datasets	PAMAP PAMAP2 Opportunity UCI: Daily and Sports Activities Data Set UCI: Dataset for ADL Recognition with Wrist-worn Accelerometer Data Set	**Subjects:** 8 **Sensors**: 3 IMU + heartrate **Activities:** lying, sitting, standing, iron, vacuum, ascend stairs, descend stairs, slow walk, normal walk, nordic walk, run, cycling, soccer, rope-jump **Subjects:** 9 **Sensors**: 3 IMU + heartrate **Activities:** lying, sitting, standing, walking, running, cycling, walking, TV, work, driving, stairs, stairs, cleaning, ironing, laundry, cleaning, soccer, jumping **Subjects**: 4, 6 sets each **Sensors**: excessive instrumentation of subjects and environment **Activities:** ADL scenario and kitchen environment. **Subjects:** 8 **Sensors:** IMUs **Activities:** sitting, standing, lying on back and on right side, ascending and descending stairs, walking, running, stepper, cross trainer, exercise bike in horizontal, rowing, jumping, basketball. **Subjects:** 16 **Sensors:** Accelerometer on wrist **Activities:** brush teeth, climb stairs, comb hair, descend stairs, drink glass, eat meat, eat soup, getup bed, liedown	

		bed, pour water, sitdown chair, standup chair, use telephone, walk	