Wrist Sensor Fusion Enables Robust Gait Quantification Across Walking Scenarios

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Abstract
Quantifying step abundance via single wrist-worn accelerometers is a common approach for encouraging active lifestyle and tracking disease status. Nonetheless, step counting accuracy can be hampered by fluctuations in walking pace or demeanor. Here, we assess whether the use of various sensor fusion techniques, each combining bilateral wrist accelerometer data, may increase step count robustness. By collecting data from 27 healthy subjects, we find that high-level step fusion leads to substantially improved accuracy across diverse walking scenarios. Gait cycle analysis illustrates that wrist devices can recurrently detect steps proximal to toe-off events. Collectively, our study suggests that dual-wrist sensor fusion may enable robust gait quantification in free-living environments.

1 Introduction
The growth of the quantified self movement has sparked substantial interest in measuring the extent of physical activity an individual performs. One widespread approach for tracking daily activity is by counting walking steps. This is often accomplished using wrist-worn pedometers containing triaxial accelerometers. Beyond the public health value of increased ambulation, step counting interventions yield modest weight loss [1], and may aid in diabetes, cardiovascular disorders, and COPD care [2]. Despite their prevalence, commercial wrist-worn pedometers often display markedly inferior accuracy compared to their counterparts located on other body parts, for instance the waist or ankles [3, 4, 5]. Indeed, wrist-based step counting does not appear robust to walking pace and other walking style variations, with double digit error rates being fairly common [3, 4, 5]. In fact, it has been argued that step counts derived using accelerometers worn on the waist and wrist are generally not comparable under both laboratory and free-living conditions [7], with waist placement being superior [5].

Body-worn micro electromechanical system (MEMS) inertial sensors including accelerometers and gyroscopes can also be used to quantify gait abnormalities in movement disorders. This is primarily achieved in controlled settings by detecting specific gait phases, especially the heel strike (initial contact) and toe-off (terminal contact) events. For example, inertial sensors have been used to track cadence inconsistencies and axial symptoms such as step time asymmetry in patient cohorts [8, 9]. In free-living environments, wrists would presumably serve as attractive sites for monitoring gait pathologies given the wide adoption of wrist-worn devices. However, due to arm movement, use of individual wrist-worn sensors for measuring lower-limb, time-dependent aspects such as initial foot contact and terminal contact is challenging. We hypothesized that concurrent use of opposing wrist sensors, via sensor fusion, may help overcome the limitations of single-wrist devices.

Sensor fusion refers to the combining of sensory data such that resulting information may be better than that from individual sources (reviewed in [10]). Algorithms used for synchronous multi-sensor fusion include, among others, averaging, Borda count voting, fuzzy logic, Kalman filters, and
inference methods. Sensor fusion architectures generally fall under three categories: low-level (raw data), intermediate-level (features), or high-level (combining decisions, in this paper detected steps).

Perhaps surprisingly, there are limited examples of sensor fusion using body-worn inertial sensors. Indeed, multi-sensor studies often compare the outputs of individual sensors rather than perform fusion to improve a measure of interest. Existing fusion examples typically focus on activity classification via intermediate-level fusion, for example by classifying daily activities \[11\] or detecting falls \[12\]. Sensor fusion for gait quantification is scarce, with one exception using ankle, thigh, and waist sensors, but not wrist devices, and focusing on a single high-level fusion approach \[13\].

Given the lack of precedent, methodical comparison of multiple fusion approaches for gait quantification would be of high value, especially using wrist sensors. The present study explores this possibility by comparing sensor fusion with single sensor results. Using eight types of walking tasks, we assess whether dual-wrist sensor fusion can facilitate robust step counting and gait phase detection.

2 Data collection and labels

Data was collected from 27 healthy volunteers (18 male, 9 female) aged between 18 and 50. Subjects received instructions and subsequently performed eight separate walking tasks that simulate multiple walking types (Table 1). A total of N=214 tasks were successfully collected. Tasks were performed while wearing six synchronized, wireless devices, each containing a 128Hz triaxial accelerometer and 128Hz triaxial gyroscope (Opal sensors, APDM). The six devices were placed on both ankles, both wrists, the lumbar spine, and the trunk, per manufacturer configuration. The entire process including instructions, placement, and removal of the devices was performed in less than 30 minutes.

Each walking task consisted of a 74.6m uninterrupted walk in a flat, rectangular course (33.5m X 3.8m) with a mean duration of 64.3s [range 30.4s-110.6s]. Subjects self-counted their steps, with a mean step count of 104.4 steps [range 67-151]. These counts were not used for training or evaluation.

Ankle gyroscope signals were used to derive step count labels and to determine heel strike and toe-off timings \[14, 15\]. The method, implemented by the device manufacturer (APDM), is considered highly reliable and has been previously used as a label \[8\]. Gait events were identified by matching a template, specifically a double pendulum model for leg swing and an inverse double pendulum for stance (foot on ground). Segments analyzed by the manufacturer software, accounting for the large majority of gait cycles, were used for step count evaluation. To further ensure accuracy, we discarded the 5% of samples with the largest cadence difference between subject step counts and ankle-derived values. This increased the correlation between the measures from r=0.81 (N=214) to r=0.96 (N=203).

| Category          | Walking type (N)                                                                 |
|-------------------|--------------------------------------------------------------------------------|
| Unconstrained     | Slow pace (25), Comfortable pace (26), Fast pace (24)                          |
| Arms constrained  | Holding bag in right hand (27), Holding cellphone with two hands (26),         |
|                   | Hands not swinging alongside body (27)                                        |
| Asymmetrical      | Without right shoe (25), pretending to use cane in right hand (23)             |
| **Total**         | **203**                                                                        |

3 Methods

This work evaluates no fusion (single sides), low-level fusion, and high-level fusion step detection approaches. All approaches first converted axis-level raw data into signal magnitude (norm) \(\sqrt{x_t^2 + y_t^2 + z_t^2}\), followed by smoothing with a centered moving average. Peak detection was used for step counting as previously recommended for non-fixed accelerometers given its high performance \[16\]. Peaks were detected using first-order difference with parameters for minimum peak height and minimum window between adjacent peaks \[17\]. In the case of multiple peaks within the minimum window, the highest peak was chosen. Each peak was considered a single step. All parameters were tuned by five-fold cross validation using all N=203 samples by minimizing the root mean square error (values shown in Table 4). This resulted in negligible smoothing for a few of the approaches.
Algorithm 1

Input: \(N_R, N_L, T_R, T_L\) and max_dist
Output: \(T_{R\cap L}\) (set of times)

1: \(T_{R\cap L} = \emptyset\)
2: for \(t_i \in T_L\) do
3: if \(\exists t \in T_R : |t_i - t| \leq \text{max\_dist}\) then
4: \(t_r = \text{argmin}_{t \in T_R} \{ |t_i - t| \}\)
5: \(t_{r_{\cap L}} = \text{argmax}_{t_r \cap t_i} \{ N_R(t_r), N_L(t_i) \}\)
6: \(T_{R \cap L} = T_{R \cap L} \cup t_{r_{\cap L}}\)
7: end if
8: end for
9: return \(T_{R \cap L}\)

Algorithm 2

Input: \(N_R, N_L, T_R, T_L\) and min_dist
Output: \(T_{R \cup L}\) (set of times)

1: \(S = T_R \cup T_L\)
2: \(T_{R \cup L} = \emptyset\)
3: while \(S \neq \emptyset\) do
4: \(P_{R \cup L} = N_R(T_R \cap S) \cup N_L(T_L \cap S)\)
5: \(p_i = \text{max}(P_{R \cup L})\)
6: \(T_{R \cup L} = T_{R \cup L} \cup t_i\)
7: \(S = S / \{ t : |t - t_i| \leq \text{min\_dist} \}\)
8: end while
9: return \(T_{R \cup L}\)

Table 2: Mean parameter values of the six algorithms using five-fold cross validation. Minimum peak amplitude values are for signal values \([0, 1]\), min-max normalized using data from all samples.

| Parameter                        | Algorithm | \(L\) | \(R\) | Sum | Diff | Intersect | Union |
|----------------------------------|-----------|-------|-------|-----|------|-----------|-------|
| Moving average smoothing         | No fusion | 0.03  | 0.03  | 0.18 | 0.02 | 0.02      | 0.40  |
|                                  | Low-level fusion | -    | -     | 0.08 | 0.02 | -         | -     |
| Peak detection                   | High-level fusion | -    | -     | 0.32 | 0.32 | -         | -     |
| Min peak amplitude (range 0-1)   | -         | 0.27  | 0.36  | 0.15 | 0.08 | 0.24      | 0.06  |
| Min window between peaks (sec)   | -         | 0.36  | 0.34  | 0.23 | 0.40 | 0.34      | 0.32  |
| Max window between peaks (sec)   | -         | -     | -     | -   | -    | 0.32      | -     |
| Min window between peaks (sec)   | -         | -     | -     | -   | -    | -         | 0.29  |

The six step detection approaches are listed below. We denote \(N_L\) and \(N_R\) the signal magnitude (norm) of left and right sensors after smoothing, respectively. We denote \(T_L\) and \(T_R\) the set of times that match the peaks of \(N_L\) and \(N_R\), respectively, as identified by peak detection.

No fusion (two approaches, one per side): Peaks from only one sensor were used, either \(T_R\) or \(T_L\).

Low-level fusion (two approaches): Fusion was performed at the raw data level after signal magnitude smoothing. Sum low-level fusion, \(N_{R+L} = \text{MovingAvg}(N_R + N_L)\), or difference low-level fusion, \(N_{R-L} = \text{MovingAvg}(|N_R - N_L|)\), were followed by peak detection to detect steps. \(T_{R+L}\) and \(T_{R-L}\) are the sets of times that match the peaks of \(N_{R+L}\) and \(N_{R-L}\).

High-level fusion (two approaches, see algorithms 1 and 2): High-level fusion consisted of signal smoothing, peak detection, and fusion (intersection or union) of detected peaks. Fusion parameters included the maximum allowable distance max_dist to be considered an intersection (upper bounded by the peak detection minimum window parameter), or the minimum allowable distance min_dist between adjacent peaks (union). In both cases, the peak with the highest amplitude was selected.

4 Results

4.1 Step count accuracy

Each one of the six algorithms were each trained using five-fold cross validation. Training was not per-task, but rather used all samples in order to evaluate algorithm robustness to different individuals and walking types. We observed that signal summation (low-level fusion) or union of peaks (high-level fusion) were better at quantifying step abundance than single side algorithms as measured by
the percent error (Figure 1a). Union fusion also had substantially higher correlation to the label (ankle step count) than single sensor methods (union, r=0.98; left sensor, r=0.78; right sensor, r=0.88), with 90% of the samples having a small step count error rate between -2.2% and 2.5% (see boxplot whiskers). Raw data fusion using difference of signal magnitudes performed poorly.

Specific walking type comparisons of the better no fusion algorithm (right side) with the best fusion approach (high-level union) highlighted the potential for robust step counting using fusion (Figure 1b). While both methods performed well in multiple walking tasks, particularly where at least one arm was constrained, the no fusion algorithm was less accurate in fast or slow walking and in simulations of pathological gait (cane). In contrast, the robustness of union high-level fusion is strikingly evident.

Figure 1: Union fusion has the lowest step counting error among sensor fusion approaches. Boxplot whiskers capture 90% of data (5th and 95th percentiles). Negative error is under counting. Left: Overall step count error. Right: Comparison of union (high-level) fusion with the better no fusion algorithm (only right sensor) per task shows the union approach is robust to diverse types of walking.

4.2 Gait phase detection

The gait phase detected by all methods was expectedly similar as all methods share the same peak detection technique (data not shown due to space limitations). Focusing specifically on union (high-level) fusion, we observed that peaks were identified relatively consistently adjacent to the toe-off phase (Figure 2). The low variation in $\Delta t$ offset relative to toe-off suggests that wrist-device fusion may enable quantification of gait asymmetries and cadence inconsistencies to a certain degree.

Figure 2: Gait phase detection by the peaks of the union (high-level) fusion approach. Left: Offset from heel strike and toe-off for all samples. Right: Offset from toe-off per walking task.

5 Conclusions

Our work has two primary contributions. First, we illustrate that mathematically simple fusion of wrist accelerometer output can overcome the shortcomings of single-wrist step counters. Further work is required to assess whether this holds in free-living environments. The second major implication of our work is the potential for dual wrist-devices to capture timing-based, gait abnormalities. As above, additional work can help evaluate this promise in patient populations.

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