Universal algorithm for exercise rate estimation in walking, cycling, and rowing using triaxial accelerometry

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Abstract: A technique that can reliably monitor exercise intensity plays an important role for the effectiveness and safety of an exercise prescription. A universal algorithm for recursive estimation of exercise rate during a variety of aerobic exercises using measurements from a body-mounted triaxial accelerometer (TA) is proposed. Information about the type of exercise is not required by the algorithm and the TA can be mounted at the same location regardless of the exercise type. The algorithm involves period detection and data fusion. Experimental results demonstrate that the algorithm is effective for common aerobic exercises.

Introduction: Rhythmic aerobic exercises which involve large muscle groups are recommended by the guidelines [1] when designing cardiorespiratory exercise for healthy adults and cardiac outpatients. By analyzing the measurements from a triaxial accelerometer (TA), exercise rates can be obtained in these exercises. Such a rate can provide a simple measure of exercise intensity that is an important parameter in exercise prescriptions [1].

The purpose of this letter is to propose a universal, simple, recursive algorithm for estimating exercise rate in a variety of exercises using a wireless body-mounted TA. The algorithm is universal in the sense that it is capable of estimating exercise rate regardless of the type of exercise. Such a universal capability is of importance for the safety of cardiac patients during rehabilitation exercise, as the guidelines [1] encourage the patients to engage in multiple activities to promote total physical conditioning. To be universal, the term *exercise rate* (ER) characterizes the fundamental frequency of the locomotion of an exercise. The term describes including, the stride rate in walking or running, pedal cadence in cycling, and stroke rate in rowing. The simple and recursive nature of the proposed algorithm is particularly useful in real-time applications, such as in cardiac pacing [2], and in regulation of heart rate during an exercise [3] as ER can be treated as a control variable in manipulating the exercise intensity. The algorithm has a wide range of potential applications; it can be used for exercise monitoring in athletics training and in rehabilitation program for the cardiac patients, and it can also be used for monitoring activities of the elderly [4] and the obese [5].

A novel feature of the proposed algorithm is that no prior information about the type of exercise and the location of the TA is required by the algorithm; the algorithm involves the same signal processing procedures. The TA can always be worn at the same location irrespective of exercise type. For instances, the algorithms proposed in [4], [6] were designed specifically for observing walking parameters and they can only track the stride rate. For various types of activities, techniques calculating the acceleration counts or the integral of acceleration signals were introduced in, e.g., [5], [7], for the purpose of predicting energy expenditure. However, these techniques cannot be used for estimating ER, namely the *frequency* of locomotion. Another novelty of the proposed algorithm is that it fuses all the measurements of a TA, giving a more robust and reliable ER estimate from some degree of redundancy of measurements.

ER Estimation Algorithm: A method for detecting fundamental frequency of a signal is to use the average magnitude difference function (AMDF), see e.g. [8]. The AMDF of a discrete signal x_t is defined by: $e_t(d) = (1/N)\sum_{i=1}^{N}|x_t(i) - x_t(i-d)|$, where $e_t(d)$ is the AMDF of lag d calculated at time index t and N is the summation window size in terms of samples. The AMDF method requires one to search for a lag $\hat{d}$ such that $\hat{d} := \min_{d_{\min}\le d\le d_{\max}}\{e_t(d)\}$. However, the technique may result in the so-called subharmonic error [8]. Thus, we propose the following search: $q = \max\left\{j : e_t(\hat{d}/j)/e_t(\hat{d}) < \beta,\ \text{for } j = 1, 2, \ldots, m\right\}$, where $m := \text{floor}(\hat{d}/d_{\min})$ and $\beta > 1$ is a pre-defined threshold. Then by using q, we define $\tilde{d} := \hat{d}/q$ and an estimate of the period of the signal x_t is given by $\tau = \tilde{d} \times T_s$, where T_s is the sampling period. To further improve the reliability of the estimate, a causal median-filter with window length L is employed for removing spikes in the period estimates, since the above search may not completely remove the sub-harmonic errors. The procedure detects the fundamental period for each of the three acceleration measurements at time instant t. The TA acceleration measurements are in fact the projections of the total body acceleration vector $\mathbf{a}_t$ on the x, y and z axes. Hence, we propose to obtain an extra period estimate by considering the acceleration vector $\mathbf{a}_t$ and the AMDF defined as follows: $e_t(d) = (1/N)\sum_{i=1}^{N} \|\mathbf{a}_t(i) - \mathbf{a}_t(i-d)\|_1$, where $\|\cdot\|_1$ is the 1-norm of a vector.

The above procedure gives $\mathbf{y}(t) = [\tau_x(t)\ \tau_y(t)\ \tau_z(t)\ \tau_{\mathbf{a}}(t)]^T$ as the four fundamental period estimates at time instant t. Since each period estimate contains some information about the ER, we propose to estimate the ER ($T(t)$), in terms of period, through the use of data fusion. Another advantage of using data fusion is that reliability is improved due to some degree of redundancy of the measurements. To perform data fusion, we consider the fusion model: for $k = 0, 1, 2, \ldots$, $T(k+1) = T(k) + w(k)$; $\mathbf{y}(k) = \mathbf{c}T(k) + \mathbf{v}(k)$; where $\mathbf{c} = [1\ 1\ 1\ 1]^T$, $T(\cdot)$ is the ER to be estimated; $\mathbf{y} = [y_1\ y_2\ y_3\ y_4]^T$ is the vector of noisy period measurements; $w(\cdot)$ is a fictitious model noise; and $\mathbf{v} = [v_x\ v_y\ v_z\ v_{\mathbf{a}}]^T$ is the measurement noise vector. The noise processes $\{w(k)\}$ and $\{\mathbf{v}(k)\}$ are assumed to be zero mean white Gaussian noise with covariance $\sigma_w(k)$ and covariance matrix $\mathbf{R}(k)$ respectively, and $E[\mathbf{v}(k)w(j)] = 0$. Our goal is to estimate $T(k)$ by using $\mathbf{y}(k)$ and the Kalman filter (KF). Let $\hat{T}(k)$ be the estimate of $T(k)$ at time k. The KF for the fusion model is given by: for $k = 1, 2, \ldots$, $\hat{T}(k) = \hat{T}(k-1) + \mathbf{K}(k)\left(\mathbf{y}(k) - \mathbf{c}\hat{T}(k-1)\right)$; $\mathbf{K}(k) = p^-(k)\mathbf{c}^T\left(\mathbf{c}p^-(k)\mathbf{c}^T + \mathbf{R}(k)\right)^{-1}$; $p^-(k) = p^+(k-1) + \sigma_w(k-1)$; and $p^+(k) = (1 - \mathbf{K}(k)\mathbf{c})p^-(k)$. The filter is initialized by $\hat{T}(0) = T_0$ and $p^+(0) = E[(T_0 - \hat{T}(0))^2]$. The covariance of $\{w(k)\}$ is assumed to be constant, namely $\sigma_w(k) = \sigma_w$, and the matrix $\mathbf{R}(k)$ is time-varying and defined as follows: for $i \neq j$, $\mathbf{R}_{i,j}(k) = 0$; and for $i = j$, $\mathbf{R}_{i,j}(k) = r_i(k) =$

$\exp(\eta|y_i(k) - \bar{y}(k)|)$; where $\eta > 0$ and $\bar{y}(k) :=$ median($\mathbf{y}(k)$). The idea behind this choice of $\mathbf{R}(k)$ is that when $y_i(k)$ is very different from the median $\bar{y}(k)$, indicating that this particular measurement $y_i(k)$ may not be reliable, then $r_i(k)$ will be a significantly large value to reflect this uncertainty. As a result, the measurement $y_i(k)$ will only have a small contribution to the filter equation.

The above proposed $\mathbf{R}(k)$ allows us to disregard any measurement $y_i(k)$ that is far way from $\bar{y}(k)$. However, it is based on the assumption that $\bar{y}(k)$ is reliable. If $\bar{y}(k)$ is unreliable, we may wrongly think a measurement that is close to $\bar{y}(k)$ reflects the actual value of $T(k)$. To avoid this, we propose to compare the current $\bar{y}(k)$ with its previous values, and we introduce the follow condition: for given threshold $\gamma > 0$ and previous ρ values of $\bar{y}$, if $|\bar{y}(k) - z(k)| > \gamma$, where $z(k) :=$ median $(\{\bar{y}(k-1), \bar{y}(k-2), \ldots, \bar{y}(k-\rho)\})$, then we set the KF gain as $\mathbf{K}(k) = 0$.

Validation & Results: Four experimental subjects were requested to exercise on a treadmill, a cycle ergometer, and a rowing machine at three specified ER's. The algorithm was tested with the four subjects each doing all three types of exercise. The TA for measuring the body's accelerations was a single wireless unit. No matter the type of exercise, the TA was always mounted on the right waist of the exerciser. The proposed algorithm calculated the ER, in terms of period, every 2 seconds. The TA recorded the body's accelerations in separate channels with a sampling frequency of 50 Hz. To remove noises, the raw signals were median and low-pass filtered. A separate TA was employed to determine the actual ER for validation. This second TA was for validation only and was strategically located depending on the type of exercise to maximally detect the ER. It was mounted on the right shin of a subject during walking and cycling exercises, and was mounted under the sliding seat during rowing exercise. The signals from this second TA were manually analyzed to extract the actual ER, and the rates calculated in this way were treated as the reference ER. For the proposed algorithm, the design parameters were chosen as follows: AMDF search range $d_{\min} = 0.5$ and $d_{\max} = 4$ secs; threshold for period detection $\beta = 1.4$; causal median filter window length $L = 3$; KF parameters $\sigma_w = 0.05$, $\eta = 10$, $T_0 = 1.5$, $p_0 = 6.25$; and outliers detection parameters $\rho = 5$, $\gamma = 0.5$.

Figure 1 shows the ER estimation results of a subject. The results from all the subjects were analyzed using the limits of agreement analysis method [9]. Table I shows the bias, random error, and limits of agreements in each type of exercise and for all exercises. The overall bias and random error between the estimated and reference ER's were -0.008 secs and 0.071 secs respectively, and the limits of agreement were 0.063 secs and -0.078 secs, demonstrating that there is a good agreement between the two ER's. Table I also shows that there is a strong and significant correlation between the estimated and reference ER's ($r > 0.954$, $P < 0.001$).

Conclusion: A novel recursive algorithm for estimating the ER by using a body-mounted TA was proposed. The algorithm is universal in the sense that no prior information about the type of exercise is needed. It has been experimentally validated for estimating the ER's in common aerobic exercises with the TA mounted at the same location irrespective of exercise type. The algorithm can be applied to the on-line activity monitoring in rehabilitation exercise for cardiac patients, and in training exercise for the athletics, the elderly and the obese. Using the proposed algorithm, an acoustically-paced exercise control system is currently under development for the regulation of HR during a variety of exercises, in order to improve the effectiveness and safety of an exercise prescription.

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	r	Bias	SD	Upper	Lower
Walking	0.993	-0.011	0.022	0.011	-0.034
Cycling	0.989	-0.011	0.030	0.020	-0.041
Rowing	0.954	-0.002	0.116	0.115	-0.118
All	0.995	-0.008	0.071	0.063	-0.078

TABLE I
RESULTS FROM THE LIMITS OF AGREEMENT ANALYSIS OF POOLED DATA FROM 4 SUBJECTS: r =CORRELATION COEFFICIENT $(P < 0.001)$, BIAS=MEAN DIFFERENCE (IN SEC), SD=STANDARD DEVIATION OF DIFFERENCE (IN SEC), UPPER AND LOWER ARE THE 95% CONFIDENCE INTERVALS FOR THE UPPER AND LOWER LIMITS OF AGREEMENT (IN SEC), RESPECTIVELY.

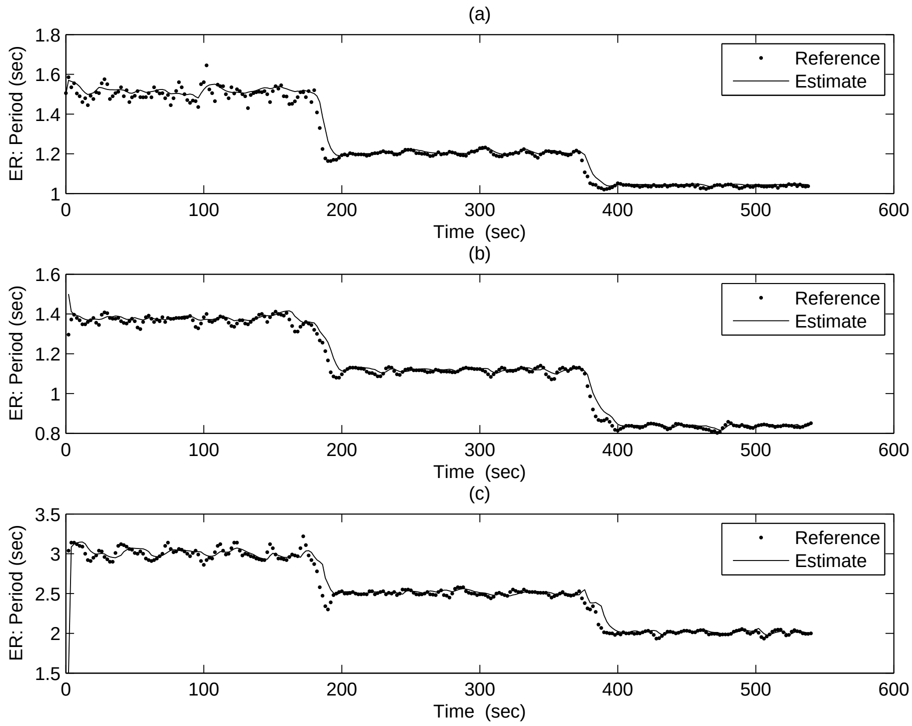

Fig. 1. Estimated (solid) and reference (dots) ER of a subject: (a) walking; (b) cycling; (c) rowing.