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# Event-based sampling for reducing communication load in realtime human motion analysis by wireless inertial sensor networks

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**Abstract:** We examine the usefulness of event-based sampling approaches for reducing communication in inertial-sensor-based analysis of human motion. To this end we consider realtime measurement of the knee joint angle during walking, employing a recently developed sensor fusion algorithm. We simulate the effects of different event-based sampling methods on a large set of experimental data with ground truth obtained from an external motion capture system. This results in a reduced wireless communication load at the cost of a slightly increased error in the calculated angles. The proposed methods are compared in terms of best balance of these two aspects. We show that the transmitted data can be reduced by 66% while maintaining the same level of accuracy.

**Keywords:** adaptive sampling; event-based sampling; human motion analysis; IMU; inertial sensor networks; send-on-area; send-on-delta.

## 1 Introduction

Human motion analysis has a multitude of applications in sports, rehabilitation, orthopedics and similar fields. The gold standard for clinical usage, i.e. optical motion analysis, is expensive and restricted to laboratory environments. Wireless inertial sensor networks have recently become popular as an alternative, enabling ambulatory human motion analysis at much lower costs. However, in such networks large amounts of data must be transmitted wirelessly, which represents a limiting factor<sup>1</sup> in realtime applications, such as biofeedback, neuroprosthetics and

<sup>1</sup> Wireless communication requires bandwidth and energy, which are both limited resources in practice.

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feedback control of active orthoses. One possible solution is to use a more sophisticated sampling and transmission strategy instead of standard fixed-rate sampling.

In contrast to standard sampling, in which samples are transmitted at a fixed rate, the core idea of event-based sampling is to only transmit samples when certain events, which are derived from the measured signals, occur.<sup>2</sup> Different event-based sampling methods have been proposed; see [1, 2] for an overview. Send-on-delta [3] is a basic sampling scheme, where a threshold on the difference between the current sample and the last sent sample is used as the transmission criterion. When integrating this difference over time the send-on-area scheme is obtained, which was proposed in [4] and [5]. In the context of state estimation, innovation-based triggering [6, 7] and variance-based triggering [8] have been proposed, where an update is sent whenever the estimator innovation (i.e. the difference between a measurement and its prediction) or its variance exceeds a threshold. These algorithms have also been used for feedback control, such as stabilization of a balancing sculpture [6].

Two related approaches are called adaptive sampling and model-based active sampling [9]. In adaptive sampling, the sampling rate is adjusted based on the signal history. See [10] for a realization of adaptive sampling as an analog circuit and [11] for an example of adaptive sampling applied to general sensor networks. For model-based active sampling, a model is used to predict sensor readings. Those predictions are either used to decide if a measured sample should be transmitted or even to avoid activating the sensor at all. An example using autoregressive (AR) models can be found in [12].

In the present contribution, we examine the usefulness of event-based sampling approaches for inertial-sensor-based analysis of human motion. To this end we consider realtime measurement of the knee joint angle

<sup>2</sup> The word sampling in the term event-based sampling can be misleading, since the term commonly refers to the event-based transmission of a signal sampled at a fixed rate.

during walking. We employ a recently developed sensor fusion algorithm [13] that avoids the use of magnetometer readings. Applying this algorithm to a large set of experimental data yields an average root-mean-square error (RMSE) of about  $3^\circ$  if standard full-rate sampling is used. We propose four different event-based sampling algorithms, apply them to the recorded data sets in a simulated-online manner and feed the resulting signals to the joint angle calculation algorithm. This leads to data compression (i.e. a lower communication load) at the cost of an increased error in the calculated angles. The proposed methods are compared in terms of best balance of these two aspects.

## 2 Proposed methods

First, consider the following standard sampling case: A sensor measures a vector-valued signal at a fixed sampling rate and transmits it with a fixed sampling rate to a receiver, which then processes the data. In contrast to this standard case, we introduce an event-based sampling protocol that defines under which conditions the sensor sends the current measurement sample to the receiver. At every sampling instant  $t$ , the sensor evaluates a transmission criterion based on current and old measurements. If the criterion is fulfilled, the current sample is sent. If a sample is sent, it is used directly for data processing. If no sample is sent, the receiver reuses the last received sample instead<sup>3</sup>, such that the reconstructed data exhibits the same constant sampling rate as the original data. The following two approaches are considered:

**Send-on-delta (SOD):** In analogy to [3], the sample is sent if the Euclidean norm of the difference between the current measurement and the last sent measurement exceeds a certain threshold.

**Send-on-area (SOA):** In analogy to [4], the Euclidean norm of the aforementioned difference is added up. If this sum exceeds a certain threshold, the current sample is sent and the sum is reset to zero.<sup>4</sup>

**Decreasing threshold:** In their current form, both approaches can result in very long communication gaps. This might be undesirable from an application point of view. Therefore, we propose the following extension that

can be combined with both send-on-delta and send-on-area: For each series of consecutively skipped samples, the threshold  $c$  is linearly decreased in  $n \in \mathbb{N}_{\geq 0}$  steps, assuring that at most  $n$  consecutive samples are skipped. For example, with  $n = 3$  the actual thresholds are  $c$ ,  $\frac{2}{3}c$ ,  $\frac{1}{3}c$  and 0.

For the present application, consider two or more Inertial Measurement Units (IMUs), which wirelessly transmit their acceleration  $\mathbf{a}(t) \in \mathbb{R}^3$  and angular rate  $\mathbf{g}(t) \in \mathbb{R}^3$  readings to a receiver, which then uses a realtime algorithm to estimate motion parameters from the reconstructed data. Each IMU applies either send-on-delta or send-on-area with either constant or decreasing threshold to the current measurements  $\mathbf{a}(t)$  and  $\mathbf{g}(t)$  separately. If one or both criteria are fulfilled, the IMU sends a combined data sample consisting of both  $\mathbf{a}(t)$  and  $\mathbf{g}(t)$  to the receiver.<sup>5</sup>

## 3 Experimental evaluation

### 3.1 Simulated-online data analysis

In our test setup, two IMUs per leg are employed to calculate the knee angle for each leg using the algorithm described in [13], which works roughly as follows: The angle  $\alpha_{\text{gyr}}(t)$  is calculated from the angular rate  $\mathbf{g}(t)$  and the angle  $\alpha_{\text{acc}}(t)$  from the acceleration  $\mathbf{a}(t)$ . The angle  $\alpha_{\text{gyr}}(t)$  is accurate but drifting, while  $\alpha_{\text{acc}}(t)$  does not exhibit drift, but is less accurate, especially during fast movement. Sensor fusion of both angles is used to obtain the final angle  $\alpha_{\text{IMU}}(t)$ . For details, please refer to [13].

A large collection of walking data, consisting of 396 trials from 11 healthy subjects, along with reference angles  $\alpha_{\text{opt}}(t)$  obtained by an optical 3D motion capture system, is available. If we use standard full-rate sampling, the RMSE<sup>6</sup> between IMU angles and reference angles is  $3.18^\circ$ . The proposed algorithms are implemented as follows: The recorded original IMU data is used as input for a simulated sender, which evaluates the described criteria. A simulated receiver feeds the reconstructed data to the knee angle calculation algorithm (cf. Figure 1).

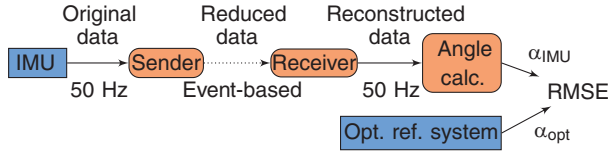
We consider four different sampling methods as shown in Table 1. Send-on-area is only applied to the angular rate  $\mathbf{g}(t)$ . The thresholds  $a_{\text{th}}$  and  $g_{\text{th}}$  are varied from zero to a manually chosen maximum in a  $16 \times 16$  grid.

<sup>3</sup> Estimating the missing sample by linear extrapolation of the last two samples was found to yield no advantage in the present case.

<sup>4</sup> Using the norm of the summation of the difference (similar to the approach described in [5]) gives very similar results to the approach proposed above.

<sup>5</sup> The overhead of data transmission typically exceeds the actual payload, hence we always send both measurements together.

<sup>6</sup> The overall RMSE is calculated by averaging the RMSE values of all trials.



**Figure 1:** Online event-based sampling is simulated by using recorded IMU data as input to an event-based sender. The receiver reconstructs the data, which is fed to the angle calculation algorithm and the results are compared to angles obtained by optical motion analysis.

**Table 1:** Event-based sampling methods. Send-on-delta (SOD) is always used for the acceleration  $\mathbf{a}(t)$ , while send-on-delta or send-on-area (SOA) is used for the angular rate  $\mathbf{g}(t)$ . When decreasing thresholds are used, this applies to both  $\mathbf{a}(t)$  and  $\mathbf{g}(t)$ .

Method	$\mathbf{a}(t)$	$\mathbf{g}(t)$	Thresholds $\alpha_{th}$ and $g_{th}$
Method 1	SOD	SOD	constant
Method 2	SOD	SOA	constant
Method 3	SOD	SOD	decreasing, $n = 5$
Method 4	SOD	SOA	decreasing, $n = 5$

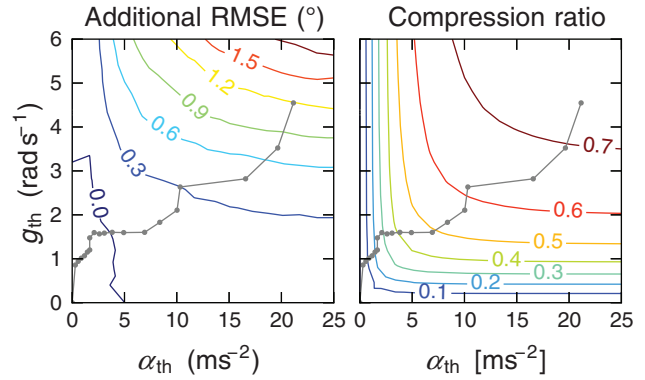
For comparison, we also test sending only every second and third sample, effectively downsampling the signal.

### 3.2 Parameter optimization and performance evaluation

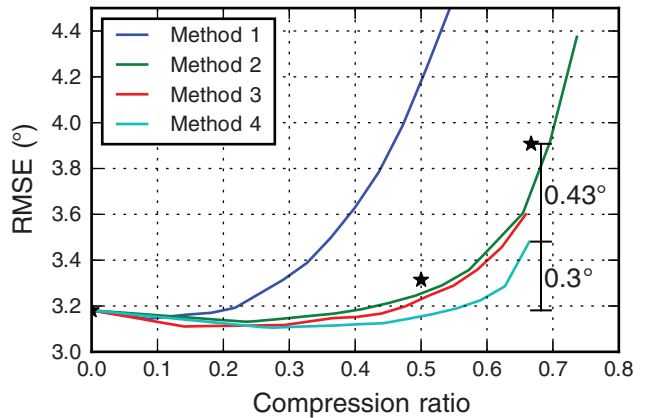
For evaluation, we analyze how the RMSE with respect to the optical reference angles changes when event-based sampling is applied. For each method, we calculate the RMSE and the compression ratio when varying the thresholds  $\alpha_{th}$  and  $g_{th}$  independently, as depicted in Figure 2. The compression ratio is calculated as

$$\frac{\text{number of skipped samples}}{\text{number of skipped samples} + \text{number of sent samples}}.$$

To compare the methods, we create a plot of the (smallest achievable) RMSE over the compression ratio. Figure 3 compares all four tested methods. This plot is obtained in the following way: The  $16 \times 16$  grids of the RMSE and the compression ratio are interpolated to a much higher resolution. We then split the range from zero to the maximum compression ratio in 20 intervals of equal size. For each interval, we find the pair of RMSE and compression ratio which has the smallest RMSE and a compression ratio within the given interval. Connecting those pairs results in the curves shown in Figure 3. For illustration, the connection line of the described pairs (for Method 2) is shown in the contour plot in Figure 2.



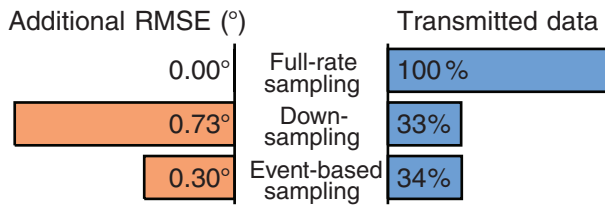
**Figure 2:** Contour plot showing the additional RMSE (i.e. the RMSE obtained with event-based sampling minus the RMSE obtained with full sampling) and the compression ratio obtained using Method 2 when varying the two thresholds  $\alpha_{th}$  and  $g_{th}$ . The gray line shows the trajectory used to generate the respective curve in Figure 3.



**Figure 3:** RMSE over compression ratio for different event-based sampling methods. The stars mark the RMSE when downsampling the sensor data by a factor of 2 and 3.

## 4 Results and discussion

Send-on-delta event-based sampling surprisingly performs far worse than simple downsampling. Using send-on-area for the angular rate significantly reduces the error, which is less surprising, since the calculation of  $\alpha_{gyr}$  involves integration of the angular rates. Compared to downsampling, however, the algorithm yields only slightly better results. The same is true for using send-on-delta in combination with decreasing thresholds. However, when combining send-on-area sampling with decreasing thresholds (Method 4), the error can be reduced further. For example, it is possible to reduce the transmitted data by 66% while increasing the total average RMSE by only  $0.3^\circ$ , as shown in Figure 4.



**Figure 4:** Compared to standard full-rate sampling, send-on-area sampling with decreasing thresholds (Method 4) can reduce the transmitted data by 66% while increasing the total average RMSE by only 0.3°.

## 5 Conclusion and outlook

We presented four event-based sampling algorithms for human motion analysis via inertial sensor networks in realtime applications like biofeedback, neuroprosthetics and the control of active orthoses. To test the proposed methods, we applied them to a large collection of walking data in a simulated-online manner and analyzed how the error increases when less data samples are transmitted. The results show a potential for greatly reducing wireless communication load with a low impact on accuracy. For example, it was found that 64% of the transmitted samples can be dropped while increasing the RMSE of a knee joint angle by only 0.3°.

The presented methods were tested for one very specific scenario. Considering other setups and algorithms for human motion analysis is planned for future work. Employing model-based predictions [6, 8] instead of zero-order hold has the potential for reducing wireless communication even further [14]. Investigating the usefulness of such approaches for the considered application is subject to future research.

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