5G-Based Body Sensor Network for Real-Time Feedback in Running

Sebastian Mayr[a] and Harald Rieser[b]
Human Motion Analytics, Salzburg Research Forschungsgesellschaft mbH, Salzburg, Austria

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Abstract: Immediate feedback is vital in sports and motor learning. Traditionally, coaches provide this feedback. However, recent developments in wearable sensing and feedback devices, state-of-the-art processing algorithms and sensor data integration allow for new applications and insights. While this allows for more direct feedback, it also introduces new demands on feedback systems in terms of network transmission speed, energy consumption and needed calculation power. The 5G networking standard is a promising technology to address these issues. It promises reduced energy usage, high availability, latency in the low millisecond range and high data rates up to 10 Gbps. Despite these characteristics, there has not been much research on the use of 5G in sports biofeedback systems. Therefore, this work aims to assess the usability of 5G for a real-time feedback system in the sports context. We did this by developing a distributed feedback system for the assessment of running gait symmetry. The system utilizes internal smartphone IMU as sensors and employs a 5G infrastructure for data transmission to an offsite server for the calculation of running metrics and generation of the feedback signal. Pilot tests, using the feedback system, showed mean roundtrip times of $140.14ms$ ($sd = 14.47ms$) for outdoor use and $128.92ms$ ($sd = 25.83ms$) for indoor use. These results indicate that promised low latencies by the 5G standard are currently not reachable outside of controlled testing environments. Nonetheless, as these times are below average reaction times in recreational athletes ($150ms$) it is still promising for real-time feedback applications in running.

1 INTRODUCTION

Immediate feedback is an essential part of motor learning. It is especially beneficial to get feedback directly after a particular movement is performed (Sigrist et al., 2013). For an athlete, this feedback task was traditionally performed by a coach. However, in recent years wearable sensing devices, called wearables, have been adopted by consumers and sports scientists alike. The huge benefit of these devices is their mobility. They allow for data acquisition during exercise and often provide simple descriptive statistics and summaries of these activities in a wide range of applications.

One particular example in the field of athlete health monitoring is described by James et al. In their study a combination of temperature-, heart rate- and movement sensors were used for the detection of hyperthermia in running under extreme conditions during the Tokyo Olympics in 2020. Here the collected data was transmitted in real-time to stakeholders like coaches and medical staff for monitoring of the athletes health status. (James et al., 2024).

The use of wearable sensors for concurrent feedback to the athlete during movement is less frequently considered. So-called real-time feedback systems try to perform such an observation and correction task on a quantitative level. Generally, they consist of layers for sensing, data processing, transmission of data, and delivery of feedback. Depending on the use case these tasks are performed by networks of independent units distributed on the human body that communicate via wireless channels (e.g. Bluetooth or WiFi). These networks are called Body Area Networks or Body Sensor Networks (BSN). Commonly, BSN are constructed in a star topology (Lai et al., 2013), which means they incorporate multiple types of sensors for data acquisition that transfer data to a central hub where computations are performed, and the feedback is generated. A separate actuator unit delivers this feedback in a suitable way to the user who can optimize the assessed action by adapting to the external feedback. Although BSN have been around for a long time there are still challenges. Lai et. al list improvement of wearability and reduction of

[a] https://orcid.org/0000-0002-7540-155X
[b] https://orcid.org/0000-0003-1407-4601

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energy consumption as the most pressing challenges (Lai et al., 2013). Engineers and researchers are trying to find the right balance between optimal sensor sample rates, optimized data transmission between nodes, efficient data processing on-site, and downsizing of the devices and therefore reduction of battery capacity.

One approach to reduce energy consumption is to outsource the calculations. In general, local computation is more efficient than transmission of data and off-site calculation. However, with the increasing computing requirements of new data processing, and, in some cases, machine learning algorithms, the limited processing power of local sensor nodes might be no longer sufficient. In such a case, sending raw data to a high-performance off-site server, for calculating results and sending them back for feedback delivery, seems to be an interesting concept to consider. This approach allows for scaling computation resources based on current demand.

Sending high amounts of data between real-time feedback systems and an off-site calculation server needs a stable connection with high throughput, low-latency and, for data collection in the field, this connection also needs to be wireless. The 5G mobile telecommunication network standard offers new possibilities for BSN implementations. Its eight specification requirements promise a plethora of improvements over current mobile communication network technology: (i) 100% coverage, (ii) Up to 10 Gbps data rate, (iii) one-millisecond latency, (iv) 1000× bandwidth per unit area, (v) Up to 100x number of connected devices per unit area, (vi) 99.999% availability, (vii) 90% reduction in network energy usage and (viii) Up to 10-year battery life for IoT devices (Attar et al., 2022).

Low latency, reduced energy usage and the proposed increase in battery life, as well as the increased transmission range in comparison to Wi-Fi, Bluetooth or BLE, are interesting propositions for the development of new 5G-based BSN systems.

Therefore, in this work we want to assess the suitability of 5G for body area networks in a sports context. The remainder of this paper is structured in 4 sections. In section 2 we describe the sensors, 5G infrastructure, how the BSN was implemented and the target metric of the feedback system. In section 3 the results are presented and discussed. Section 4 provides final conclusions and a future outlook.

2 METHODS

2.1 Infrastructure

The system consists of three main parts (Figure 1). First, the local BSN, that is made up of two smartphones that act as sensors, actuators, and transmission devices. Second, an off-site server that is connected to the BSN via a 5G network. Here, all calculations of running metrics and feedback are performed. Third, a data-logging service and a dashboard to display the collected data, which is accessible via public internet.

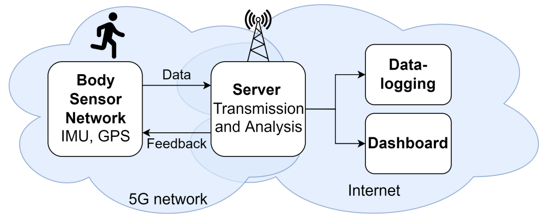

Figure 1: Overview of system components.

Data is transmitted over a commercial-grade private 5G-Standalone (5G-SA) network that operates in Time Division Duplex (TDD) mode within the n78 frequency band (3500 MHz) with 80 MHz bandwidth. This TDD setup utilizes a subcarrier spacing (SCS) of 15 kHz and follows Time Division-Long Term Evolution (TD-LTE) frame configuration 2, incorporating subframe configuration 6 with a downlink-uplink ratio of 3:1, in compliance with regulatory requirements (Telekom-Control-Kommission (TKK), 2018; Tanenbaum and Wetherall, 2010). The 5G-SA network consists of MIMO-capable outdoor and indoor cells in a remote radio head setup.

The off-site server is connected to the 5G core with a low latency, high-speed cable connection to minimize transmission time in this part of the network. All time-critical back-end components are located on this server:

- A messaging subsystem/server (based on MQTT). For this server, we opted for a low-latency configuration. Therefore low quality of service (QoS) levels were chosen.
- The algorithms for data analysis (see Section 2.3)

For non-time-critical sections in the back-end, a logging service and a dashboard providing information in near-real-time on an additional server were implemented. The logging service was connected to the messaging service and collected all sent data. The dashboard provides a web-based user interface for visual display of the collected data. Physically, these services were provided on a server accessible by a standard internet connection.

2.2 Sensors

Dedicated consumer grade 5G IMU sensors are not available on the market yet. As modern smartphone-integrated IMU deliver reliable and valid measurement results compared with a gold standard (Grouios et al., 2022), we used mobile phones as sensing, actuation and transmission devices in the BSN. Most current smartphones are capable of receiving and sending 5G-SA on a hardware level. However, manufacturers often fail to deliver the required software updates. For data collection, we used a Moto g5G and Moto edge30 smartphone (Motorola Mobility LLC, USA) to collect acceleration and angular velocity in three axes as well as the GPS signal. The devices were placed on the lower back at the 5. lumbar vertebrae and the lateral side of the upper Tibia – directly under the knee. Positioning of the sensors is depicted in Figure 2.

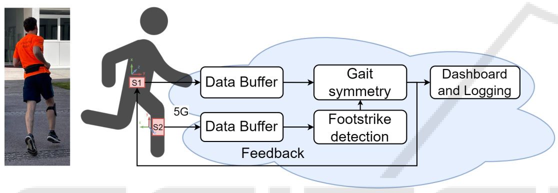

Figure 2: Sensor position on the body: Sensors are placed at the 5. lumbar vertebrae and lateral side of the upper Tibia – directly under the knee (left).
Schematic overview of calculation of running gait metrics and feedback (right).

2.3 Movement Metric – Gait Symmetry

In their review of feedback systems in running van Hooren et. al pointed out that modification of running technique via real-time feedback can reduce injury risk and increase performance. Suitable for feedback are parameters related to injuries or performance, that can be measured accurately and are easily modifiable (Van Hooren et al., 2020). Hence, for testing this prototype feedback system, we used the running gait symmetry metric employed by Lee et. al, where a single sacral-mounted IMU is used to assess the symmetry of the COM vertical acceleration between the left and right step within each stride (Lee et al., 2010). This metric is easily measurable, and according to Radzak et. al, increasing asymmetry is linked to fatigue (Radzak et al., 2017).

Gait symmetry is calculated as the ratio of COM vertical acceleration at the time of foot strike of the left and right step during a single stride.

$$Symmetry = \frac{a_{COM\_right} - a_{COM\_left}}{a_{COM\_right}} \quad (1)$$

A positive symmetry score indicates a greater acceleration during the right step, whereas a negative score denotes a dominance of the left step. Values near 0 occur when the acceleration on the left and the right are similar. To foster comprehensibility for the users, the symmetry score was min-max normalized between $a = -1$ and $b = 1$. The normalization was performed according to equation 2.

$$Symmetry_{normalized} = \frac{2 \cdot (x - \min(x))}{\max(x) - \min(x)} - 1 \quad (2)$$

For foot-strike detection we used two methods. First, we used the mediolateral hip acceleration to distinguish between left and right steps. According to the inverted pendulum model by Zijlstra and Hof, COM is accelerated to the right during a left step and to the left during a right step due to the tilting motion of the hips (Zijlstra and Hof, 2003). In addition to this method we apply a second IMU on the right shin for the detection of a right reference step by a simple peak finding algorithm based on the comparison of neighboring values (Virtanen et al., 2020), which we consider as the starting point of a stride.

Data is continuously streamed from the sensors to the off-site server. In regular intervals, the buffered data is evaluated for step events. A subsequent calculation of the step symmetry is performed on the last 10 steps. Figure 2 and Algorithm 1 show this schematically.

Data: IMU Data
Result: Feedback Signal
while *Data is sent to server* **do**
  Collect data from cache
  Calculate anterior-posterior- and mediolateral acceleration
  Calculate total acceleration of leg sensor data
  Calculate steps from acceleration data of shin-mounted IMU
  Calculate steps from acceleration data of sacrum-mounted IMU
  Calculation of step symmetry (equation 1)
  Scale step symmetry between -1 and 1 (equation 2)
  Publish feedback to device
end

Algorithm 1: Schematic calculation of the running gait symmetry.

2.4 Android Application

The implemented android application (see Figure 3) had four main purposes:

1. Collect IMU data (accelerometer and gyroscope) and GPS (not used by the algorithms) from the smartphone
2. Synchronize data collection between devices (start/stop of data collection, local time of the devices)
3. Send data to the server to further analyze the IMU data
4. Log Round Trip Times for upload and feedback

For data collection, the standard Android Sensor APIs were used. The sample interval for the accelerometer and gyroscope was configured with 10ms (100Hz), for GPS the interval was 1s. Collection was started only on the main device, the secondary device was started automatically by a control interface that was provided via the 5G network. Additionally, time synchronization (based on Network Time Protocol - NTP) via this control interface was realized to minimize time drift between devices involved. Collected data were sent to the server by both devices, where it was analyzed using the aforementioned algorithms. The results were sent back to all devices using a result channel, and results (with timestamps) were logged and presented to the users.

Figure 3: Android Application for data collection.

2.5 Testing

For a demonstration of the functionality of the system, it was tested by a single subject in an indoor and outdoor environment. For the outdoor test, the subject ran a round course with a length of 130 meters 5 times. The indoor test was performed 10 times in a straight corridor of 20 meters.

3 RESULTS AND DISCUSSION

The average time taken to deliver a feedback signal to the user varied between the settings. During the outdoor run, the mean time was $140.14ms$ ($sd = 14.47ms$). In contrast, with the indoor antenna, the mean time was $128.92ms$ ($sd = 25.83ms$).

In real-time feedback, there is a limit for the minimal achievable feedback delivery time, which Umek and Kos call the biofeedback delay (Umek and Kos, 2016). It consists of the feedback loop delay (FLD) and the reaction time delay (RTD). The former is composed of the communication delays from the sensors to the processing unit and from there to an actuator as well as the processing time delay itself. By using a 5G network for data transmission the communication delays can be reduced and by using an off-site server for time-critical data processing the processing delay can be minimized.

Average marathon runners run with a cadence of 180 steps per minute (Tenforde et al., 2019), which roughly amounts to making a step every $330ms$. As the mean reaction time of an average athlete is $150ms$ (Umek and Kos, 2016) a FLD smaller than $330ms–150ms = 180ms$ is needed to enable the runner to react properly to the feedback signal within the next stride. The biofeedback delay measurements in the in- and outdoor setting fall below this theoretical threshold by around 40ms to 50ms (see Figure 4). These results indicate the suitability of 5G data transmission in distributed BSN applications in running.

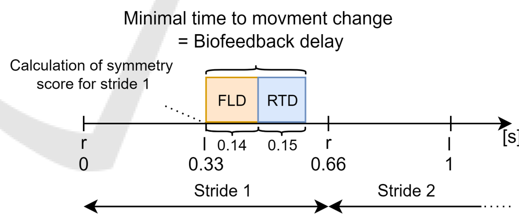

Figure 4: Minimal time to initiation of movement change is the sum of feedback loop delay (FLD) and reaction time delay (RTD).

4 CONCLUSION

Although 5G does not meet expectations in terms of low-latency, measurements with the developed real-time feedback system show its usability for running applications. Since the described BSN-based biofeedback system is merely a demonstrator, there are several areas that could be improved. One limitation is seen in the used hardware. Naturally, smartphones have a higher weight and exhibit different inertia than smaller, dedicated IMU measurement systems. We tried to counteract this behavior by fixing the sensor as securely as possible to the subject without hindering the runner. Since there are no consumer-ready 5G IMU sensors available the choice of smartphones as a replacement was only pragmatic.

One of the benefits of a distributed BSN is the increased processing power on the off-site processing device. Nonetheless, the gait-symmetry algorithm can hardly be described as very resource-intensive. It would certainly be possible to do the same calculations on the smartphones themselves. This was done intentionally, as the point of this work was mainly to assess the overall performance of a distributed 5G-based BSN biofeedback system.

In the future it would be interesting to leverage the increased (off-site) processing power and include more resource intense machine learning algorithms and new physiological sensor data like skin temperature, power or heart-rate.

Another critical point is the fact that the system was tested with only one BSN in the 5G network. This was done to eliminate potential interactions of devices and effects on the performance of the 5G network. In the future, a comparison of the behavior of the network and the time delays in scenarios with several simultaneously active devices would be interesting.

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