Sensor Signal Processing for Biofeedback Applications in Sport

Anton Umek, Anton Kos, and Sašo Tomažič
Faculty of Electrical Engineering, University of Ljubljana, Slovenia
anton.umek@fe.uni-lj.si, anton.kos@fe.uni-lj.si, saso.tomazic@fe.uni-lj.si

***Abstract*—This article explains technological challenges of real-time biofeedback in sport. Motion tracking systems, in connection to the biomechanical biofeedback, help in accelerating motor learning. Requirements about various parameters important in real-time biofeedback applications are discussed. Studies are done on specific biofeedback problems in various sports. Problems addressed are sensor accuracy, movement dynamics, system data rate, and processing demands. Inertial sensor tracking system accuracy is tested in comparison with a high performance optical tracking system. Sensor signal acquisitions and real-time processing challenges, in connection to biomechanical biofeedback, are presented.**

I. Introduction

Technology and science are being increasingly valued in modern sports. They offer new knowledge, expertise, and tools for achieving a competitive advantage. One such example is the application of biomechanical *biofeedback systems*. In this paper, the word biofeedback denotes a body activity in the sense of physical movement and it is classified as a biomechanical movement biofeedback [1].

One of the most common uses of biomechanical biofeedback is motor learning in sports, recreation, and rehabilitation [2]-[6]. A combination of wearable devices and ubiquitous computing can provide the means for the mobile implementation in motor learning tasks. The process of learning new movements is based on repetition [1]. Numerous correct executions are required to adequately learn a certain movement. Biofeedback is successful if the user is able to either correct a movement or abandon its execution given the appropriate biofeedback information.

The concurrent biofeedback can reduce the frequency of improper movement executions and speed up the process of learning the proper movement pattern. Such movement learning methods are suitable for recreational, professional, and amateur users in the initial stages of the learning process [2].

The general configuration of the biomechanical biofeedback system is illustrated in Figure 1. It includes sensors, a processing device, a biofeedback device, and communication channels. Together with a user they form a biofeedback loop.

Sensors represent the capture side of the system and are usually attached to the user's and/or integrated in sport equipment (sport shoes, tennis rockets, golf clubs, boots, skis, ski-boards). They are the source of different type of signals and data used by the processing device.

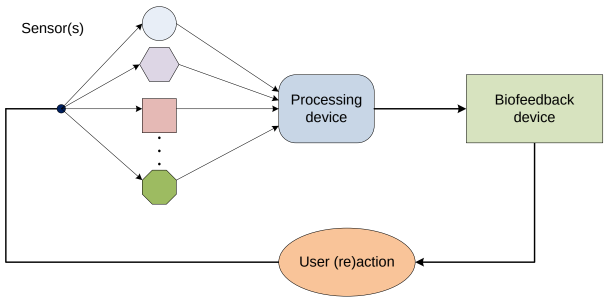

Figure 1. Architecture and operation of a biomechanical biofeedback system. Multiple sensors feed their signals to the processing device for real-time signal analysis. Analysis results (biofeedback signals) drive the biofeedback device activity. User's (re)action alters sensor signals, thus closing the biofeedback loop.

Motion capture systems employ various sensor technologies for motion acquisition. High precision motion tracking systems are camera based systems that use passive or active markers for determining their position in space and time. Inertial sensor based motion tracking systems are generally mobile and have no limitation in covering space. Modern inertial sensors are miniature low-power devices integrated into wearable sensor devices. Sport equipment sensory can be supplemented with flex sensor, force sensors, pressure sensors, etc.

The *processing device* is the core of the system. The processing device analyses sensor signals, generates, and sends feedback signals to the biofeedback devices. The employed processing devices should have sufficient computational power. While this is generally not critical with terminal biofeedback that uses post-processing, it is of outmost importance with concurrent biofeedback that uses real-time processing. When sampling frequencies are high, this demand can be quite restricting, especially for local processing devices attached to the user.

The *biofeedback device* uses human senses to communicate feedback information to the user. The most commonly used senses are hearing, sight, and touch. It is desirable to use the sense with the least cognitive load induced by other activities. For skiing learning support application illustrated in Figure 2, headphones can be used as a simple feedback device. In more complex biofeedback applications audio feedback can be supplemented with visual information by using a head-up display helmet.

Communication channels enable communication between biofeedback system devices. Although wireless communication technologies are most commonly used, wired technologies can also be used if processing device is installed locally.

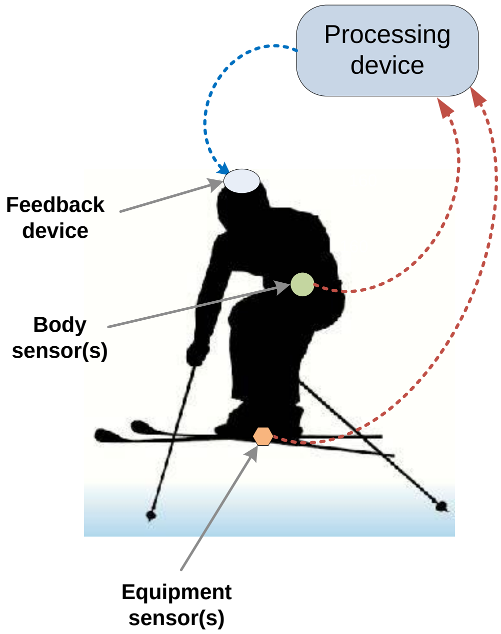

Figure 2. Skiing assistant biofeedback concept. User movement and equipment performance are captured by sensors and their signals are sent to the processing device for analysis. Feedback device can use one or more human modalities: audio (headphones) and visual (helmet with integrated head-up display).

II. Challenges in Real-Time Biofeedback

An ideal real-time biomechanical biofeedback system is an autonomous, wearable, lightweight system with large enough number of sensors to capture all the important motion parameters. Sensor signals exhibit high enough sampling frequency and accuracy. Processing is done instantly and the feedback modality is chosen in a way that it is not interfering with the principal modality of the motion. The main challenges in this effort are various and often contradictory. For example, under the constraints of technology, the ideals of being wearable and lightweight contradict the ideals of autonomy and processing power because of the battery time.

The first challenge is to achieve the desired accuracy of motion capture. Inaccuracies and errors present in various capture systems limit the usability in certain cases. For example, the direct use of MEMS accelerometers for position tracking is problematic because even a small inaccuracy in sensor readings will induce a rapid, square-time positional error.

Another challenge is the sampling frequency and with it related issues. While achieving high enough sampling frequency is generally not a problem, it leads to large amounts of sensor data that needs to be first transferred to the processing device and then analyzed. Problems that may occur are available bandwidth of the communication channels and the computational power of the processing device. The latter is especially a problem in real-time biofeedback systems.

Communication channel bandwidth, range and delays are yet another set of potential problems. Low power wearable devices usually have low channel bandwidth, with very limited communication range.

III. Capturing of Human Motion

An important area of research connected to biofeedback is various motion capture systems. The majority of motion capture systems are based upon various optical systems and inertial sensors, such as accelerometers and gyroscopes. Motion is captured through measurement of various physical quantities such as acceleration, velocity, position, angular velocity, rotation angle.

Experimentally we have evaluated two different motion capture systems: (a) passive marker based optical system, and (b) MEMS gyroscope based system.

We used a professional optical motion capture system Qualisys™**.** This is a high-accuracy tracking system [8] with eight Oqus 3+ high-speed cameras that offers real-time tracking of multiple marker points as well as tracking of pre-defined rigid bodies. Sampling frequency of the system is up to 1000 Hz. As stated in [10] the measurement noise for a static marker is given by its standard deviation for each individual coordinate: stdx=0.018 mm, stdy=0.016 mm and stdz=0.029 mm. In view of the given results, we can regard the measurement inaccuracy of the optical tracking system as negligibly small. Inertial sensor accuracy is limited by the precision of self-adhesive reflective marker positioning.

Despite the fact that Qualisys has video frame rates of up to 1000 Hz, the comparison with inertial sensors could be done only up to sampling frequencies of 60 Hz. We identified the reason in processing load of real-time calculation of the 6DoF orientation that could not be met by laptop processing power. It should be mentioned here that Qualisys is by itself already a HPC system. It has 8 cameras with integrated Linux system doing parallel processing of captured video. The results of marker positions are communicated to the central processing device (laptop) for synchronization and further processing.

Figure 3. Experimental setup for golf swing motion. Four infrared reflecting markers are attached directly to smartphone to form the defined QTM rigid body orthogonal vector basis.

For inertial sensor based motion tracking a smartphone iPhone 4 is used. Is has the embedded the following MEMS inertial sensors: ST Microelectronics LIS331DLH accelerometer, and STMicroelectronics L3G4200D gyroscope [11].

For the golf swing movement the smartphone was attached directly onto the forearm of the player, see Figure 3. Four infrared reflecting markers are attached directly to the smartphone in a way to form the orthogonal vector basis of the x-y plane of the local coordinate system of the rigid body. Gyroscope was first calibrated to reduce the errors imposed by biases, scaling factors and body axes misalignment [12].

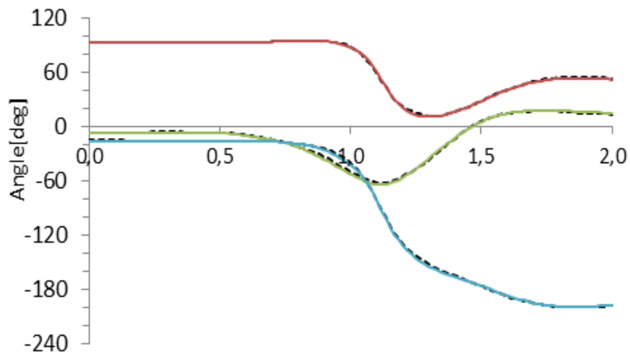

Figure 4. Comparison of smartphone embedded gyroscope (doted black plots) and QTM body rotation angles (solid colored plots: red=roll, green=pitch, blue=yaw). Figure shows the first part of the golf swing movement in 2 seconds time interval from address to top of the backswing.

A testing rotation pattern was generated in golf swing movement, recorded from the beginning (address) phase to top of the backswing. Figure 4 shows the comparison of the body Euler rotation angles, measured with both tracking systems. The calculated root-mean square deviation is 1.15 degrees. Such accuracy is good enough for golf biofeedback application.

A. Motion dynamics and sampling frequency

Due to real-time communication speed limitations of Qualisys and inertial sensor device, the above experiments are performed at sampling frequencies of 60Hz [8], [9]. While such sampling frequency is sufficient for evaluation of capture system accuracies, it is too low for capturing high dynamics movements in sport. To estimate the required sampling frequencies for capturing human motion in sport, we performed a series of measurements with wearable Shimmer3™ inertial sensor device. Shimmer3 allows accelerometer and gyroscope sampling frequencies of up to 2048 Hz.

A set of time and frequency domain signals for a handball free-throw movement is shown in figure 5. The sensor device was attached at the dorsal side of the hand. Measured acceleration and rotation speed values shown in Figure 5(a) are close to the limit of the sensors dynamic range. High sampling rate enables the measurements of actual spectrum bandwidth for both physical quantities. Most of the energy of finite time signals on is within upper limited frequency range, as shown in Figure 5(b). The bandwidth containing 99% of signal energy is a useful measure of signal bandwidth as shown in Figure 5(c). The signal spectrum bandwidths differ in each dimension and are higher than for absolute 3D values. The highest measured values on Figure 5(c) are 59Hz for acceleration and 40Hz for rotation speed. For some other, more dynamic, explosive movements we have measured the energy spectrum bandwidth f (99%) that exceeds 200 Hz, and thus requiring sampling frequency of 500 Hz or even more. All the experiments were performed by the amateurs and it is expected that professional athlete's movements are even more dynamic.

IV. Real-time processing of human motion

To assure real-time operation of the system, all operations on received data frame must be done within one sampling time, before the next frame arrives. The threshold of real-time operation of the processing device depends on many factors: computational power of the processing device, sampling time, amount of data in one streamed frame, number of algorithms to be performed on the data frame, complexity of algorithms, etc. It is therefore difficult to set an exact threshold or values of each parameter of the processing device.

Delay is the primary parameter defining the concurrency of a biofeedback system, as viewed from the user's perspective. The feedback delay that is the sum of all delays of the technical part of the biofeedback system (sensors, processing device, actuator, communication channels), should not exceed a small portion of the user's reaction delay. To present an exemplary calculation, let us set the sampling frequency at 1000 Hz and maximal feedback delay at 20% of user's reaction delay. Considering that reaction delay is around 150 ms [7], the maximal feedback delay is at most 30 ms.

While many simple examples of biofeedback applications, that do not require huge amounts of processing, exist, one can easily find enough examples of use that do need high performance computing. One such example is a high performance real-time biofeedback system for a football match. Parameters in the capture side of the system are: 22 active players, 3 judges, 10 to 20 inertial sensors per player, 1000 Hz sampling rate. The data includes 3D accelerometer, 3D gyroscope, 3D magnetometer, GPS coordinates, and time stamp. The first three sensors mainly produce 16 bit values in each of the axes, GPS coordinates are 64 bits each, and timestamp is 32 or 64 bit long. Taking the lower values of parameters (10 sensors, 32 bits for time stamp) the data rate produced is 92 Mbit/s. The presented example clearly implies some form of high performance computing and some form of high speed communication, especially when complex algorithms and processes are used on them.

Algorithms that are regularly performed on a streamed sensor signals are: statistical analysis, temporal signal parameters extraction, correlation, convolution, spectrum analysis, orientation calculation, matrix multiplication, etc. Processes include: motion tracking, time-frequency analysis, identification, classification, clustering, etc. Algorithms and processes can be applied in parallel or consecutively.

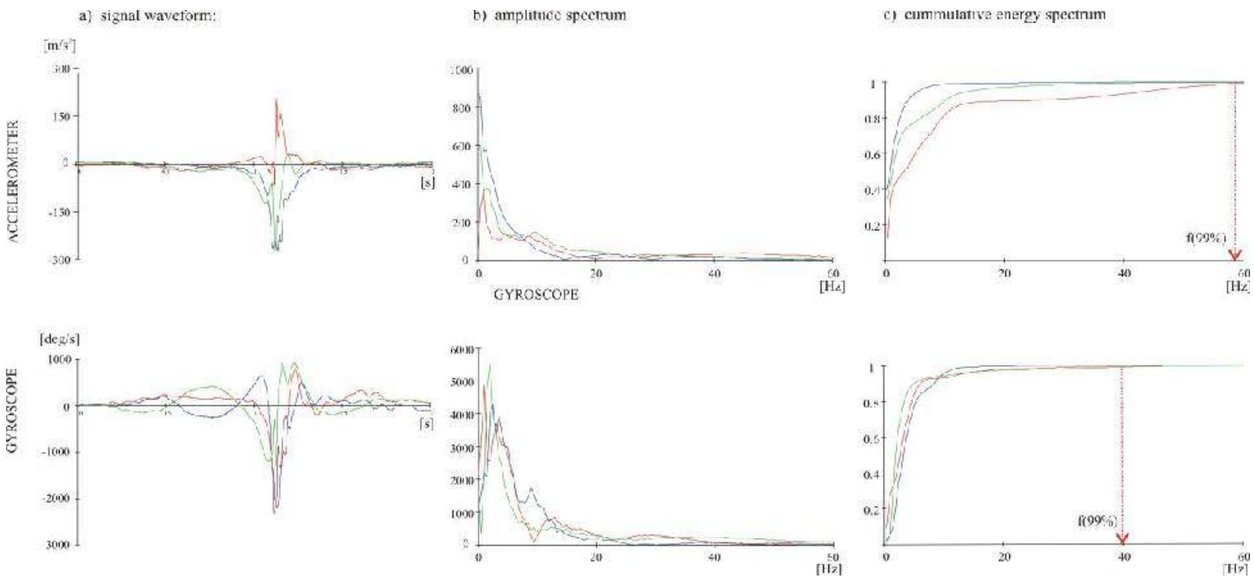

Figure 5. An example of a high dynamic movement: a handball free-throw hand movement measured by a 6DoF sensing device: (a) Accelerometer and gyroscope signals are sampled with 1024 Hz. (b) Signal spectrum (DFT) is calculated on the sequence of 2048 data points inside the 2 s time frame. c) Signal bandwidth is measured and calculated by the relative cumulative energy criterion: f(99%).

V. CONCLUSION

In sport sensory systems signal processing is a crucial process. Many specific biofeedback problems in various sports exist. We addressed several problems, using a different sport example for each one. Sensor accuracy is tested on a golf swing, where we found that the rotation accuracy requirement can be met by smartphone gyroscopes. Movement dynamics on handball free-throw is measured; we found that the sensor dynamic range of professional body attached sensor device hardly meets the experiment requirements. A multi-user signal processing in football match is recognized as an example for high performance application that needs high speed communication and high performance remote computing. With growing number of biofeedback applications in sport and other areas, their complexity and computational demands will grow as well.

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