2021 5th Scientific School Dynamics of Complex Networks and their Applications (DCNA) | 978-1-6654-4283-1/21/$31.00 ©2021 IEEE | DOI: 10.1109/DCNA53427.2021.9587078

Wireless personal training tracker for sports shooting

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***Abstract*—The article describes the process of developing a wireless software arrapat complex for measuring and logging various aspects of sports shooting training. The purpose of the development is to optimize and personalize the training process. This paper proposes an approach that allows synchronization up to 1 ms over a wireless network. As well as a method of writing a large amount of this on a microSD flash drive with minimal latency.**

***Index Terms*—sensors, optimization of training, synchronization of wireless devices**

I. Introduction

Today, the field of cognitive research on human activity during various sports exercises is developing at a rapid pace [1]–[3]. This provides great opportunities to create more effective workouts and allows for a personalized approach to each individual. One of the main components of this kind of research is the measurement of brain activity during exercise. This can be done with various EEG or fNIRS sensors which can be placed on the athlete's head [4]–[18]. Note that modern methods of studying the activity of the brain are inconceivable without numerical simulation of neural network activity by using different neuron's models [19]–[23] which allows to investigate the processes of inter-neuron interaction or collective neural dynamics [24]. In addition, studying the brain is unthinkable using artificial intelligence methods and statistical analysis [25]–[30]

But for a complete analysis of brain activity, it is necessary to know with high precision all the factors influencing the changes of each potential at any given time. This also requires measurements of various external factors. For sports shooting, for example, it is necessary to measure the movements of the weapon during aiming and firing. It is also necessary to accurately determine the moment of firing based on the sound wave. The measuring equipment must not interfere with the athlete's natural movements, as this would create additional distractions.

Therefore, as part of this paper, a wireless measuring device has been developed that can measure the above parameters at high frequency and also synchronized with other measuring devices, such as an electroencephalograph, eyetracker, and another [31].

II. Sensor Design

Sport Shooting is a sporting discipline in which competitors compete in accuracy and precision in hitting targets with a variety of weapons. During shooting, many different cognitive processes take place in the brain. For example, the process of aiming requires a high level of concentration and accuracy on the part of the athlete. Aiming is accompanied by moving the weapon to the desired position and then firing. In order to study such actions, it is necessary to accurately measure the movements and vibrations of the weapon, to know the moment of the shot and track the sound wave, and to measure brain activity. In order to match all the data, the devices in the network must be precisely synchronized, this will allow accurate identification of triggers for further study and analysis. The "synchronization" section describes a method for solving this problem.

In order to perform all of the above environmental measurements, a hardware-software module was developed. The motion measurements are made with the IMU module Figure 1, and the measurement of the firing torque with the microphone.

Due to the fact that the use of wires interferes with the natural movements of a person, the tracker uses a controller that supports wireless communication ESP32. A class 4 microSD flash drive is used for data logging, also sensitive microphone is used to measure the moment of shot and sound wave.
To work in wireless mode, the tracker has a battery that connects to the built-in charging module. Figure 2 shows an example of how to place the tracker, IMU, and microphone on a sport shotgun.

To record data in real time at 2 kHz, software was developed to allow recording of memory blocks with minimal latency. The basic idea is that the data is written to the RAM in 512 bytes, then when the stick controller is available the data is

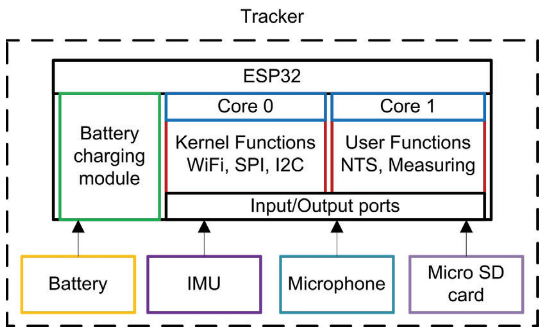

Fig. 1. Functional diagram.

written to the stick. To speed up writing and optimize the storage of values, the data is stored in binary form as a structure. Conversion from binary format to character format is performed during post processing on a personal computer. The TCP protocol is used to control the process of starting, stopping recording and transferring files.

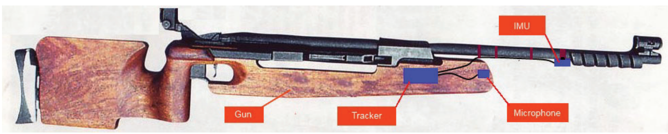

Fig. 2. Example sensors placement.

III. Synchronization

To perform neurophysiological experiments it is necessary to synchronize measuring equipment as accurately as possible. Today there are many technologies of clock synchronization, of which the most popular is NTP, which allows obtaining accurate time through a local network or public access network, such as the Internet. But this technology has a number of disadvantages: synchronization accuracy less than 10 ms, high hardware requirements. These criteria are especially important when used in embedded systems. On-board microcontrollers have a small amount of RAM as well as a small processor frequency. The use of NTP server in such devices slows it down and complicates the performance of measurement tasks.

To solve this problem, a simple and effective algorithm for time synchronization in the local network with an accuracy of 1 millisecond was developed and implemented called Network Time Synchronization (NTS). Figure 3 shows a block diagram of this algorithm.

After starting the controller connects to the wireless network Wifi and if the connection was successful the NTS client object is created. Then the object must be initialized by specifying the synchronization period, server IP and port. After that asynchronous callback function is automatically created in a separate thread. This function is triggered when the server sends a response. The UDP protocol is used to transmit packets over the network that does not require confirmation of the message transmitted due to this protocol is recommended for use in real-time systems.

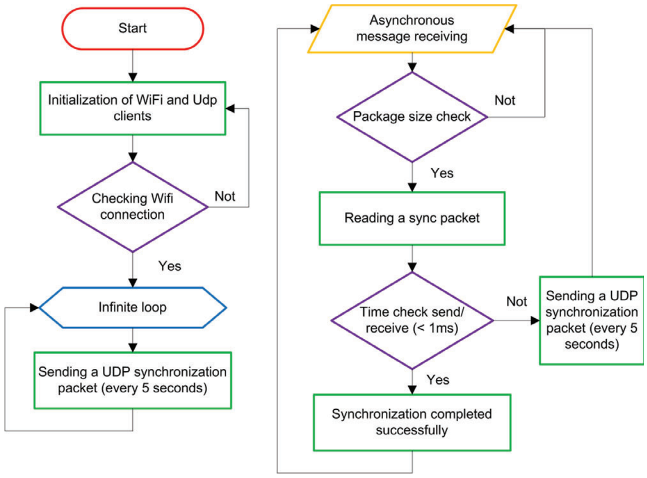

Fig. 3. Block diagram.

Each packet NTS client has two 32-bit data fields: PC time (T_{server}) and packet key. The packet key is necessary to correctly identify the response from the server because UDP does not guarantee that the packet will be delivered and that the receiving queue will not be broken.

After receiving the response from the NTS server the client compares the time of sending the packet T_{sp} and the time of receiving T_{rp}.

$$\begin{cases} dt = T_{rp} - T_{sp} \\ dt <= 1 \text{ (ms)} \end{cases} \tag{1}$$

If condition 1 is not true, the client generates a new message key and sends a second request to the server. If after n (n - number of attempts, set to unload the microcontroller) attempts the condition was not true, the repeated request will be made after the time interval set during the initialization.

If condition 1 is true, then the new estimated server time T_{ns} is calculated according to Eq. (2).

$$T_{ns} = T_s + (T_{rp} - T_{mc}) \tag{2}$$

where T_s - server time received after the last synchronization, T_{mc} - time of the microcontroller at the time of the last successful synchronization. Due to the fact that the time on different devices is different and there may be non-deterministic delays in the network it is necessary to calculate the "time offset" T_{os} if condition 3 is correct.

$$T_{os} = T_{ns} - T_{server}, \text{ if } T_{ns} > T_{server} \tag{3}$$

where T_{server} - the actual server time received inside the packet.

After a successful calibration, the current server time with millisecond accuracy can be obtained at any time using Eq. (4).

$$\begin{cases} T_s, \text{ if } (T_{client} - T_s) < T_{os} \\ (T_{client} - T_{mc}) + T_s, \text{ else} \end{cases} \tag{4}$$

where T_{client} - the current time of the microcontroller in milliseconds. This technology significantly offloads the CPU and RAM of the microcontroller, allowing resources to be used for other more important tasks.

IV. CONCLUSION

In the process, a wireless tracker was developed to measure various shot parameters during sport shooting training. Using the IMU module, the tracker can measure angular velocities, accelerations, temperature and magnetic field. The microphone can also be used to measure sound flow. Thanks to the onboard microSD stick, the module can log data at up to 2 kHz. This tracker is not only suitable for sport shooting, it can be used in many other experiments where it is necessary to measure the above mentioned parameters.

REFERENCES

[1] C.-H. Wang, D. Moreau, and S.-C. Kao, "From the lab to the field: potential applications of dry eeg systems to understand the brain-behavior relationship in sports," *Frontiers in neuroscience*, vol. 13, p. 893, 2019.

[2] S. Perrey and P. Besson, "Studying brain activity in sports performance: Contributions and issues," *Progress in brain research*, vol. 240, pp. 247–267, 2018.

[3] A. Gong, J. Liu, C. Jiang, and Y. Fu, "Rifle shooting performance correlates with electroencephalogram beta rhythm network activity during aiming," *Computational intelligence and neuroscience*, vol. 2018, 2018.

[4] A. N. Pavlov, E. N. Pitsik, N. S. Frolov, A. Badarin, O. N. Pavlova, and A. E. Hramov, "Age-related distinctions in eeg signals during execution of motor tasks characterized in terms of long-range correlations," *Sensors*, vol. 20, no. 20, p. 5843, 2020.

[5] N. S. Frolov, E. N. Pitsik, V. A. Maksimenko, V. V. Grubov, A. R. Kiselev, Z. Wang, and A. E. Hramov, "Age-related slowing down in the motor initiation in elderly adults," *Plos one*, vol. 15, no. 9, p. e0233942, 2020.

[6] V. Maksimenko, A. Badarin, V. Nedaivozov, D. Kirsanov, and A. Hramov, "Brain-computer interface on the basis of eeg system encephalan," *Proc. SPIE*, vol. 10717, p. 107171R, 2018.

[7] S. Kurkin, V. Maksimenko, and E. Pitsik, "Approaches for the improvement of motor-related patterns classification in eeg signals," in *2019 3rd School on Dynamics of Complex Networks and their Application in Intellectual Robotics (DCNAIR)*. IEEE, 2019, pp. 109–111.

[8] A. E. Hramov, V. Grubov, A. Badarin, V. A. Maksimenko, and A. N. Pisarchik, "Functional near-infrared spectroscopy for the classification of motor-related brain activity on the sensor-level," *Sensors*, vol. 20, no. 8, p. 2362, 2020.

[9] S. Kurkin, A. Badarin, V. Grubov, V. Maksimenko, and A. Hramov, "The oxygen saturation in the primary motor cortex during a single hand movement: functional near-infrared spectroscopy (fnirs) study," *The European Physical Journal Plus*, vol. 136, no. 5, pp. 1–9, 2021.

[10] A. A. Badarin, V. V. Skazkina, and V. V. Grubov, "Studying of human's mental state during visual information processing with combined eeg and fnirs," *Proc. SPIE*, vol. 11459, p. 114590D, 2020.

[11] T. Daikoku, "Neurophysiological markers of statistical learning in music and language: hierarchy, entropy and uncertainty," *Brain sciences*, vol. 8, no. 6, p. 114, 2018.

[12] S. Paulmann, Z. Ghareeb-Ali, and C. Felser, "Neurophysiological markers of phrasal verb processing: Evidence from l1 and l2 speakers," 2015.

[13] J. Hanna, Y. Shtyrov, J. Williams, and F. Pulvermüller, "Early neurophysiological indices of second language morphosyntax learning," *Neuropsychologia*, vol. 82, pp. 18–30, 2016.

[14] S. Kurkin, A. Hramov, P. Chholak, and A. Pisarchik, "Localizing oscillatory sources in a brain by meg data during cognitive activity," in *2020 4th International Conference on Computational Intelligence and Networks (CINE)*. IEEE, 2020, pp. 1–4.

[15] S. Kurkin, P. Chholak, V. Maksimenko, and A. Pisarchik, "Machine learning approaches for classification of imaginary movement type by meg data for neurorehabilitation," in *2019 3rd School on Dynamics of Complex Networks and their Application in Intellectual Robotics (DCNAIR)*. IEEE, 2019, pp. 106–108.

[16] V. A. Maksimenko, A. E. Hramov, N. S. Frolov, A. Lüttjohann, V. O. Nedaivozov, V. V. Grubov, A. E. Runnova, V. V. Makarov, J. Kurths, and A. N. Pisarchik, "Increasing human performance by sharing cognitive load using brain-to-brain interface," *Frontiers in neuroscience*, vol. 12, p. 949, 2018.

[17] T. Bukina, M. Khramova, and S. Kurkin, "Modern research on primary school children brain functioning in the learning process," *Izvestiya VUZ. Applied Nonlinear Dynamics*, vol. 29, no. 3, pp. 449–456, 2021.

[18] S. A. Kurkin, V. V. Grubov, V. A. Maksimenko, E. N. Pitsik, M. V. Hramova, and A. E. Hramov, "System for monitoring and adjusting the learning process of primary schoolchildren based on the eeg data analysis," *Informatsionno-upravliaiushchie sistemy [Information and Control Systems]*, no. 5, pp. 50–61, 2020.

[19] A. V. Andreev, M. V. Ivanchenko, A. N. Pisarchik, and A. E. Hramov, "Stimulus classification using chimera-like states in a spiking neural network," *Chaos, Solitons & Fractals*, vol. 139, p. 110061, 2020.

[20] V. V. Makarov, D. Kirsanov, M. Goremyko, A. Andreev, and A. E. Hramov, "Nonlinear dynamics of the complex multi-scale network," *Proc. SPIE*, vol. 10717, p. 1071729, 2018.

[21] A. Andreev, V. Makarov, A. Runnova, and A. Hramov, "Coherent resonance in neuron ensemble with electrical couplings," *Cybernetics and Physics*, vol. 6, no. 3, pp. 135–138, 2017.

[22] V. Ponomarenko, D. Kulminskiy, A. Andreev, and M. Prokhorov, "Assessment of an external periodic force amplitude using a small spike neuron network in a radiophysical experiment," *Technical Physics Letters*, vol. 47, no. 2, pp. 162–165, 2021.

[23] A. V. Andreev, V. A. Maksimenko, A. N. Pisarchik, and A. E. Hramov, "Synchronization of interacted spiking neuronal networks with inhibitory coupling," *Chaos, Solitons & Fractals*, vol. 146, p. 110812, 2021.

[24] A. Andreev and V. Maksimenko, "Synchronization in coupled neural network with inhibitory coupling," *Cybernetics and Physics*, vol. 8, no. 4, pp. 199–204, 2019.

[25] A. E. Hramov, N. S. Frolov, V. A. Maksimenko, V. V. Makarov, A. A. Koronovskii, J. Garcia-Prieto, L. F. Antón-Toro, F. Maestú, and A. N. Pisarchik, "Artificial neural network detects human uncertainty," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 28, no. 3, p. 033607, 2018.

[26] N. S. Frolov, V. V. Grubov, V. A. Maksimenko, A. Lüttjohann, V. V. Makarov, A. N. Pavlov, E. Sitnikova, A. N. Pisarchik, J. Kurths, and A. E. Hramov, "Statistical properties and predictability of extreme epileptic events," *Scientific reports*, vol. 9, no. 1, pp. 1–8, 2019.

[27] A. E. Hramov, V. A. Maksimenko, S. V. Pchelintseva, A. E. Runnova, V. V. Grubov, V. Y. Musatov, M. O. Zhuravlev, A. A. Koronovskii, and A. N. Pisarchik, "Classifying the perceptual interpretations of a bistable image using eeg and artificial neural networks," *Frontiers in neuroscience*, vol. 11, p. 674, 2017.

[28] V. A. Maksimenko, A. Pavlov, A. E. Runnova, V. Nedaivozov, V. Grubov, A. Koronovslii, S. V. Pchelintseva, E. Pitsik, A. N. Pisarchik, and A. E. Hramov, "Nonlinear analysis of brain activity, associated with motor action and motor imaginary in untrained subjects," *Nonlinear Dynamics*, vol. 91, no. 4, pp. 2803–2817, 2018.

[29] E. Pitsik, N. Frolov, K. Hauke Kraemer, V. Grubov, V. Maksimenko, J. Kurths, and A. Hramov, "Motor execution reduces eeg signals complexity: Recurrence quantification analysis study," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 30, no. 2, p. 023111, 2020.

[30] P. Chholak, G. Niso, V. A. Maksimenko, S. A. Kurkin, N. S. Frolov, E. N. Pitsik, A. E. Hramov, and A. N. Pisarchik, "Visual and kinesthetic modes affect motor imagery classification in untrained subjects," *Scientific reports*, vol. 9, no. 1, pp. 1–12, 2019.

[31] F. Artoni, A. Barsotti, E. Guanziroli, S. Micera, A. Landi, and F. Molteni, "Effective synchronization of eeg and emg for mobile brain/body imaging in clinical settings," *Frontiers in human neuroscience*, vol. 11, p. 652, 2018.