Experimental results show that the activity discrimination performance of arbitrarily designated activity state is 96%. The reason is that is considered to be an error caused by difficulty in maintaining the exact speed of the test subject during the activity state. Then, the performance of the data packet generated rate was evaluated through the activity state experiment. When the activity state data is measured at a sampling frequency of 360Hz for 1,987 seconds, it is assumed that a packet of 2,861,280 bytes is generated, and CR was derived by calculating the ratio of the amount of data packets generated in the experiment. Therefore, since 83 abnormal heartbeats occurred in the data packet, the total packet generated 48,384 bytes of packet also, CR was calculated as 59.14.

IV. Conclusions

In this research, we implemented a real-time ECG monitoring system using pattern matching and state classification method to provide not only continuous cardiac activity monitoring during daily life but also multiple heart health analysis based on abnormal heartbeat detection and activity classification. The implemented system minimizes the number of packets generated during wireless data transmission as well as abnormal heartbeat detection and activity information and enables monitoring of heart activity status and activity information in real time through a smartphone. For this purpose, a belt type electrode was used to minimize the inconvenience of measurement.

In addition, we implemented a measurement section using a 2-lead ECG measuring instrument for ECG measurement and 3-axis acceleration for extracting activity information. Moreover, we implemented the system controller section to convert the analog signal to digital and wirelessly transmit heartbeat and activity information. The implemented system has a merit that it can analyze it by various kinds of activity state classification even when an abnormal heartbeat detection error occurs due to a change of ECG signal due to excessive activity in daily life. To evaluate the data packet transmission and restoration performance of the system implemented in this research, the MIT / BIH Arrhythmia Database 100 record was embedded in the system controller section, and the packet was transmitted to the smartphone. Also, ECG evaluation experiments were conducted according to the activity status during daily life.

As a result of the performance evaluation, both experiments confirmed the data packet generated and signal restoration performance. In future research, it is necessary to develop advanced diagnostic parameters through correlation analysis between activity information and ECG and to provide health analysis considering user environment such as temperature, humidity, altitude, topographical information as well as activity information.

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