Elements of a Real-Time Vital Signs Monitoring System for Players during a Football Game

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***Abstract*—We have developed a real-time vital signs monitoring system for two years in 2012 and 2013. Just by putting a single vital sensor node to the back waist position of each player and placing four data collection nodes around a field, the system can monitor at a note PC heart rate (HR), energy expenditure (EE) and body temperature (BT) for all players during a football game in real-time, periodically and reliably. The system is based on novel vital sensing technique and wireless data transmission technique. This paper introduces the two techniques in the system, presents some problems encountered in the system development and discusses solutions for them.**

Keywords—vital signs; real-time monitoring; sensing technique; wireless data transmission technique

I. INTRODUCTION

From the view-points of sport physiology and healthcare, it is important to monitor in real-time vital signs such as heart rate (HR), energy expenditure (EE) and body temperature (BT) for athletes in training. For example, the Karvonen formula gives adequate HR for athlete during training [1]: adequate EE depends on the age, weight and sex of athlete: BT should be below 37^{o} C before training and cannot go beyond 40^{o} C even during training. In this way, for effective training and injury/disease prevention, real-time HR, EE and BT monitoring is essential, and training based on feeling, experience and intuition has been gone; now it is the time of training based on scientific evidence using vital data.

However, it has been common that data are once stored in the memory of vital sensor put to each athlete during training, and after training, by checking the log, a coach or trainer can understand the today's physical condition of the athlete. This is useful only for scheduling tomorrow's training menu. If real-time vital signs collection and analysis is possible in a field, the coach or trainer can adaptively control today's training menu personalized for each athlete in a field by feed-backing his real-time vital data. On the other hand, an unhappy incident happened in Japan in 2011 that Naoki Matsuda, a former defender of Japanese national football team, collapsed during training due to a cardiac arrest *after finishing a 15-minute warmup run*, and two days later he died at the age of 34 [2].

The main reason of disturbing real-time vital signs collection and monitoring from athletes during training is the lack of adequate vital sensing technique and wireless data transmission technique.

First, training is hostile to sensing of vital signs. To sense a vital sign, we need to put a sensor close to a body and keep the sensing condition and environment stable. However, the motion of athlete during training makes the condition and environment unstable. Furthermore, a vital sign has an adequate position to be sensed. For instance, HR sensor should be put closer to the heart, and tri-accelerometer should be put to the lower part of body. However, putting several vital sensors to different positions of body is prohibitive.

Second, training is also hostile to wireless transmission of vital data. During training, athletes spread in a large field, randomly in one time and with a coordinated mobility in another time. The unlicensed 2.4GHz industrial scientific and medical (ISM) band is now commonly used in various wireless applications over the world. However, the wireless signal of typical data transmission tools in the frequency band has a relatively short transmittable range and is easily blocked by an obstacle such as another athlete.

We have developed a vital signs monitoring system for two years in 2012 and 2013 [3-7]. It can collect and monitor vital signs such as HR, EE and BT from all (twenty two) players during a football game in real-time, periodically and reliably. The reason of selecting football game is that the condition and environment are very hostile to vital signs sensing and wireless data transmission; many vital sensor wearers (footballers) spread in a large field and take vigorous exercises such as running, sprint, jumping, tackling and sliding.

In this paper, we introduce the system based on novel vital sensing and wireless data transmission techniques and show the results obtained in in-house experiments and field experiments. We have solved a lot of problems encountered in the experiments and have selected best-suited techniques. However, unfortunately, several problems have remained unsolved. In this paper, we mention some unsolved problems and discuss promising solutions for them.

This paper is organized as follows. Section II explains the elements of the developed systems. Section III presents the developed vital signs sensing technique, and Section IV presents the developed wireless data transmission technique.

Finally, Section V concludes the paper with some future directions.

II. OUTLINE OF REAL-TIME VITAL SIGNS MONITORING SYSTEM

The real-time vital signs monitoring systems is composed of three elements such as vital signs sensing technique, wireless data transmission technique and human interface technique. The vital signs sensing technique is furthermore composed of HR, EE and BT sensing techniques. The wireless data transmission technique is developed for links from vital sensor nodes (VSNs) to data collection nodes (DCNs) and those from data collection nodes to a sink node (SN), namely, a note PC at a trainer or coach. And, the human interface technique means how we can show the collected data in the display of the note PC. In the first year, we developed the vital signs sensing technique and wireless data transmission technique separately, and in the second year, we integrated the two techniques into a single system. For the vital signs sensing and wireless data transmission techniques, we improved them through many in-house and field experiments, on the other hand, for the human interface technique, we developed it by interviewing professional coaches and trainers on what and how they really want to check in the display. They are usually unfamiliar with information communications technology (ICT), so easy handling of the system is also important.

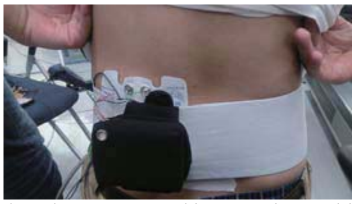
III. THREE ELEMENTS OF VITAL SIGNS SENSING TECHNIQUES

BT can be sensed at any position of body, but HR should be sensed at a position closer the heart to get stronger information from the heart, whereas a tri-accelerometer should be put to the lower position of body to estimate the EE due to walking, running and sprint. To avoid an HR sensor and an EE sensor separately put to a body, we decided to put a single node to the back waist position of body jointly sensing HR, EE and BT. The position is far from the heart, so it made development of HR sensor more difficult.

A. *HR Sensing*

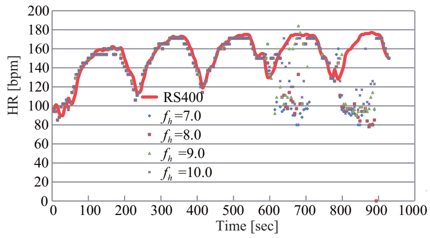
We can sense HR by means of electro-cardio-graphy (ECG) or photo-plethysmo-graphy (PPG). ECG measures the electrical activity of the heart directly contacting the electrodes to the skin, whereas PPG is based on opto-electronic technique, which illuminates the skin by an LED and measures the intensity of the light changed by the blood volume pulse (BVP) under the skin by a photo detector (PD). They are simple and non-invasive for HR sensing suited for athlete during training, but they are highly sensitive to motion artifact.

For ECG sensor, we can estimate HR by measuring the R-R interval in sensed ECG waveform, but during training, the ECG waveform is contaminated with motion artifact. To mitigate the motion artifact, we developed an adaptive ECG-based HR sensing scheme which is based on novel two techniques [3]. One is an adaptive threshold technique for rejecting wrong R-wave peaks due to motion artifact which adaptively changes the threshold level for extracting R-wave peaks according to the levels of previously measured R-waves.



(a) ECG-based HR sensor and its mounting position

(b) In-house experiment using a treadmill



(c) Sensed HR versus the time

Fig. 1. Detail and result on the ECG-based HR sensing.

The other is a median filter technique for reducing wrong HR counts which outputs a median value of HR counts within a certain time period as an HR value.

Fig. 1 shows the detail and result on the ECG-based HR sensing, where the sampling rate and AD resolution were 50.0 sps and 10 bits, respectively. A bandpass filter was used for rejecting motion artifact with a fixed low-end cut-off frequency f_l=3.0 Hz and an adjustable high-end cut-off frequency f_h Hz. As shown in Figs. 1 (a) and (b), we put a developed ECG-based HR sensor and a Polar RS 400 (as a reference) to a subject and measured the HR using a treadmill, where the subject repeated a set of two-minute running (10.0 km/h) and one-minute standing still (rest). Fig. 1 (c) shows the sensed HR versus the time which was recently obtained. The HR sensor works well in the time range of 0 to 600.0 sec for any value of f_h because there is no difference in the sensed HR between the developed HR sensor and the Polar RS400, but for the time range more than 600.0 sec, the developed HR suddenly worked inaccurate. The cause was found to be "sweat." That is, the subject sweated during repeating running and standing still, and an electric current flowed between the electrodes of the ECG sensor, resulting in sudden and variable voltage drops. This is a fundamental problem of ECG-based HR sensor for sports applications. Therefore, we decided not to take the ECG approach in HR sensing during training.

For PPG sensor, we can also estimate HR by measuring the fundamental period of sensed BVP waveform, and the sensed BVP waveform also contaminates with motion artifact. During training, the frequency component of motion artifact overlaps with that of BVP waveform, so a nonlinear canceller based on adaptive algorithm is necessary, where a key is how we can sense only motion artifact separately from BVP plus motion artifact. We found that the light intensity detected by the PD contains both BVP and motion artifact components when either of an LED and a PD contacts the skin, whereas it contains only motion artifact component when the LED and PD do not contact the skin.

Fig. 2 shows the detail and result on the PPG-based HR sensing [7]. Fig. 2 (a) shows its principle using two LED/PDs; one is a normal PPG sensor where an LED/PD contacts the skin to detect BVP component (and inevitably motion artifact) and the other is a motion artifact sensor where an LED/PD does not contact the skin (the air gap height is 7.5 mm) to detect only motion artifact. The locations of the two sensors should be closer (the distance is 13.0 mm) to make the motion artifacts detected by the two sensors be more correlated. The same green LEDs are used for the two sensors, because it is advantageous to detect light reflected by capillary vascular bed located shallower under the skin of the back, and the motion artifacts detected by the two sensors should be more correlated. Fig. 2 (b) shows the block diagram of an adaptive canceller used in the PPG-based HR sensor, which is composed of a K-tap transversal filter and an adaptive weight control algorithm. It has two inputs, which is adequately sampled in f_s sps; one is from the normal PPG sensor $d(n)$ (n=0, 1, 2, …) and the other from the motion artifact sensor $u(n)$ (n=0, 1, 2, …). Defining the tap weight vector $(K \times 1)$ and input vector of the transversal filter $(K \times 1)$ respectively as

$$\mathbf{w} = [w_0, \ldots, w_{K-1}]^T \tag{1}$$

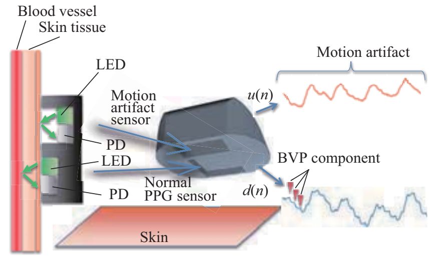
$$\mathbf{u}(n) = [u(n-K+1), \ldots, u(n)]^T \tag{2}$$

the transversal filter output is given by

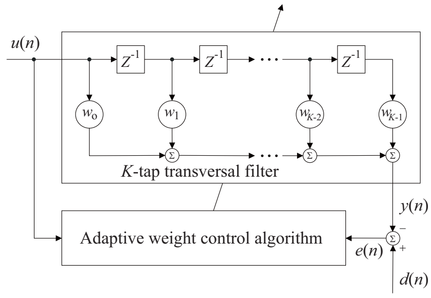
$$y(n) = \mathbf{w}^T \mathbf{u}(n). \tag{3}$$

In principle, the adaptive canceller algorithm tries to make the error between $d(n)$ and $y(n)$ be zero, but it should be noted that the BVP component is obtained in the canceller output as "a residual error." Therefore, if the sampling rate is higher and the number of taps is larger, the canceller output contains a smaller BVP component as it can better cancel not only the motion artifact but also the BVP component, using the output of the motion artifact sensor. This means that choice of the sampling rate and the number of taps is important. We tested several adaptive algorithms such as least mean squares (LMS), normalized (N) LMS and recursive least squares (RLS) for the motion artifact cancellation. In our experiment, by a preliminary experiment, the sampling rate was set to 20.0 sps, and the AD resolution of PD was set to 12 bits.

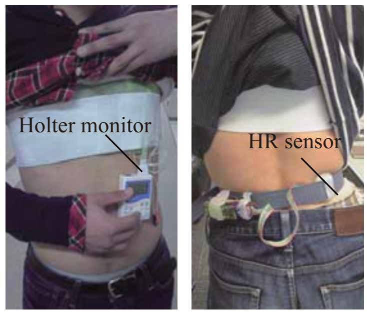
Fig. 2 (c) shows a subject with a Holter monitor (as a reference) and an HR sensor. One experimental session is composed of four times of one-minute standing still (rest) and two-minute running or jumping. Figs 2 (d) and (e) show the HR versus the time for the cases of running and jumping, respectively. In these figures, the performances of the Holter monitor are considered to be a reference. Here, for the motion artifact cancellation, we employ the NLMS (K=30 and the controlling parameter μ=0.5) and RLS (K=50 and the forgetting factor λ=0.99) algorithms. Furthermore, for comparison purpose, these figures also contain the performances of a linear motion artifact canceller, that is, a band-pass filtering (BPF) of 0.8 to 3.0 Hz. We can see from these figures that for the two exercises, the linear canceller does not work well at all, but our proposed canceller works very well; the performance is almost the same as that of the



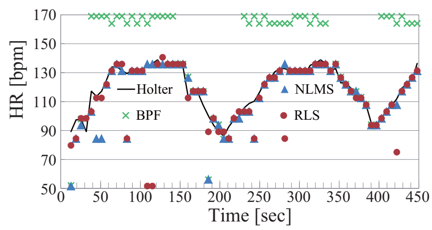
(a) Principle of the developed PPG-based HR sensor



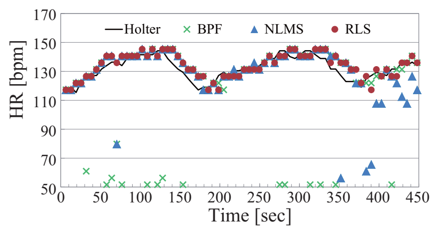
(b) Block diagram of the adaptive canceller



(c) A subject with a Holter monitor and the HR sensor



(d) Sensed HR versus the time (running)



(e) Sensed HR versus the time (jumping)

Fig. 2. Detail and result on the PPG-based HR sensing.

Holter monitor. In real training, an athlete suddenly changes his exercises, so finally, we decided to apply the RLS-based PPG to the HR sensing during training because of its quicker tap convergence time.

B. EE sensing

Oxygen consumption (VO2) is the best measure of EE. VO2 can be directly and accurately sensed by a VO2 meter, but it is impossible during normal training because it requires measurement of ventilation and oxygen and carbon dioxide concentration of the inhaled and exhaled air. VO2 is also estimated by tri-acceleration data. Defining the acceleration of gravity as g and the measured tri-accelerations driven during an exercise at time of t as $a_x(t)$, $a_y(t)$ and $a_Z(t)$, respectively, the EE can be calculated [8]

$$I_{total}(t) = \int_{t-T_w}^{t} \sqrt{a_x^2(\tau) + a_y^2(\tau) + \left(a_z(\tau) - g\right)^2}\, dt \qquad (4)$$

$$VO2(t) = k_1 \times I_{total}(t) \qquad (5)$$

$$EE(t) = k_2 \times VO2(t) \times m \qquad (6)$$

where T_w (=1.0 min) is a time-integration window width, k_1 and k_2 are predetermined constants and m is the weight. Therefore, knowing the weight of a subject, by measuring his accelerations with a tri-accelerometer, we can estimate his EE.

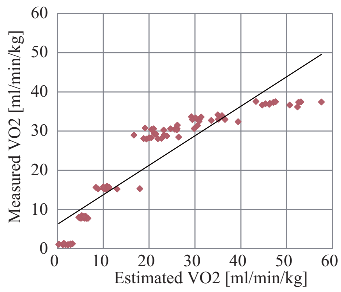
Fig. 3 shows the detail and result on the EE sensing. We conducted an in-house experiment with five subjects. As shown in Fig. 3 (a), while each subject took several exercises on a treadmill, such as standing still (0 km/h), walking (4.0km/h), fast-walking (6.6 km/h), jogging (8.4 km/h), running (10.0 km/h), and sprint (16.0 km/h), we measured VO2 directly with a VO2 meter and accelerations with a tri-accelerometer put to the back waist position of the subject. Fig. 3 (b) shows the measured VO2 (by the VO2 meter) versus the estimated VO2 (by the tri-accelerometer). In the figure, as the VO2 increases, the exercise intensity increases (from standing to sprint). We can see from this figure that the VO2 estimation by (4) and (5) gives underestimates when the exercise strength is stronger, which is typical in training. Prof. Hiroshi Nose, MD., Ph.D. M, who is an inventor of (4)-(6), told us that the conventional equation is applicable only for exercises where either of two legs always touches the ground, because it is developed for EE calculation up to fast-walking [8].

Eq. (4) includes only the second-order moment of accelerations, which may result in the underestimation of VO2 for stronger exercises. Therefore, taking into consideration up to the Lth-order moment of accelerations, we modified (3) as

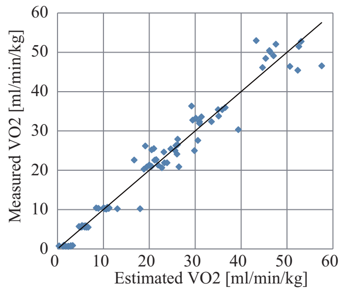
$$I_{total}(t) = \int_{t-T_w}^{t} \sqrt{\sum_{l=2}^{L} b_l \left\{a_x^l(\tau) + a_y^l(\tau) + \left(a_z(\tau) - g\right)^l\right\}}\, dt \qquad (7)$$

where b_l is a parameter. Fig. 3 (c) shows the relationship between the measured VO2 and the estimated VO2 by (7) with L=3 instead of (4). We can see in the figure a good agreement between the measured and estimated VO2s, but there is still a big problem in the EE sensing. The conventional equations (4)-(6) do not contain any adjustable parameters, so just putting the weight of a subject, we can estimate his EE, whereas the proposed equation (7) has parameters to be adjusted for each subject. Development of EE sensing without adjustable parameters is necessary which is applicable to any kinds of exercises.

(a) In-house experiment using a treadmill



(b) VO2 estimation by the conventional equation (4)



(c) VO2 estimation by the proposed equation (7)

Fig. 3. Detail and result on the EE sensing.

C. BT sensing

BT can be sensed at any position of body, just by contacting a thermistor to the skin. It is not true body temperature but surface skin temperature; sensing true body temperature is very difficult. However, we consider the time variation of surface skin temperature during training has some information on healthcare condition.

IV. Two Elements of Wireless Data Transmission Techniques

The unlicensed 2.4GHz ISM band (2.4-2.4835 GHz) is widely used over the world where low-to-high data transmission rates are supported by several standards, but the signal in the frequency band has a shorter transmittable range

Table 1 Specification of nodes.

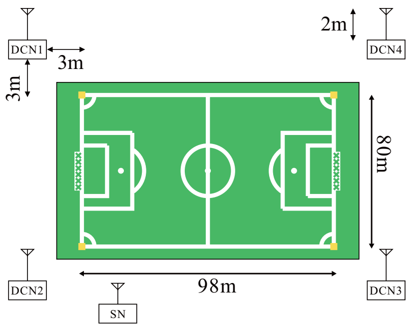
Vital sensor node	
Number of nodes	22
PHY 1	IEEE802.15.4 (2.4 GHz)
	250 kbps, 10 mW
PHY 2	IEEE802.15.4g (920 MHz)
	100 kbps, 20 mW
Packet broadcast interval	10 seconds
Payload size	180 Bytes
MAC	CSMA
Data collection node	
Number of nodes	4
PHY 1	Virtual WiFi (2.4 GHz)
	56 Mbps, 200 mW
PHY 2	IEEE802.15.4g (920 MHz)
	100 kbps, 20 mW
MAC	CSMA
Data aggregation window	1.0 second
Sink node	
Number of nodes	1

and easily blocked by an obstacle such as another player in a football field. On the other hand, the unlicensed 920MHz band (920.5-928.1 MHz) is not used over the world, but the IEEE 802.15.4g standard supports typically 50-100 kbps data transmission rates enough for supporting vital signs monitoring and the signal in the frequency band has a longer transmittable range and is insensitive to blocking. Therefore, we decided to make a fair comparison between wireless data transmission techniques in the two frequency bands. For the comparison, we developed prototype vital sensor nodes which can transmit packets with almost the same payload lengths in the two frequency bands at the same timings.

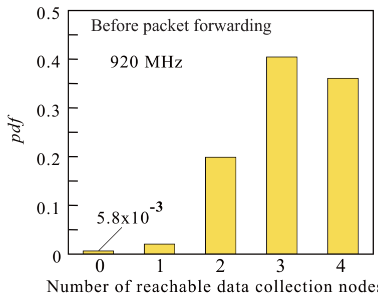
To collect at a single note PC vital signs from all players in a football field, we employed a two-layered network using data collection nodes (DCNs) placed around a football field. In the first communication links, vital sensor nodes (VSNs) put to players broadcast sensed data to DCNs and in the second communication link, DCNs forward their received vital data to a sink node (SN) directly or indirectly through other DCNs. The function of the VSN is to broadcast its own data when needed, so VSN can go to sleep for saving the battery power. To select a frequency band suited for each of the two links, we conducted 10 field experiments. In each field experiment, we put a VSN to the waist positions of each of 22 (11+11) players and placed four or six DCNs around a football field. During a 45-minutes halves game with 10-minute rest period, all the sensor nodes periodically broadcast packets, and we measured and stored the information of packets successfully received at DCNs before packet forwarding and at an SN after packet forwarding. Note that the subjects, namely, the players were 22 members belonging to the Kansai University's Soccer Club which was champion of the 2013 All Japan University Soccer Tournament. Table 1 summarizes the specifications of nodes used in the field experiments.

A. Broadcasting links from VSNs to DCNs

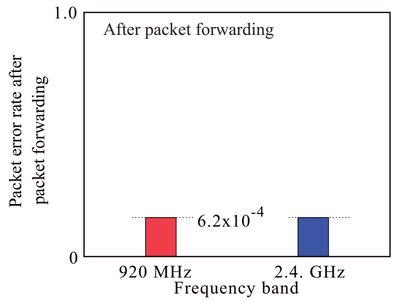
To select a suited wireless data transmission scheme in the broadcasting links, we conducted four field experiments. The result showed that, when placing three or four DCNs around a football field, the packet success rate can be close to 1.0 in the



(a) Experimental layout



(b) Distribution of the number of reachable data collection nodes



(c) Packet success rate

Fig. 4. Detail and result on the forwarding links.

920MHz band, whereas even placing four DCNs, the packet success rate cannot go beyond 0.8. Therefore, we decided to employ the 920MHz band in the broadcasting links. In the field experiments, we also compared the packet success rates for the DCN antenna heights of 1.0 m and 2.0 m, and we found that the antenna height of 2.0 m is always advantageous. The more detail of the field experiment and results are reported in [4].

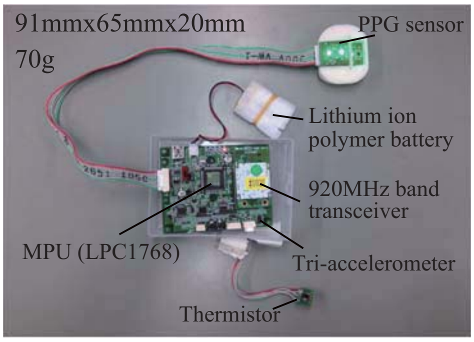
B. Forwarding links from DCNs to an SN

After selecting the suited wireless data transmission scheme in the broadcasting links, to select a suited wireless data transmission scheme in the forwarding links, we conducted two field experiments using the prototype vital sensor nodes. Fig. 4 shows the detail and result on the forwarding links. As shown in Fig. 4 (a), we placed four DCNs at the corners of a football field, and we compared the success error rates between the single-hop forwarding directly from DCNs to an SN in the 920MHz band and the multi-hop forwarding from DCNs to an SN through other DCNs. Figs. 4 (b) and (c) show the packet error rate before and after packet forwarding. We can see that, placing four DCNs, packets from VSNs can always reach more

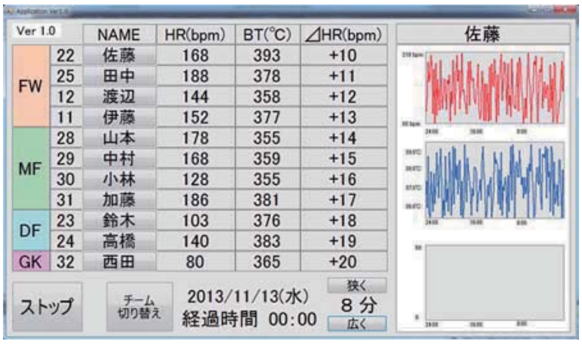
(a) Attaching a VSN to a player

(c) A field experiment (football game)

(d) Real-time vital sign monitoring



(b) A developed vital sensor node



(e) Display of a sink node (note PC)

Fig. 5 Detail on the developed system and photos of field experiment.

than two DCNs in the broadcasting links and packets are lost in the forwarding links, but there happens to be no difference in the single-hop forwarding and multi-hop forwarding. The more detail of the field experiment and results are reported in [6].

C. Developed system and field experiments

We developed vital sensor nodes which can sense and transmit HR by PPG, EE by tri-accelerometer and BT [5], and using them, we conducted four field experiments for collecting vital signs from all players during a football game and showing them at the display of a note PC. Fig. 5 shows the detail on the developed system and photos of a field experiment. The developed vital sensor node is still large, but the answers from players for our questionnaires revealed that not its size but its thickness is a problem. Furthermore, as shown in Fig. 5 (a), we need to attach the vital sensor node with a kind of supporter with a relatively high pressure such as 20-30 hPa, which is found to be a big problem for players.

As shown in Fig. 5 (d), we have been successful in the reliable, periodical and real-time vital signs monitoring during a football game, but on the other hand, we have encountered several new problems. The vital sensor node was made with thin plastic case, so some vital sensor nodes were broken in the field experiments. We need to develop a durable hardware of vital sensor node. In addition, the sweat of players invaded and broke the vital sensor nodes by shorting the circuit. We need to develop a waterproofing hardware/circuit of vital sensor node.

V. Conclusions

In this paper, we have presented sensing techniques and wireless data transmission techniques developed for a real-time vital signs monitoring system for players during a football game. In in-house and field experiments, we have encountered several problems and have overcome them. Now, we are still improving the system through in-house and field experiments.

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