A Thesis for the degree of Master

Pulse Oximetry-based SpO_2 and Pulse Rate Detection for Mobile Health Care Devices

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Information and Communications University

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We certify that this work has passed the scholastic standards requested by the Information and Communications University as a thesis for the degree of Master

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Abstract

In this thesis, we propose a pulse oximetry-based SpO_2 and heart rate detection algorithm for mobile devices. Because strong motion artifacts occur during exercise, it is needed to develop a new artifact-robust algorithm for SpO_2 and heart rates. However, the researches related to pulse oximetry are mostly on the use of hospital care systems. In this research, we analyze the effect of motion artifacts to the pulse oximetry algorithm and develop a new artifact-robust pulse oximetry algorithm for people in exercising. This research deals with two sub-algorithms. One is related to SpO_2 detection, and the other is the algorithm for HR detection. In the case of SpO_2 detection, we reduced processing time of Masimo's Discrete Saturation Transform(DST), which is the most widely utilized to SpO_2 detection in artifact environments, for mobile devices. We achieved 91.31% of error reduction with the proposed SpO_2 detection algorithm. In the case of heart rate detection, the performance improvement is realized by the average magnitude difference function and median filtering for artifact robustness. The proposed heart rate detection method achieved 88.23% of improvement in an error reduction sense compared with the conventional method based on bandpass filtering. Experimental results confirm that the proposed algorithms can be sufficiently applied to mobile healthcare systems during exercise.

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List of Abbreviations

AMDF	Average Magnitude Difference Function
ACF	Autocorrelation Function
DST	Discrete Saturation Transformation
HR	Heart Rate
SpO_2	Oxygen Saturation of Arterial blood measured by a pulse oximeter
SaO_2	Oxygen Saturation of Arterial blood measured by a CO oximeter
ANC	Active Noise Cancellation
LED	Light Emitting Diode
AC	Alternating Current
DC	Direct Current
BPM	Beat Per Minute
MAC	Multiple Accumulates
PDA	Personal Digital Assistants
PC	Personal Computer
CPU	Central Processing Unit
RAM	Random Access Memory
ROM	Read Only Memory
PPC	Pocket PC
IIR	Infinite Impulse Response
BPF	Bandpass Filter

I Introduction

The term of pulse oximetry means technology of obtaining bio-signal related to pulsation of blood in transparent part of body like bloody tissue. In the reason, pulse oximeter which is application of the pulse oximetry is broadly used for monitoring vital signal of human or animals. Sometimes, pulse oximeter could be observed with extreamly dangerous drivers like aviators. However the most widely accepted field of pulse oximetry is in hospital care. During recovery, pulse oximeter can monitor emergency of patient. In that case, because a nurse could not be fully assigned to patient all the time, a pulse oximeter is best solution for monitoring hospital emergency [1].

Though it works very well in hospital, pulse oximety never stop spreading to the other usage. The prospective filed of pulse oximetry is exercise like jogging[2]. Until now, in order to obtain data related to exercise, he/she has to go to the sport center or the health clinic and run on the detection machine using electro cardiogram sensor or airflow detection mask. However, with pulse oximeter instead of the conventional equipment, a runner who wants to find convenient method can be satisfied. Pulse oximeter does not need to attach sticky disposable sensor to chest and to wear mask which is as big as face. It only requires simple clip such as ear-clip, finger-clip, headband, etc. The characteristic is attractive to outdoor jogger.

Unfortunately, even though the convenience of pulse oximetry, its weak signal noise ratio against motion artifact and low perfusion makes it difficult to be accepted to exercise devices[3]. When conventional handheld pulse oximeter is employed to exercise, false alarm by wrongly measured SpO_2 value and heart rate value could not be avoided. It is because of low computational power of handheld devices. Not enough computational resource allows low level of anti-noise signal processing algorithm such as simple frequency filtering, median filtering and average filtering[4][5][6]. However, high performance signal processing algorithm requires high computational power. Under this condition, if more complex and more stable artifact-robust algorithm is developed as small as possible with low computational power consumption, pulse oximeter can be popularly used during exercise. In this research, SpO_2 value and heart rate value detection strategy during exercise will be covered with proposed SpO_2 detection algorithm and AMDF method.

The main point about SpO_2 detection is algorithm complexity reduction for PDA related to Masimo's DST which is highly developed SpO_2 detection algorithm in the world, and the main point about heart rate detection is performance improvement using AMDF algorithm during exercise. Because the conventional algorithm is designed to monitor hospital emergency of patient, it has high precision on dedicated hospital equipment. However, in case of exercise like jogging, dedicated hardware equipment is inappropriate for joggers. Usually, PDA or Portable music player is carried on their hand.

To apply adaptive noise processing structure to SpO_2 detection algorithm, modification related to redundancy reduction is proposed in this research. As the result of the proposed SpO_2 detection algorithm, it could be possible to implement SpO_2 detection software using adaptive noise processing in real time on PDA. In the process of Masimo's DST, to find proper signal ratio corresponding to SpO_2 value, 200 signal ratio tests are performed [7]. It is because of improvement of avoiding false alarming rate in hospital. However, because of noise by motion artifact, those many tests are not needed to be performed during exercise. In this research, processing time is reduced by reduction of the redundancy.

In the case of heart rate detection, conventional noise processing method is implemented with lower computation which is typically under several tens MAC for very small and low price chip. Therefore, those methods are limited to IIR filtering, median filtering, and sample averaging filtering[5][6]. However, the performance of PDA is similar to that of low level PC. We proposed AMDF method to measure heart rate during exercise.

By motion artifact, raw signal from sensor of pulse oximeter is extremely distorted. After processing with conventional method the effect of noise hardly removed from expected informative signal. Even though there is strong effect of motion artifact, statistically meaningless characteristic of noisy signal component and repeated heart rate component give possibility of AMDF to heart rate detection.

Namely, this research is related to algorithm optimization of pulse oximetry for PDA which is hardware platform of mobile health care devices. Its computational performance is in the middle of those of very low price one-chip and dedicated hardware (or personal computer). With this research result, I hope there will be expansion of pulse oximetry from hospital equipment to mobile healthcare devices.

In this paper, proposed SpO_2 detection algorithm and heart rate detection using AMDF will be explained with some plotting results and figures. This paper is organized as follows. In section 2, the related work is described with two each algorithm; Masimo's DST for SpO_2 detection and light weight simple filtering method for heart rate detection. And then, basic principal and information related to pulse oximetry is offered in section 3. In section 4 and 5, proposed SpO_2 detection algorithm and heart rate detection algorithm using AMDF is explained, respectively. Finally, experiment, results and conclusion follow in Section 6, 7 and 8.

II Related work

Pulse oximetry typically has two sub-components. One is detection of SpO_2 value, the other is detection of heart rate. Previously, most kinds of researches related to pulse oximetry was concentrated on how to reduce the rate of false alarming in hospital room. During monitoring vital signal of patient, the reason of motion artifact is caused by unconsciously occurred finger motion[8]. In special case of children, they never care their sensor clip. Even they treat a pulse oximeter sensor their toy. The noise from children is caused by biting, waving and putting on/off their finger[9].

Even though there can hardly find researches related to noise during exercise, with the researches about false alarm by motion artifact in hospital, pulse oximetry algorithm for processing motion artifact during exercise is proposed in this research.

2.1 Masimo's Discrete Saturation Transformation (DST)

Before Masimo's approach, adaptive noise cancellation using the signal reference which is made up ratio of two wavelength signals, conventional method of measuring SpO_2 was 'red over infrared' ratio approach. The assumption of the approach is theoretical light absorption of hemoglobin with various wavelength of light. Without physical deformation of bloody tissue or pulse oximeter surface, there is only one signal ratio between two signals of two wavelengths. However, in practical case, there is not only signal ratio by light absorption of hemoglobin but also signal ratio by motion artifact which makes unexpected light absorption path. Therefore, the result of 'red over infrared' is mixed value of both two kinds of signal ratios.

On the other hand, Masimo's structure using repeated adaptive noise cancellation tests has ability to separate those multiple ratios between both two signals of two wavelengths[7]. Because of different assumption of Masimo's DST from conventional SpO_2 detection method based on theoretical assumption, Masimo can insist that Masimo's DST is designed to eliminate the problem of low signal-to-noise signal processing such as motion artifact and low peripheral perfusion.

The EQ. 2.1.1 describes what causes the problem of conventional method mathematically. In conventional method, the terms of 'N_{red}' and 'N_{ir}' are not considered. Contrastively, in practical case, those two terms are obviously existed. In the case of the terms Ns are much bigger than Ss, Ss become meaningless in the EQ 2.1.2

$$Ratio(r - value) = \frac{\mathrm{I}_{red}}{\mathrm{I}_{IR}} = \frac{\mathrm{S}_{red} + \mathrm{N}_{red}}{\mathrm{S}_{IR} + \mathrm{N}_{IR}}$$ ………….. (EQ. 2.1.1)

If: N>>S,

Then: $$\frac{\mathrm{I}_{red}}{\mathrm{I}_{IR}} = \frac{\mathrm{N}_{red}}{\mathrm{N}_{IR}} \cong 1 \Rightarrow 82\%(SpO_2)$$ ………… (EQ. 2.1.2)

Basically, it is same that signal ratio is the purpose of SpO_2 detection. In contrast, adaptive noise cancellation structure using reference, 'I_{red} - r · I_{ir}', is repeating to investigate all possible signal ratios between those two signals. Every moment that a ratio 'r' is proper ratio between those two signals, reference signal become to lose its correlation to arterial pulse. And then, I_{red} is hardly cancelled out. Therefore, at that point, ANC output power makes peak in ANC power plot.

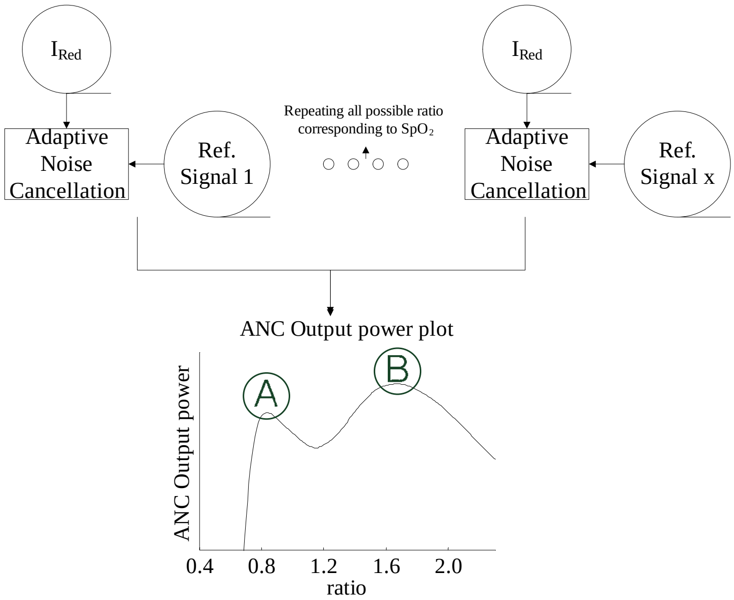


Fig. 2.1.1 Structure of repeatedly tested with reference signal (above) and the result, 'DST plot' (below), I_{red}: red signal, Ref. signal = $I_{red} - r \cdot I_{ir}$ (r = ratio corresponding to all possible SpO_2), Point A: ratio to be mapped to real SpO_2, Point B: ratio by artifact

In the result, 'DST plot', there are two peaks. The left side one is caused by the hemoglobin and the right one is caused by motion artifact. Ideally, in Masimo's DST plot, two kinds of peaks are observed. Because statistical characteristic of noise signal could not be focused on one point, the peak caused by hemoglobin has sharpness and the other peak has dullness.

According to Masimo's technical document about DST, to obtain DST plot, Masimo's DST repeats to get ANC-Output-power 200 times from 0% SpO_2 to 100% SpO_2 (0.5% step size) every 0.4 second. This exhaustive search is good for detecting exact SpO_2, but bad for saving computational power.

The exhaustive ratio search of Masimo's DST is intended to improve accuracy of measuring SpO_2. Even though the amount of repetition makes the

DST more precise, in the case of the algorithm for mobile healthcare devices, there is redundant point with noisy signal during exercise. Because a SpO_2 algorithm during exercise is expected not to monitor medical emergency but to observe exceed exercise load, the accuracy is not needed for the algorithm. In this research, the unnecessary redundancy for precision is converted to reduction of computational power consumption.

2.2 Heart rate detection by bandpass filtering

On the other hand, in the case of measuring heart rate, conventional methods are simple algorithm such as bandpass filtering, median filtering, averaging filtering, etc[5][6]. Usually, noise caused by motion could not be obviously defined. Therefore, a certain frequency characteristic could not be also expected with acquired pulse signal. Because of the noise property, designing proper solution for heart rate extraction is difficult.

A simple approach for noise processing is moving average or median filtering of distorted pitch. However, there is not consideration related to cause of noise but discard of worthless pitch data. And the other method which is most popular is bandpass filtering especially bandpass filtering. With selecting pass band corresponding to possible heart rate, rejection of unnecessary signal is performed by bandpass filter. In practice, as type of IIR filter, bandpass filter is implemented on embedded system[4].

However, because of in-band noise and insufficient bandpass filter performance, the bandpass filtered result from noisy arterial pulse is not enough to find pitch for heart rate. As the intensity of noise increases, the bandpass filtering result also contains more strong noise distortion which is not eliminated by the bandpass filter. Because frequency band of expected heart rate is low (usually 0.5~2.5 Hz), designing sufficient quality of IIR filter is not easy. In this research, AMDF method which uses auto-correlation of signal is applied to measuring heart rate. This method is free against in-band noise and no needed to consider problems related to IIR filter design.

III Pulse Oximetry

3.1 The clinical usefulness of pulse oximetry

It must be remembered that the pulse oximeter measures the oxygen saturation of the blood. When oxygen saturation level falls, it means that the patient has hypoxia. There are 4 widely accepted forms of hypoxia as presented in table 3.1.1.

Table 3.1.1. Four types of hypoxia

Type of hypoxia	Clinical situation
Hypoxic hypoxia	Arterial blood is poorly oxygenated.
Anaemic hypoxia	There are insufficient red blood cells to transport the required oxygen.
Circulatory hypoxia	Cardiac output is insufficient or there is failure in tissue perfusion.
Histotoxic hypoxia	Tissue is unable to use the oxygen supplied to it.

Under normal conditions, blood keeps 100% of saturation with an oxygen partial pressure of 160mmHg. At half of pressure, this level of blood keeps still 95% of saturation. Therefore, it should be expected that our patients have at least 95% of saturation under normal conditions. At 90% of saturation, the oxygen partial pressure becomes down to 65mmHg and the degree enters the steep downward part of the curve. In this lower part of curve, a further drop of only 10mmHg causes oxygen saturation levels to about 80%[13].

Therefore, it is commonly expected that oxygen saturation levels is kept with 95% of saturation or greater. If the saturation level falls below 95%, clinical warning has to given to patient and the cause should be investigated. Even If the saturation level falls below 90%, some kinds of quick treatment should be performed.

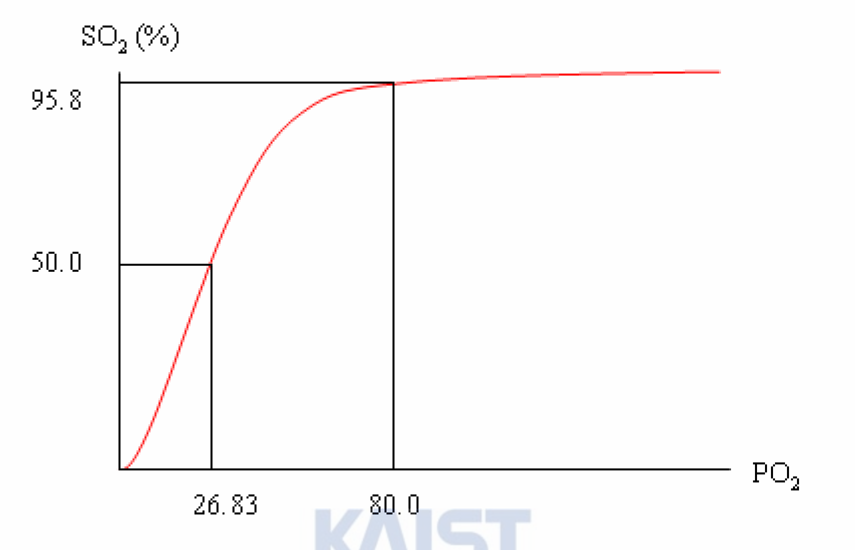


Fig. 3.1.1. Standard Oxyhemoglobin Dissociation Curve

3.2 Brief history of pulse oximetry

In 1935, Matthes developed first two-wavelength oxygen saturation meter with red-colored and green-colored filters. Later, that was substituted by red and infrared filters.

In 1942, Millikan developed optical blood oxygen saturation method because Air Force fighter pilots were blacking out at high ‘G (Gravity)’ forces.

In 1964, Shaw developed first absolute-reading ear-type oximeter by using eight wavelengths commercialized by Hewlett Packard. However, because of its cost and size, it was limited to pulmonary function and sleep laboratories.

In 1972, Aoyagi at Nihon Kohden invented conventional Pulse Oximetry using the ratio between red light absorption and infrared light absorption. And then, it was commercialized by Nellcor and Ohmeda in 1981. They introduced smaller probes equipped light emitting diodes (LEDs).

In 1989, Masimo proposed well developed type of pulse oximetry algorithm using adaptive signal processing. It named discrete saturation transformation (DST). And then, in 1998, Masimo unveiled this technology to clinicians. So, today, more than 70% of the world's pulse oximetry manufacturers have licensed Masimo technology.

3.3 SpO_2 and SaO_2

The two terms SaO_2 and SpO_2 are interchangeably used within pulse oximter. It is similar but not same exactly. The term SaO_2 refers to the oxygen saturation of arterial blood measured by a CO-oximeter. And the term SpO_2 refers to the oxygen saturation of arterial blood measured by a pulse oximeter.

In blood, there is more than one form of hemoglobin. These are oxyhemoglobin, methemoglobin, carboxyhemoglobin, sulfhemoglobin and carboxysulfhemoglobin. Even though oxyhemoglobin predominate the others, dysfunctional hemoglobins are always existed. A typical two-wavelength pulse oximeter cannot distinguish difference between oxyhemoglobin and the dysfunctional hemoglobins. In order to compensate for this phenomenon, most manufacturers of pulse oximeters assume a level of around 2% error standing for the dysfunctional haemoglobins. And the assumed error is considered during processing SpO_2 value. Because of hemoglobin type, only a true CO-oximeter has ability to determine an accurate value for SaO_2.

$$SaO_2 = \frac{\mathrm{HbO_2}}{\mathrm{HbO_2 + Hb + COHb + Methb + SfHb + COSfhb}} \quad \ldots\text{(EQ. 3.3.1)}$$

(HbO_2: oxyhemoglobin, Hb: hemoglobin, Methb: methemoglobin, SfHb: sulfhemoglobin, COSfhb: carboxysulfhemoglobin)

$$SpO_2 = \frac{\mathrm{HbO_2}}{\mathrm{HbO_2 + Hb}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. \text{(EQ 3.3.2)}$$

3.4 Beer Lambert model

As basic principal of pulse oximetry, physical model named ‘Beer Lambert model’ is now introducing in this section. The model deals with what factors determine the transparency of some material. Of the two researchers who offered this model, Lambert defined relation between optical density and thickness of material, Beer defined relation between optical density and concentration of material.

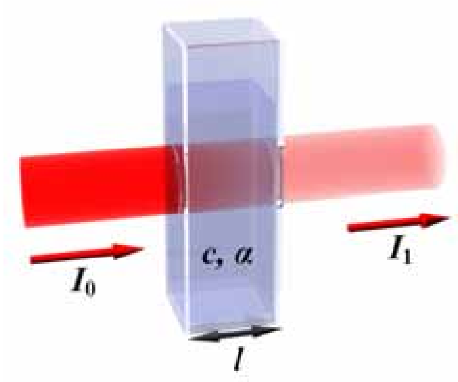


Fig 3.4.1. Beer-Lambert model

Lambert model: Optical density(A) $\propto$ thickness(l)……..(EQ. 3.4.1)

Beer model: Optical density(A) $\propto$ Concentration(C)..(EQ. 3.4.2)

Beer Lambert model: $A = \alpha lc$ …………………………(EQ. 3.4.3)

(A: optical density, α: coefficient, l: thickness, c: concentration, I_1: intensity of transmitted light, I_0: intensity of light incident)

3.5 Human skin and light absorption

It is possible that pulse oximeter have any type of sensor such as ear clip, headband, finger clip, etc. The main principle of design consideration is bio-component under skin and light absorption. In the view of blood, body components under skin consist of arterial blood, venous blood, tissue, and bone (not all the time, for example, ear). Among these components, arterial blood generates AC signal component of measured data of arterial pulse. And the other components (such as arterial blood, venous blood and tissue) effect to DC signal component of measured data of arterial pulse. Oscillating arterial blood is effected by heart beat and constant venous blood is hardly effected.

In case noisy signal is mixed into normal arterial pulse, arterial blood is not changed, and the other components are distorted by motion effect. Abnormal condition of sensor clip attachment also is also related to these inactive components. In the normal case, the path of light passing through the components is stably unchangeable. Otherwise, the motion artifact makes this stable light transmission path disturbed.

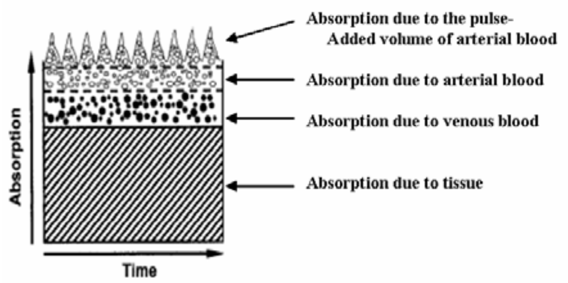


Fig. 3.5.1. Skin and light absorption

3.6 Transmission versus reflectance probes

There are two methods of measuring oxygen saturation either by using a transmission type probe or by using a reflectance type probes. The transmission type probe works on light passing through the thin part of body such as finger or earlobe. And the other one, the reflectance probe obtains its signal from light reflected back at the tissue. And, so it can be placed on plain areas such as palms or thigh. There are subtle differences in the way of producing signal. However, essentially, it is same transmission type.

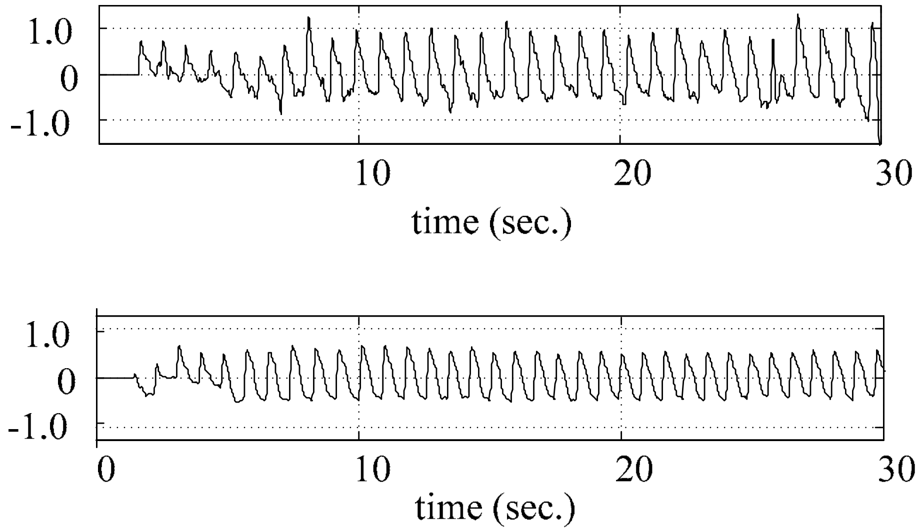


Fig. 3.5.2. Arterial pulse plot of two pulse oximeter type, (above): On palm, with reflectance probes, (below): on finger, with transmission probes

3.7 Principal of pulse oximetry operation

In order to measuring SpO_2 value, a pulse oximeter uses two wavelengths of light, typically at 660nm (red) and 950nm (infrared) to determine the color and oxygen saturation of arterial blood.

$$SpO_2 = \frac{\text{Oxyhaemoglobin}}{\text{Oxyhaemoglobin} + \text{Reducedhaemoglobin}} \quad \text{..... (EQ. 3.7.1.)}$$

Two kinds of hemoglobins which are reduced haemoglobin and oxyhaemoglobin have different absorption coefficients at different wavelengths of light. The two curves cross over at the point about 805nm. This meaning is that below 805nm reduced haemoglobin absorbs more light than oxyhaemoglobin and above 805 nm oxyhaemoglobin absorbs more light than reduced haemoglobin. Because of this characteristic, the oxygen saturation level can be determined by using two wavelengths of light.

Theoritically, Beer's law could be accepted to the determination. However, because tissue does not follow Beer's law exactly, all pulse oximeter manufacturers make a test for their equipment against well known standard equipment like a CO-oximeter, and then define an empirical adjustment to estimate actual SpO_2 value. This means that a SpO_2 value on any pulse oximeter is valid when the conditions of a patient match the conditions of the original reference.

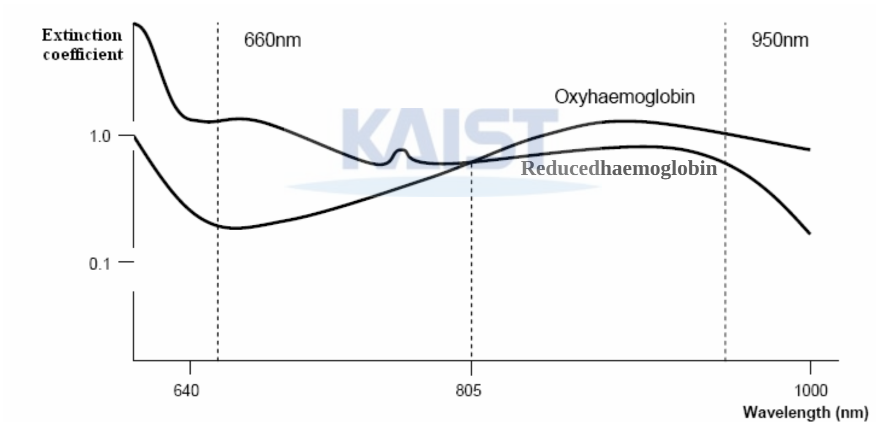


Fig 3.7.1. Relation between wavelength and extinction coefficient

The signal result (Fig. 3.7.2) of two waves could be obtained by the relation between wave length of light and hemoglobin (Fig. 3.7.1). In the case of oxihemoglobin, red light (about 660nm wave length) has lower extinction coefficient than that of infra-red light (about 950nm). Therefore, magnitude of arterial pulse signal related to red light is bigger than that of infra-red. As the Fig. 3.7.2 shows, two signals have similar shape. However, magnitudes of two signals are different from each other. There is one constant t ratio between two signals.

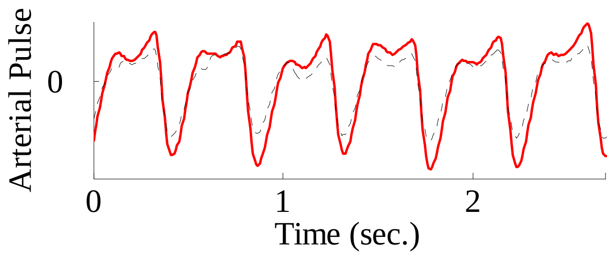


Fig 3.7.2. Two signals from red light and infrared

Until now, SpO_2 detection method using two different wave-length lights are mentioned as main principal of pulse oximetry operation. Of two signals, with one signal, heart rate detection could be possible. As you can see in Fig 3.7.2, because of similarity of two signals, any signal could be selected to measure signal pitch for heart rate. Typically, when pulse oximeter is designed, only one signal is determined to be displayed on its monitor device.

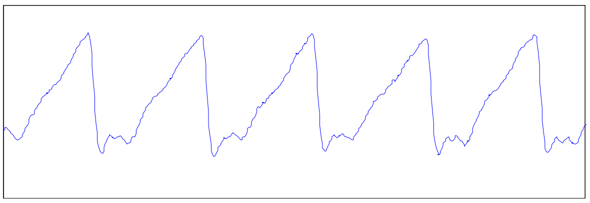


Fig 3.7.3. HR: One light signal is arterial pulse

In EQ. 3.7.1, the definition of SpO_2 is mentioned with two hemoglobins which are oxyhemogrobin and reducedhemogrobin. In practical system, SpO_2

value is obtained from ratio of two signal power like EQ. 3.7.2. And then, the obtained ratio from EQ. 3.7.2 is converted to SpO_2 value mapped by 'R to SpO_2 curve'.

The fundamental theory of 'R to SpO_2 curve' is based on 'Beer-Lambert model'. However, because the model considers transmission characteristic of simple material, the mapping graph shape is linear. Therefore, in practical case, empirical calibration is necessary for a system implementation. In the reason, each manufacturer has different 'R to SpO_2 curve' and the performance caused by the curve is appraised by consumer.

$$(R = \frac{AC\_signal\_power\_of\_IR\_light}{AC\_signal\_power\_of\_RED\_light})$$

..............EQ. 3.7.2. Optical density ratio equation

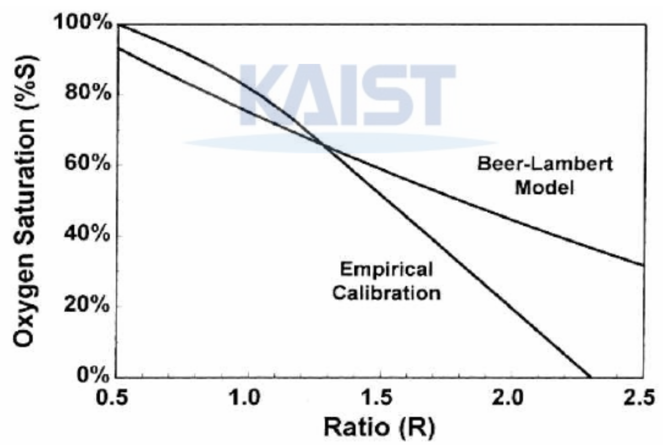


Fig. 3.7.4. R to SpO_2 curves during supine status, empirical calibration referred to Texas Instruments, Inc.

Finally, after the processing which is mentioned until now, a pulse oximeter (like Fig. 3.7.5) could be complete with SpO_2 value and heart rate.

Typically, SpO_2 value and heart rate are displayed with form of number. And the arterial pulse signal is displayed with form of graph. The unit of SpO_2 is usually percent and the unit of heart rate is rate per minute (RPM).

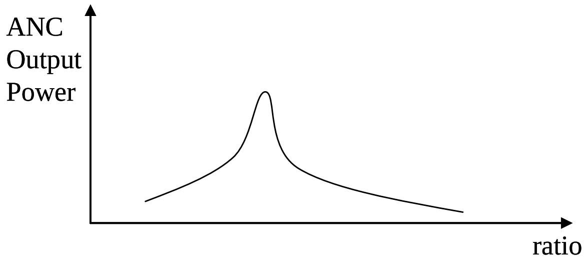
Fig. 3.7.5. A pulse oximeter

IV Fast algorithm for DST-based SpO_2 detection algorithm for mobile device

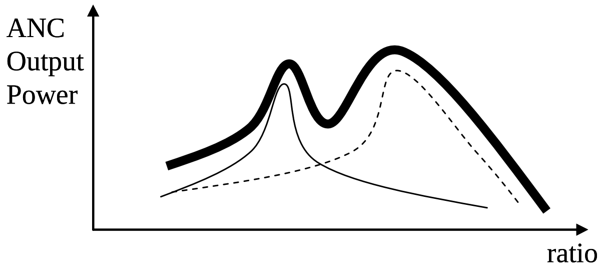
The point of this algorithm development is reduction of computational power consumption. It does not need to keep the accuracy of Masimo's DST. What we want to use is the structure of repeated ratio test with ANC. And the reduced processing time consumption has to be required for the algorithm. Before main algorithm is described, the study about ANC Output power plot of DST will be mentioned.

4.1 Study about ANC Output power plot of DST

In this section, in order to design new algorithm about DST, multiple peaks in ANC output plot of DST are explained with some figures. In the technology document of corporation Masimo, they explain that the DST algorithm and its multiple peaks result is very important point of separation between signal and noise. But they do not mention the exact reason of multiple peaks. They just report the experimental tendency about DST. They determine left peak of two peaks as the peak induced by arterial pulse. And on the other hand, the other right signal is determined peak induced by motion artifact.



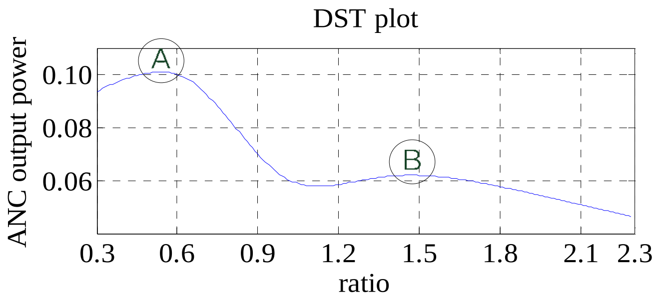
(a) Result without artifact



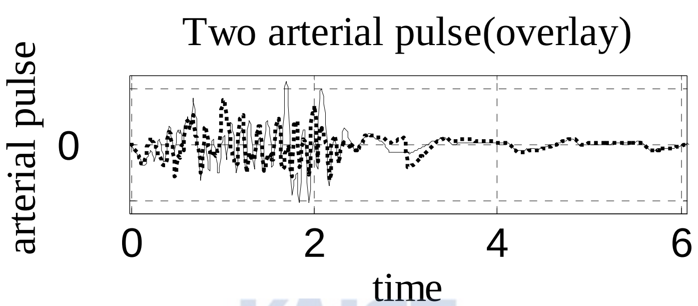
(b) Motion artifact added result during exercise

Fig. 4.1.1. Multiple peaks in DST ANC Output power plot

However, in this research, we make it sure that the peak of arterial pulse has more sharp shape than that of noise. Because noise do not have statistical characteristic, peak by noise has dull peak as B of Fig. 4.1.2(a). Namely, point ‘A’ of Fig 4.1.2(a) means result regularly generated by human heart, and point ‘B’ of Fig 4.1.2(a) means result caused by noisy motion artifact.



(a)



(b)

Fig. 4.1.2. Multiple peaks and the signal characteristic

4.2 Overall system diagram and description of two SpO_2 detection algorithms

By using the method which was mentioned until now, the overall system is developed like Fig. 4.2.1. As the figure shows, instead of reduced ANC repeat, Peak estimation part is added to the proposed SpO_2 detection algorithm.

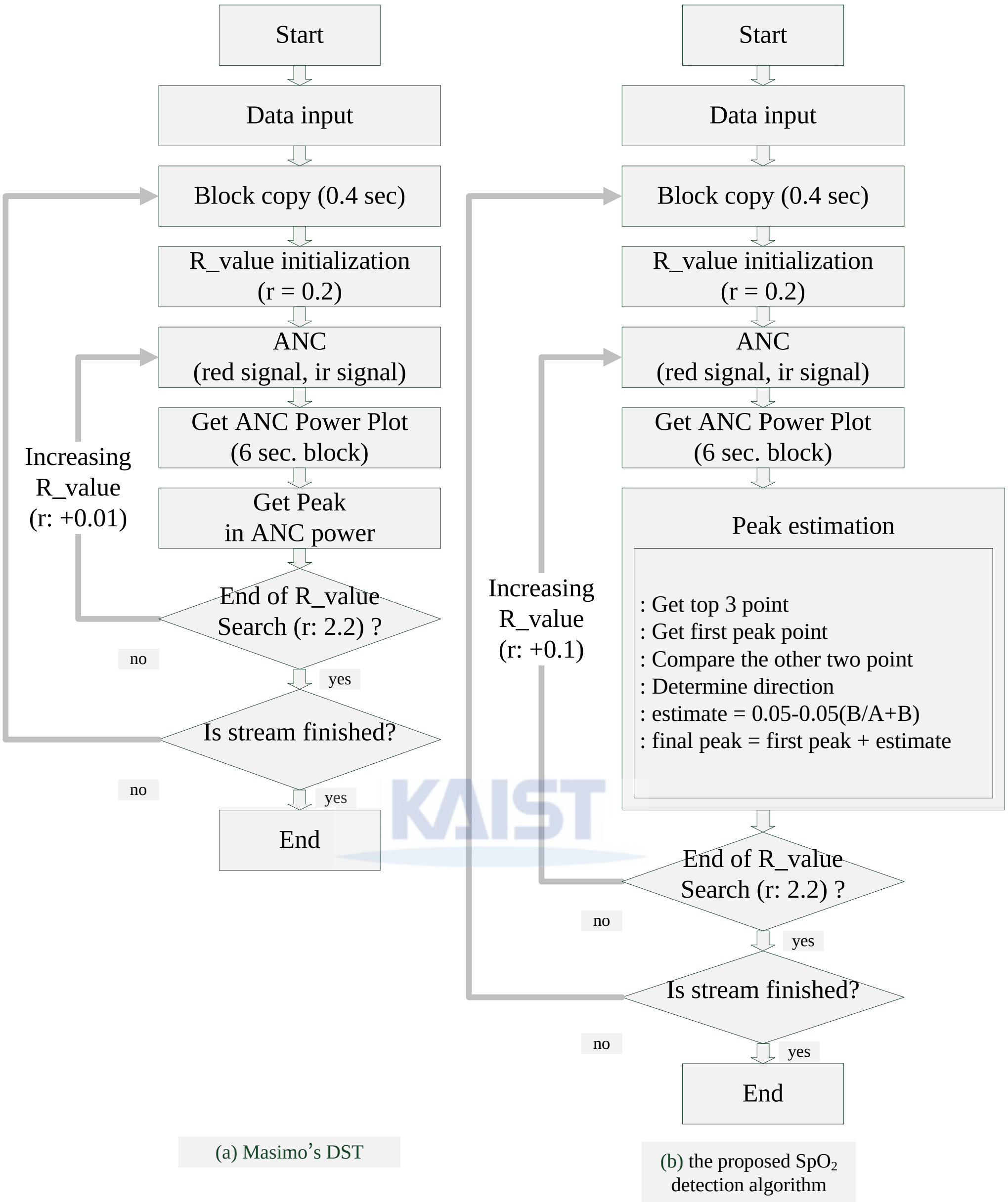


Fig. 4.2.1 Overall system diagram of two SpO_2 detection algorithms

4.3 The proposed SpO_2 detection algorithm

The first approach of proposed SpO_2 detection algorithm is reduction of ANC test count. Because of the reduction, the proposed SpO_2 detection algorithm earns processing time. While Masimo's DST has 200-time of repeat, the proposed SpO_2 detection algorithm only has 20-time of repeat. Therefore it is expected that about 90% of processing time save could be achieved by this algorithm.

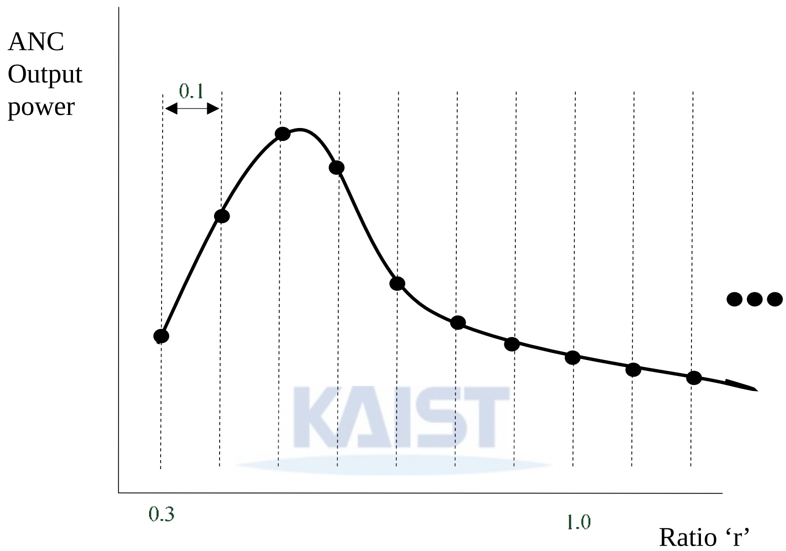


Fig. 4.3.1. Sparse search

And then, the algorithm has to compensate the problem of accuracy. So, the proposed SpO_2 detection algorithm has peak estimation method using gradient with A and B of Fig. 4.3.2. Increment toward real peak could be estimated by using gradient. When the estimation is not applied to the proposed SpO_2 detection algorithm, the worst ratio error could be 0.05. However, by using this estimation, 0.01 of ratio error is occurred.

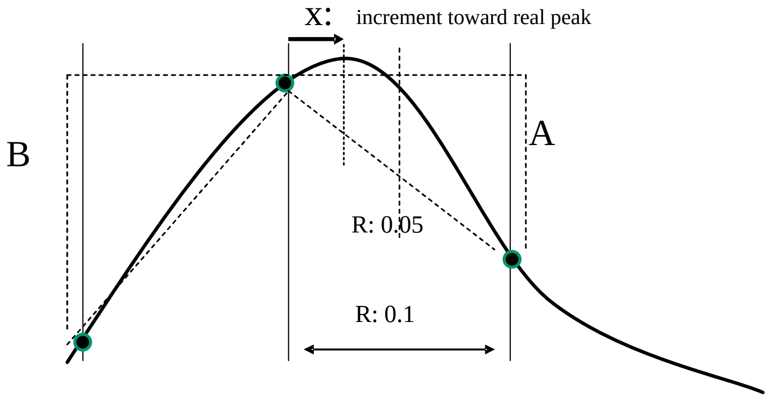


Fig. 4.3.2. Precise search (ratio estimation using gradient with A and B)

$$x = \left(\frac{0.1}{2}\right) - \left(\left(\frac{0.1}{2}\right) \times \left(\frac{A}{A+B}\right)\right) \quad \text{.......... (EQ. 4.3.1)}$$

$$= \left(\frac{0.1}{2}\right) \times \left(1 - \left(\frac{A}{A+B}\right)\right) \quad \text{................ (EQ. 4.3.2)}$$

$$= 0.05 \times \left(\frac{A+B-A}{A+B}\right) \quad \text{.................... (EQ. 4.3.3)}$$

$$= 0.05 \times \left(\frac{B}{A+B}\right) \quad \text{......................... (EQ. 4.3.4)}$$

As the explanation mentioned, increment toward real peak could be estimated by A and B of Fig. 4.3.2. As special cases, two cases are now given with illustrations.

When A is equal to B, increment ‘x’ becomes zero in Fig 4.3.2. In this case, the in Fig 4.3.2 makes decision that right peak is found.

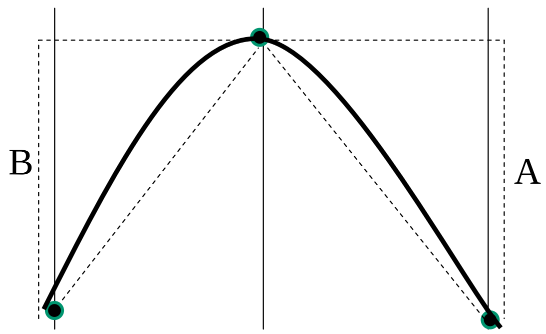


Fig. 4.3.3. The case of A=B and x =0

As the other special case, the situation which is ‘A’ or ‘B’ is zero could be occurred during estimation. In this case, the proposed SpO_2 detection algorithm recognizes the increment is 0.05 (middle of first top two points).

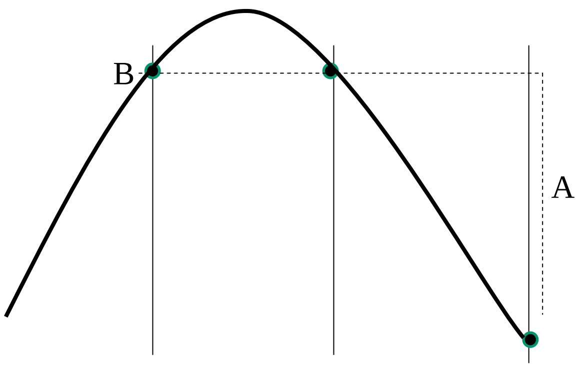


Fig. 4.3.4. The case of A or B is zero

V Heart rate detection using Average magnitude difference function (AMDF)

There are multiple manufacturers which provide heart rate detection devices. Some manufacturers make big equipment for hospital and some others make small heart rate detection devices like wristwatch. Though there are many types of heart rate detection devices, most of all is designed with very light-weight performance of digital processor. These kinds of embedded systems usually allow only tens or hundreds of MAC. So, bandpass filter, especially, IIR filter is usually utilized to pulse oximeter. Moreover, of research papers approaches, frequency-based processing is the most popular research topic.

The strong point of bandpass filtering is that implementation on an inexpensive chip is very economic. And its performance for hospital uses is not too bad to monitor patient on a bed. And it is also needed to block electronic circuit problem such as 60Hz power noise and interference circuit elements. Because this problem is always occurred in a pulse oximeter and is always related to electronic frequency characteristic, it is very effective to pulse oximeter. However, in the case of strong motion artifact, the noisy does not have identifiable frequency characteristic. Moreover, if motion artifact is in-band noise, bandpass filtering becomes to be ineffective.

During exercise, motion artifact is caused by body motion to keep running with swinging arms and stepping feet. And unstable sensor attachment adds noise into arterial pulse. These are mostly unidentified frequency noise or in-band noise. Therefore in this case, frequency approach is not appropriate for measuring heart rate.

In order to solve this problem during exercise, autocorrelation based method could be the solution. During exercise, though signal of heart rate seems to be inseparable, it keeps its periodicity. However, noise by motion artifact is not related to heart beat signal due to its different causes. The sensed result is just superposition of pure heart beat and noise by motion artifact. Therefore, in this research, AMDF method which is based on statistical autocorrelation is adapted to measure heart rate during exercise. Because this method requires thousands of MAC and more memory spaces, it is not appropriate for cheap small chip. On PDA hardware, it is easy and strong method to measure heart rate during exercise.

As EQ. 5.1 shows, AMDF method is basically based on self subtraction as shifting itself. It is same as autocorrelation but faster to implement with integer arithmetic without multiplies.

$$AMDF(t) = \frac{1}{\mathrm{L}} \sum_{i=1}^{L} \left| s(i) - s(i-t) \right| \qquad \text{...... EQ. 5.1}$$

Where

s(i): input signal, i:1~L

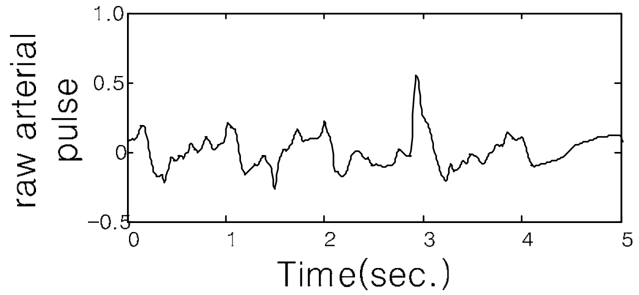
S(i-t): time-shifted signal

L: length of signal

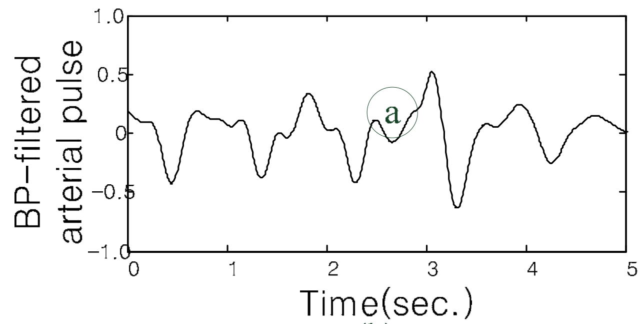
From now, the reason why AMDF is proper method during exercise is dealt with the following case studies. For generating each result by bandpass filtering and AMDF, following setting (table 5.1) is applied to implement test codes.

Table 5.1. Setting for case studies

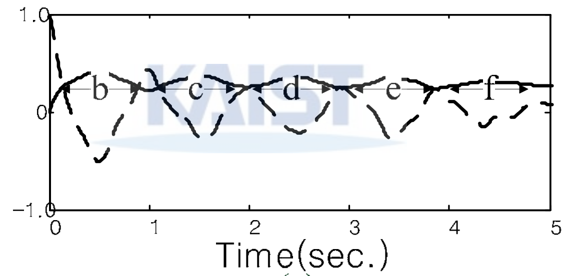
AMDF	Frequency filtering
- Search block size setting: 20 sec. - Reference block size: 5 sec.	- Ellip bandpass IIR filter(7tabs: each of a, b) - 0.5Hz ~ 2.5Hz pass (120 rpm ~ 24 rpm: possible range of heart rate) - Other freq. range: -60dB



(a)



(b)



(c)

Fig. 5.1. Case 1: no exercise, finger swing; (b) reduced ripple, but local minima problem like circle a. mark b-f of (c) is pitch for heart rate, (c) solid line: AMDF result, dashed-line: ACF

From Fig 5.1 to Fig. 5.3, there are three case studies. First case shows good performance of both two methods. However, in the case of bandpass filtering, local minima which can cause pitch halving could be occurred like marker a. On the other hand, the result of AMDF is not distorted by artifact. In case 2, the motion artifact of exercise is mentioned. In the cases of raw signal and filtered result, there are more local minima than case 1. However, in the case of AMDF result, distortion by motion artifact is appeared in upside of graph. Because signal pitch is detected within the downside of AMDF plot result, there is no problem to detect heart rate.

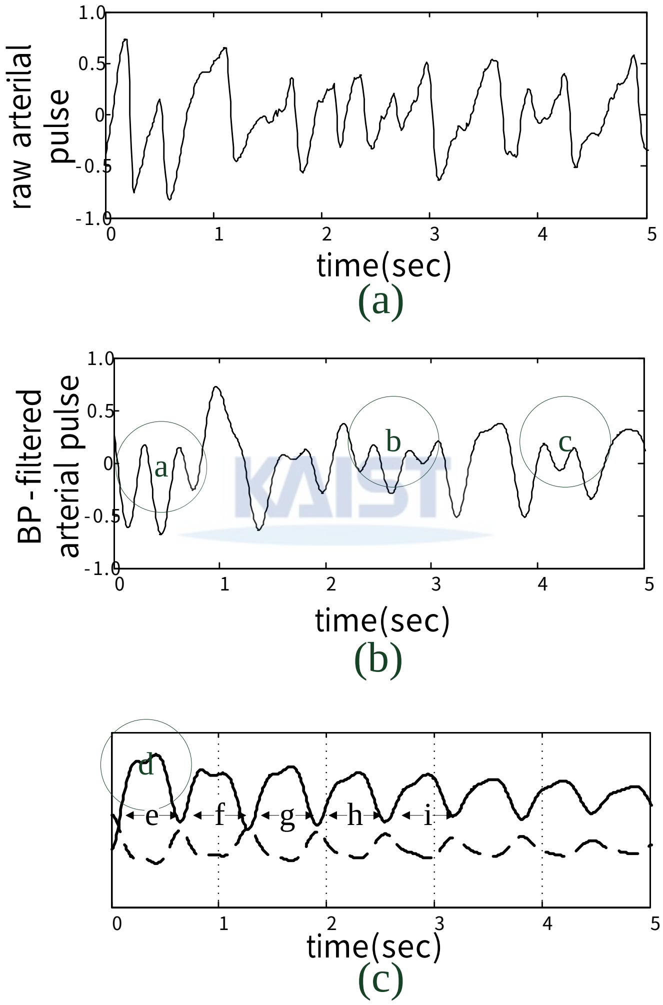


Fig 5.2. Case 2: during less intensive exercise, (c) solid line: AMDF result, dashed-line: ACF

The most important result for anti motion artifact algorithm is shown in the case 3. With the raw signal, it is very difficult to detect signal pitch. And, in the case of filtered result, it is hard to avoid failure of pitch detection like halving or doubling. Nevertheless, AMDF result shows stable pitch detection performance. Noise hardly effects to pitch of down part of AMDF plot.

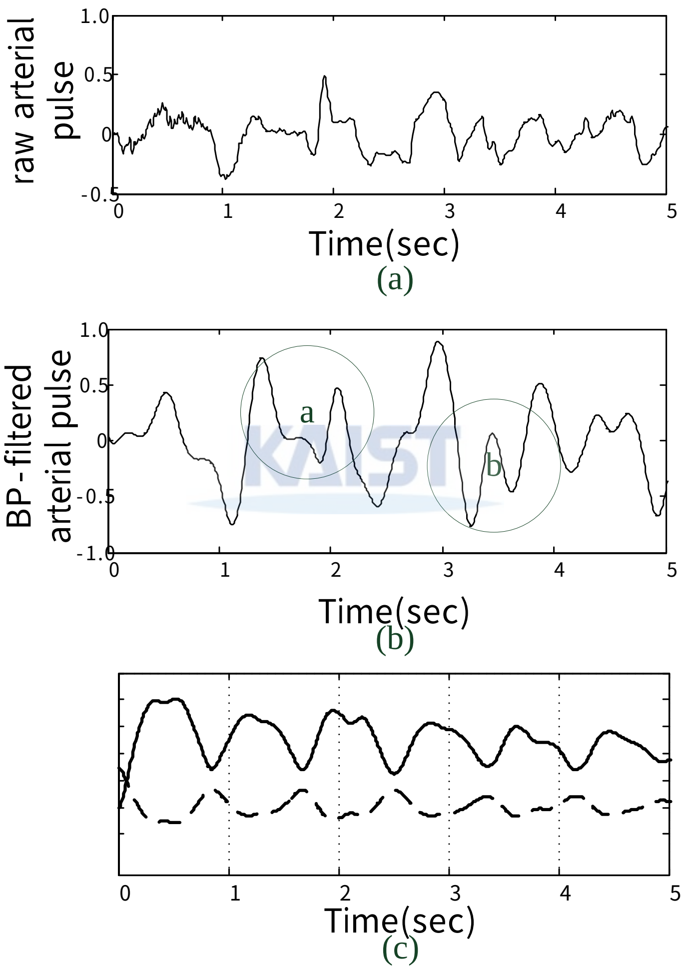


Fig 5.3. Case 3: most intensive artifact, (c) solid line: AMDF result, dashed-line: ACF

Through these case studies, it is proved that AMDF is more strong method against motion artifact during exercise. In this research, artifact-robust HR detection algorithm using AMDF is proposed. The overall algorithm flow is described in Fig 5.4.

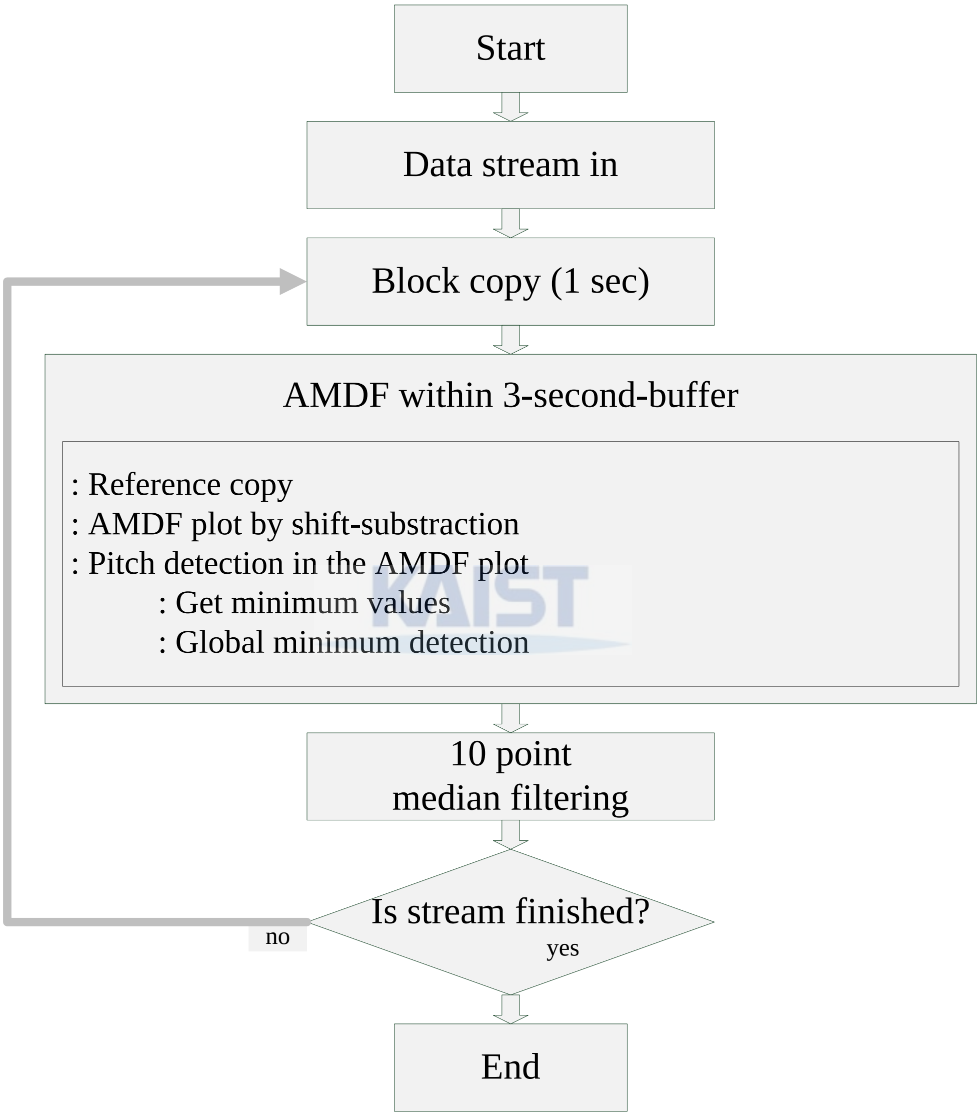


Fig 5.4. Overall algorithm flow of detecting HR using AMDF

VI Experiment

6.1 Data acquisition from subjects

The important point of this research is evaluation of the performance of pulse oximetry algorithms for exercise on mobile devices. Therefore, this experiment was designed for data processing during exercise. With simulation of jogging situations outdoor, a treadmill was selected to control subject's running speed constantly. For testing general jogger's exercise patterns which are fast walking and running, the two speeds of 5km/h and 7km/h were chosen for male, the two speeds of 4km/h and 6km/h were chosen for female.

The main purpose of this research is investigation of the effectiveness of algorithms to various kinds of people. In the reason, the subjects were five men who are aged from 20's to 50's and one woman who are 55-year old. The given task was running on computer controlled treadmill. During exercise, to acquire time-regulated dataset, a software tool (Fig. 6.1.2) for subject was used.

Rest (1 min.)	5(4)/7(6) km/h	Rest (1 min.)

Fig 6.1.1. Given task. (x) is speed for women

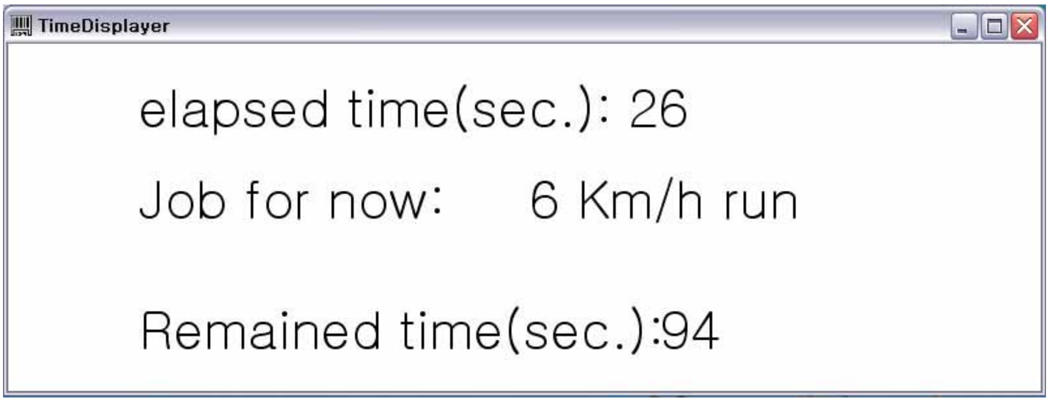


Fig. 6.1.2. Software tool to inform job for now

When a subject runs on the machine, pulse oximetry data was recorded by pulse oximeter with finger clip type sensor. Especially, in this research, there was special modification of pulse oximeter. Because there was no pulse oximeter output data of IR signal and red signal with our pulse oximeter, the raw signal from the sensor was directly recorded by soundcard of PC. Therefore, the recorded data had to be preprocessed on PC after an experiment was finished.

6.2 Processing acquired data

Processing acquired data was focused on two views. One view is processing time of each method on PDA and the other view is error rate of each method. The consideration of processing time of algorithms was usefulness on PDA. In this research, PDA which has following specification (Table 6.2.1) was employed to measure time consumption of algorithms. For measuring actual processing time, a function, 'GetTickCount()', which has precision of millisecond was used. Because there is no CPU performance gauge on PDA, an estimation using ratio between input data time and actually measured processing time is used for evaluating system resource requirement.

Table 6.2.1. PDA specification

Model name	HP iPAQ Pocket PC h5450
OS	Pocket PC version 4.20.1081(build 13100) PPC2003
Processor	Intel® PXA250 (400MHz)
Memory	64MB RAM and 48 MB ROM (20 MB of which is accessible to user)

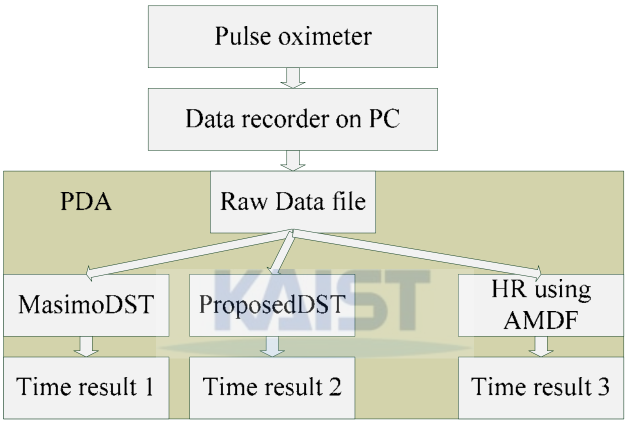


Fig. 6.2.1. Processing time evaluation on PDA

In the view of error rate of algorithms, the results of proposed SpO_2 detection algorithm were compared to those of Masimo's DST. The evaluation of both two HR detection algorithm, artifact-robust HR detection algorithm using AMDF and HR detection using bandpass filtering were performed with a HR value which is measured right after finishing exercise. Because HR is unchanged and there is little motion artifact by exercise motion in short-term, the value was used as actual HR value during exercise.

During data processing for two SpO_2 detection algorithms, as active noise cancellation algorithm, N-LMS method was used with 48 taps (corresponding to output-update-time, 0.4 sec) and 0.0004 of learning rate which is experimentally optimized to the test codes. To process HR data, as conventional method, bandpass filter had following factor; IIR elliptic bandpass filter, stopband attenuation: -60dB, passband: 0.5~2.5Hz, sampling rate: 120Hz. For artifact-robust HR detection using AMDF, 6-second of data search range was provided.

VII Result

7.1 DST error of the proposed SpO_2 detection algorithm

The ratio error of the proposed SpO_2 detection algorithm against Masimo's DST was measured by EQ.7.1.1. Totally, ratio error was 0.0123. The ratio error during 5km/h exercise and 7km/h exercise was 0.0125 and 0.0121, respectively. Because possible ratio range is typically from 0.5 to 2.5, those 0.01 of error are quite small enough to ignore.

$$AverageError = \frac{\sum_{i=0}^{N-1} \left| Rp_i - Rm_i \right|}{N} \quad \text{…….(EQ. 7.1.1)}$$

(Rp: ratio from proposed SpO_2 detection algorithm,

Rm: ratio from Masimo's DST, N the number of estimates)

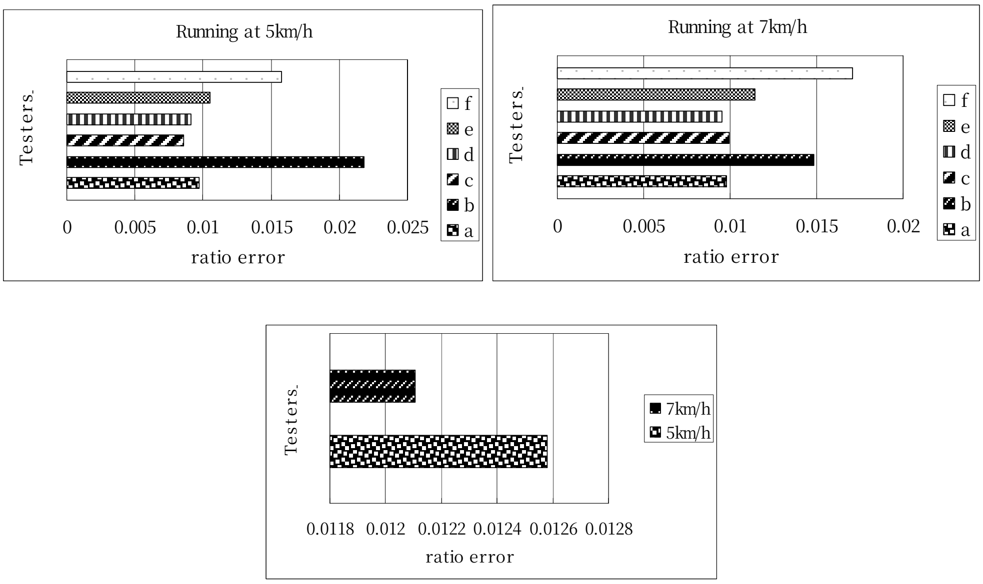


Fig. 7.1.1. Ratio error

The average normalized error of ratio of proposed SpO_2 detection algorithm against Masimo's DST was measured by EQ.7.1.2. Totally, the average normalized error of ratio was 3.1953%. The average normalized error of ratio during 5km/h exercise and 7km/h exercise was 3.5282% and 2.8070%, respectively.

$$AverageNormalizedRatioError = \sum_{i=0}^{N-1} \frac{|Rp_i - Rm_i|}{Rm_i} \times 100 \quad \text{....(EQ. 7.1.2)}$$

(Rp: ratio from proposed SpO_2 detection algorithm,

Rm: ratio from Masimo's DST, N the number of samples)

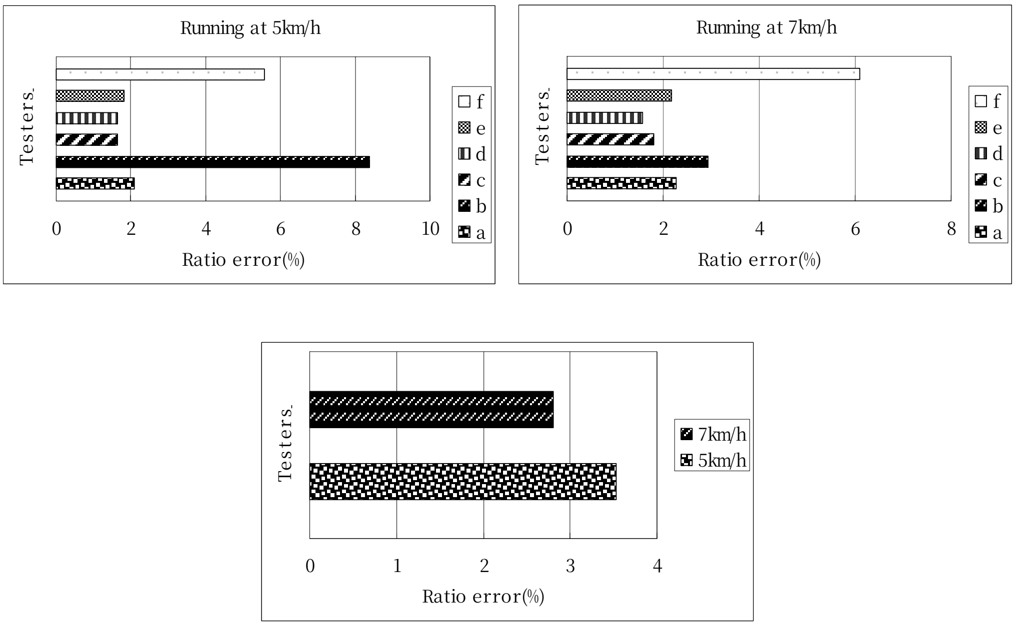


Fig. 7.1.2. The average normalized error of ratio

The average normalized SpO_2 error of proposed SpO_2 detection algorithm against Masimo's DST was measured by EQ.7.1.3. Totally, the average normalized SpO_2 error was 0.1387%. The average normalized SpO_2 error during 5km/h exercise and 7km/h exercise was 0.1178% and 0.1631%, respectively. For converting ratio to SpO_2, R to SpO_2 mapping of Fig. 3.7.4 was used. The mapping was calibrated with supine status.

$$AverageNormalizedSpO_2Error = \sum_{i=0}^{N-1} \frac{|Rp_i - Rm_i|}{Rm_i} \times 100 \quad \ldots\text{(EQ. 7.1.3)}$$

(Rp: SpO_2 from proposed SpO_2 detection algorithm,

Rm: SpO_2 from Masimo's DST, N the number of estimates)

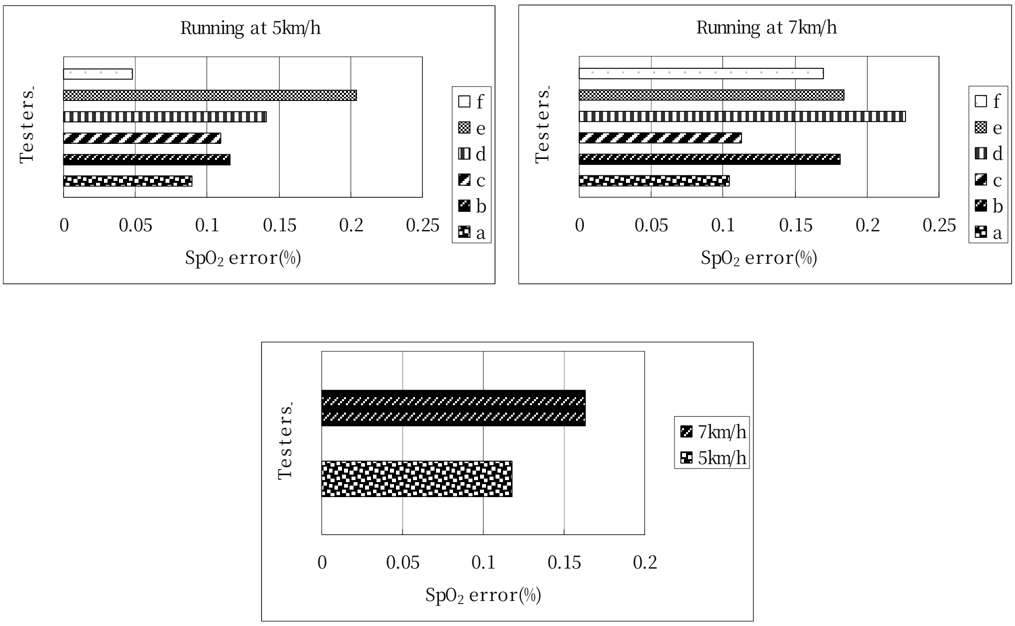


Fig. 7.1.3. Average normalized SpO_2 error

As Fig 7.1.3 shows, there is error under 0.2%. Consequently, we could use the proposed SpO_2 detection algorithm within tolerance error range.

7.2 Processing time analysis of two SpO_2 detection methods

In the case of processing time result, there was nearly same processing time consumption. Because the experiments related to measure processing time of each case use same software code, there used average of whole case without consideration about each exercise and subject. Processing power requirement was evaluated by EQ. 7.2.1.

In the case of Masimo’s DST, the processing time consumption of 300 sec. data input was 905.506 sec. Therefore, it requires 301.835% of PDA system resource. It could not be performed in real-time. On the other hand, in the case of proposed SpO_2 detection algorithm, the processing time of 300 sec. data input was 78.658 sec. So, it requires 26.219% of PDA system resoure. It could be performed in real-time. And the remained about 70% of resource could allow resource for GUI or other multi-processing application.

$$\mathrm{Re}\,source\,\mathrm{Re}\,quirement = \frac{a}{b} \times 100 \quad (\%) \ldots\ldots \text{ (EQ. 7.2.1.)}$$

(a: processing time, b: given data length: 300 sec.)

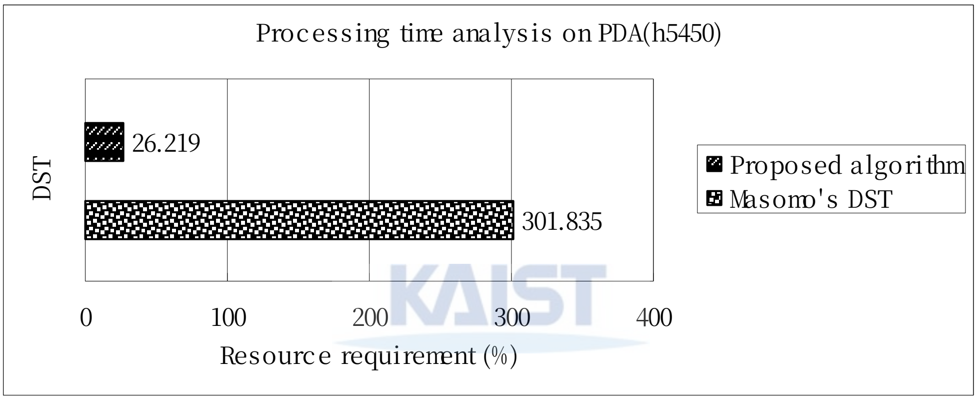


Fig. 7.2.1. Processing time analysis

7.3 Processing time reduction of proposed SpO_2 detection algorithm

The measured processing time reduction is evaluated with EQ 7.3.1. for analysis in the sense of processing time reduction. By EQ 7.3.1, the processing time reduction was 91.31%. It means that unnecessary portion of conventional algorithm is 91.31% during exercise.

$$\mathrm{Pr}\,\mathit{oces}\,\mathrm{sin}\,\mathit{gTime}\,\mathrm{Re}\,\mathit{duction} = \frac{|a-b|}{a} \times 100\ (\%) \text{........ (EQ. 7.3.1.)}$$

(a: peak search time of Masimo’s DST,

b: peak search time of Proposed SpO_2 detection algorithm)

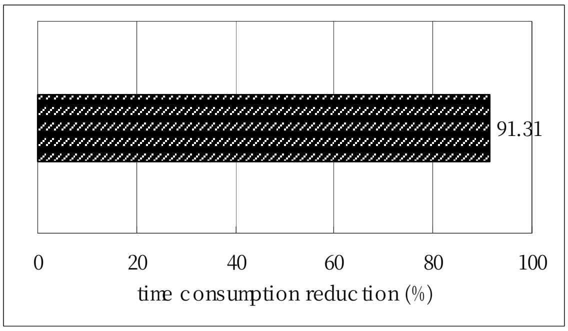


Fig. 7.3.1. Processing time reduction

7.4 Processing speed improvement

The measured processing time reduction is evaluated with EQ 7.4.1. for analysis in the sense of processing speed improvement. By EQ 7.4.1, the processing speed improvement was 11.512 times.

$$\mathit{Speed}\quad \mathit{improvement} = \frac{\mathrm{a}}{\mathrm{b}} \times 100 \quad (\%) \text{ .....(EQ 7.4.1.)}$$

(a: original exhaustive search time, b: proposed fast search time)

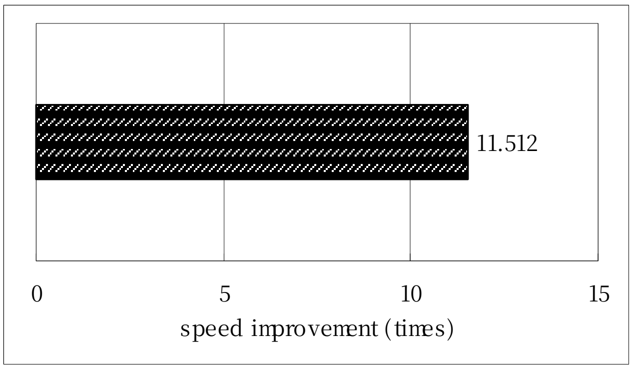
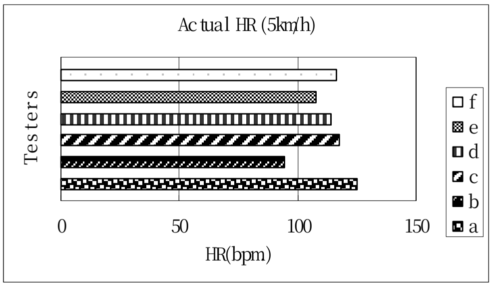


Fig. 7.4.1. Processing speed improvement

7.5 HR error of AMDF & frequency filter

For error evaluation of HR algorithms, actual HR data was collected with clean data of measured pulse oximetry data. There was an assumption like this. Though it is impossible to obtain actual heart rate with noisy data, there could be possible to get actual heart rate right after finishing exercise. At that time, there is no body motion and heart rate is kept.



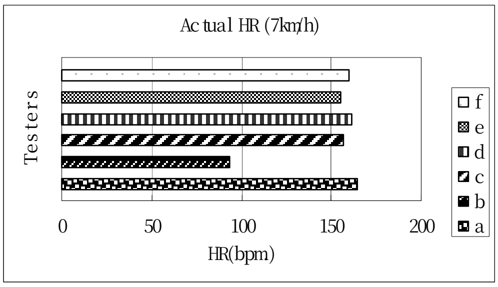


Fig 7.5.1. Actual heart rates

Firstly, HR detection errors of both two methods were measured with bpm. unit. In the case of artifact-robust HR detection using AMDF, HR detection error of 5km/h exercise and 7km/h exercise was 3.8221 and 2.9616, respectively. In the case of bandpass filtering, HR detection error of 5km/h exercise and 7km/h exercise was 39.3265 and 29.3335, respectively.

Secondly, HR detection errors of both two methods were measured with normalized unit, percent. In the case of artifact-robust HR detection using AMDF, HR detection error of 5km/h exercise and 7km/h exercise was 4.23% and 4.63%, respectively. In the case of bandpass filtering, HR detection error of 5km/h exercise and 7km/h exercise was 40.37% and 34.89%, respectively.

Totally, In the case of artifact-robust HR detection using AMDF, there was 4.43% of HR detection error. On the other hand, in the case of BPF method, there was 37.63% of HR detection error. In an error reduction sense, artifact-robust HR detection using AMDF achieved 88.23% of improvement. Usually, the possible range of heart rate is from 100(rpm.) to 180(rpm.). Under this situation, tens of error means that detection system is unreliable. This result shows why artifact-robust HR detection using AMDF is needed to detect heart rate.

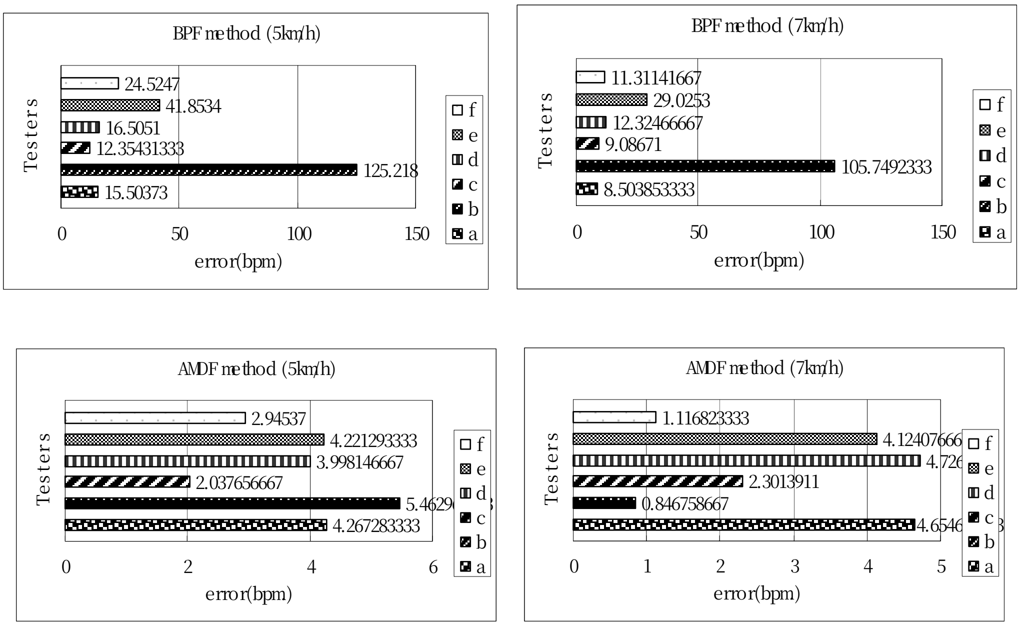


Fig 7.5.2. HR detection error analysis (bpm.)

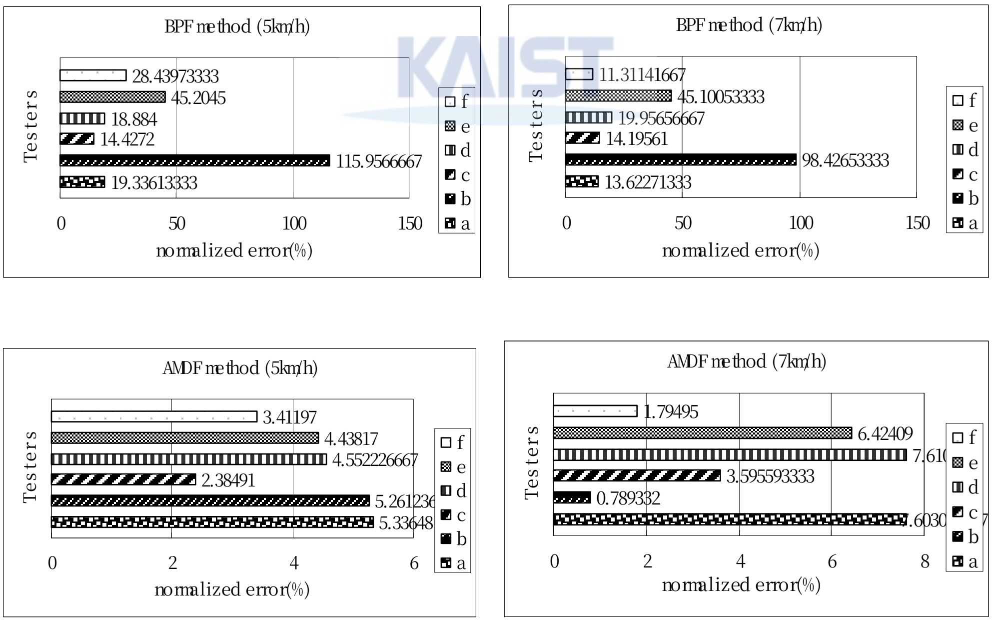


Fig 7.5.3. Normalized HR detection error analysis (%)

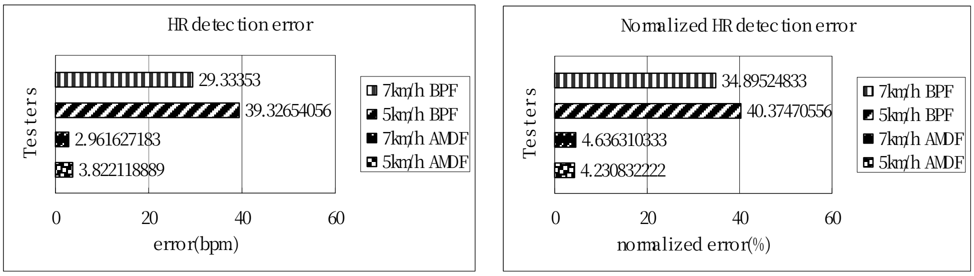


Fig 7.5.4. Overall HR detection error analysis (%)

7.6 Processing time for heart rate detection using AMDF

The purpose of this research is development of algorithms optimized to mobile device for exercise. Therefore processing time requirement of each algorithm is very important. In this section, artifact-robust HR detection algorithm using AMDF was measured in the sense of processing time consumption. The measured processing time of 300 sec. input data was 14.97 sec. It requires 4.99% of the PDA system resource. The time was evaluated with EQ. 7.6.1. Because it requires a little portion of system resource, it could be used with proposed DST algorithm at the same time.

$$Re\,source\,Re\,quirement = \frac{a}{b} \times 100 \quad (\%) \;....\; (EQ.\ 7.6.1)$$

(a: processing time, b: given data length: 300 sec.)

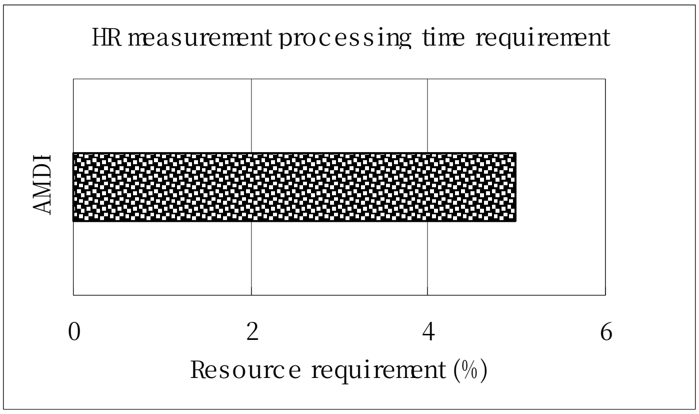


Fig 7.6.1. HR detection processing time requirement

VIII Conclusion

In this research, we proposed algorithms for mobile health care devices. One was related to fast algorithm for DST-based SpO_2 detection algorithm, and the other was artifact-robust HR detection algorithm. As the research motivation, development of pulse oximetry algorithms for exercise was focused on portable devices.

More detail purpose of this research was reduction of processing time of SpO_2 detection and improvement of HR detection. In order to achieve these detail purposes, we developed fast algorithm for DST-based SpO_2 detection algorithm as a SpO_2 detection algorithm and artifact-robust HR detection algorithm as a HR detection algorithm. The evaluation related to processing time was performed with a very cheap PDA product. Therefore, the sufficient results of performance evaluation mean that it is easy to make a pulse oximeter using the proposed pulse oximetry algorithms.

In the experiment, the proposed pulse oximetry algorithms achieved expected performance improvement. In the case of the proposed SpO_2 detection algorithm, there were affordable low errors and processing time reduction to use on PDA during exercise in real time. In the case of the artifact-robust HR detection algorithm using AMDF, the detection performance is sufficiently improved.

Through this research, we could become to know problems of pulse oximetry during exercise. Based on the research, now we have artifact-robust pulse oximetry algorithms for exercise. As future work, we need advanced researches about more intensive exercise or other type of exercise except jogging. Now, we are at the beginning of pulse oximetry research for exercise. The pulse oximetry researches for exercise will be more broadly fulfilled more than pulse oximetry researches for medical uses.

석사학위논문

모바일 건강 관리 기기를 위한 펄스 옥시메트리 기반의 혈중산소포화도와 펄스레이트의 측정

공학부 서호준

본 논문은 기존의 펄스 옥시메트리 기술을 응용하여 운동 중에도 사용할 수 있도록 하려는 연구 동기에 의하여 수행되었다. 기존의 펄스 옥시메트리 기술이나 장비 등은 대부분 의료용 장비를 위한 것이었으므로, 운동을 위한 데이터 처리 플랫폼으로서 PDA 를 선택하였고, 그 위에서 적용 가능한 펄스 옥시메트리 신호 처리 알고리즘의 개발이 연구의 가장 큰 목적이었다.

현재의 펄스 옥시메트리 기술이 휴대용 기기에 적합한 만족스러운 성능을 갖지 않기 때문에 펄스 옥시메트리의 두 가지 하위 기술인 혈중산소포화도 측정 기술과 맥박수 측정 기술을 모두 다루어 연구를 진행하였다.

혈중 산소 포화량을 측정하는 알고리즘은 그 측정 성능을 개선하기보다는 그 수행 시간을 줄여 PDA 등의 휴대용 기기에서 운용하기 적합하도록 구조를 개선하는 작업을 진행하였다. 맥박수를 측정하는 알고리즘은 낮은 노이즈 신호 비 상황에서 그 측정 성능을 향상 시키는 데에 중점을 두었다.

연구 결과 혈중 산소 포화도 측정 알고리즘은 성능 저하량은 매우 미미하면서도 수행 시간 부담을 줄여 휴대용 기기인 PDA 에서 운용하기에 적합하도록 만들 수 있었다. 맥박수 측정 알고리즘의 경우 기존 주파수 필터링 방법이 37.63%의 측정 오류를 갖는 데에 비하여 4.43%의 개선된 오류를 갖

게 되어 에러 개선의 측면에서 볼 때, 88.23%의 개선을 보였다.

이러한 두 펄스 옥시메트리 기술의 개선으로 병원에서의 환자 감시뿐만 아니라 운동 중에도 간단하게 맥박수나 혈중 산소 포화량과 같은 신호를 측정할 수 있게 되었다. 이러한 알고리즘 개발을 통하여 앞으로 다양한 형태의 응용 제품이 가능할 것으로 기대한다.

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