

Time-efficient BER estimation approach using jitter characteristics for HBC channel

ISSN 1751-8822

Received on 13th June 2016

Revised 19th June 2017

Accepted on 25th September 2017

E-First on 25th October 2017

doi: 10.1049/iet-smt.2016.0257

www.ietdl.org

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Abstract: As a physical layer of body area network, human body communication (HBC) has become a prospective candidate with advantages of less interference and intrinsic transmission for implanted devices. Currently, its bit error rate (BER) performance has not been thoroughly reported with high confidence because the traditional BER testing method in commonly used wireless radio and optical system communication, if directly applying in HB channel, is both time-consuming and problematic due to significant physiological limitations. In this study, a time-efficient approach using jitter characteristics is proposed to tackle this problem. To practically measure the BER in HBC channel, experiments based on human arms are carried out with 600 records of jitter data (5 subjects, 3 modulation schemes, 4 separation distances, and 10 transmit power levels). By using both normal probability plot and Kolmogorov–Smirnov test, the authors found that the HBC experimental jitter data mainly followed normal distribution. Additionally, the comparison between estimated BERs using their approach match well with those via the theoretical prediction based on additive white Gaussian noise channel. Finally, the proposed approach can be an effective measurement method not only for the BER of body channel, but also applicable in other similar low rate systems.

1 Introduction

The problem in coping with the ever-increasing high cost of healthcare system poses a major health burden in many countries with the increasing ageing population. Body area network (BAN) as shown in Fig. 1 is an alternate wireless network consisting of wearable computing devices or implanted sensors and has been proposed to be a solution to this problem. Through the analysis of various vital physiological signs (e.g. electroencephalography, electrocardiogram, electromyography, and blood pressure) by diverse on-body sensors, preliminary prognosis can be generated for patients as front-end screening and the central control can record personal health information into database for better diagnosis by corresponding healthcare check-ups. As a result, the

heavy healthcare system loading could be greatly relieved from this approach, especially for the chronically monitoring [1].

In many medical applications, the sensors attached on or implanted inside the human body (HB) need to communicate with each other and those outside the body. Several stringent requirements such as reliable transmission with low bit error rate (BER), low-power consumption to extend battery life, and avoid the eavesdropping are required. Fortunately, for effectively transmitting the basic biosignals, a moderate data rate of few kbps to few dozen kbps would suffice [2]. To satisfy the above requirements, HB communication (HBC), a novel approach utilising the HB as the communication channel, has been researched.

HBC technology is based on the conduction property of body tissues to establish a communication connection among the diverse implanted or surface devices with very little outside leakage [3]. Compared to other transmission techniques, e.g. Bluetooth, Zig-Bee, and wireless local AN, HBC has its advantages for medical applications such as low attenuation, low transmission power, low carrier frequency, and provides enough data rate for transmitting the biosignals with high security to prevent eavesdropping [4]. Consequently, HBC has been becoming a capable candidate for the communication backbone of BAN.

The first successful implementation for HBC system is capacitive coupling HBC, reported by Zimmerman [5]. Its principle is based on the HB as the transmission medium exploiting certain parts of the near field and nearby environment. Galvanic coupling HBC is another implementation originally reported by Handa *et al.* [6] and its propagation is based on coupling alternating current into the HB. For galvanic coupling approach, the propagation only takes place within the HB. The transmission process no longer depends on the return path and environment. Thus, galvanic coupling HBC avoids the external interference and

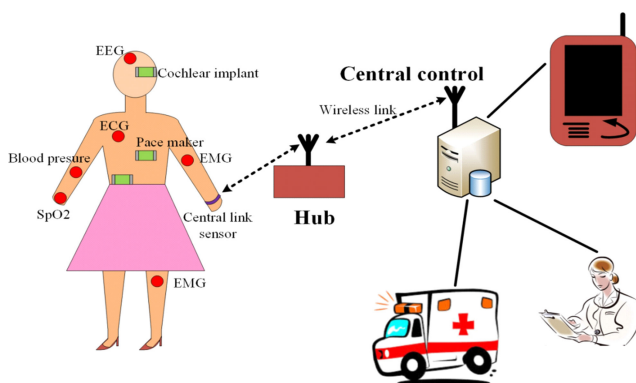


Fig. 1 Sample BAN. Physiological data are transferred from the central link sensor to hub, and then to the central control access point, from where it can be accessed by hospital and emergency centre

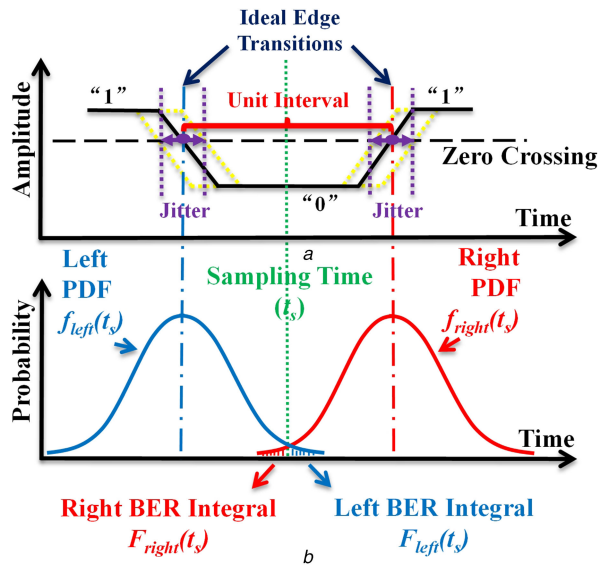


Fig. 2 Proposed methodology

(a) Illustration of jitter in the transmitting digital signals on edge transitions, (b) Relationship between jitter and BER

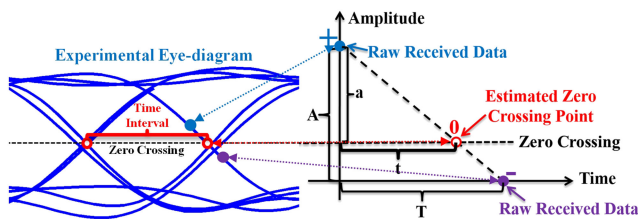


Fig. 3 Sample recorded data with graphical illustration to estimate the zero-crossing point position

can be considered as a suitable approach for the privately reliable communications among medical implanted devices with the trade-off of lower transmission data rate.

For biosignals transmission, the reliability of communication link is one of the major considerations and the BER performance can indicate the reliability. However, the BER of HBC has not yet been thoroughly reported. In recent studies, most of them concentrated on the characteristics of body channel model [7–11], or the effect of experimental setting [12, 13]. Few of them had briefly mentioned the BER derived from either theoretical calculation [14] or simulation [15] only. The reason of very few investigations on BER over HBC is that in low transmission rate of galvanic coupling HBC, the relative long measurement time needed by traditional measurement of low BER, which compares the output and input to obtain the reasonable number of errors, encounters complications, especially on the HB. Thereby, in this paper, the idea of our proposed approach is to use an indirect way based on jitter characteristics in HBC channel to estimate the BER results, so that the total measurement time can be reduced to within a reasonable period.

The arrangement of this paper is as follows: Section 2 briefly reviews the fundamental jitter theory and introduces the proposed method. The *in vivo* experiments based on human arm channel and the bio-jitter data with normal distribution analysis are reported in Section 3. Section 4 discusses the BER of HBC with experimental results and theoretical calculation based on additive white Gaussian noise (AWGN) channel characteristics. Finally, conclusion is provided in Section 5.

2 Proposed methodology

Jitter is defined as a time-domain phenomenon reflecting the deviations of a signal from its ideal occurrence [16]. In an ideal communication, all the edge transitions should happen at the same instant in each unit interval (UI) (the black solid line in Fig. 2a). A UI means the ideal time duration of a single bit. However, in a

realistic communication channel, both the rising and falling edges (the yellowish dot lines in Fig. 2a) are deviated from the ideal timing locations due to the channel imperfections caused by electromagnetic interference, thermal noise, and crosstalk. Hence, this time-domain phenomenon (denoted as jitter) uncertainty affects the quality of system and reflects the errors of data stream.

Generally, the jitter information can be found from the received data or waveforms of system based on the differences between the time intervals of received data (from one zero crossing to another adjacent zero crossing) and their corresponding ideal time durations. However, if the precise zero-crossing points in the raw received data are unknown in advance, some sort of approximations should be first applied to estimate the zero-crossing points.

In Fig. 3, we have constructed experimental eye diagram from receiving data over HBC. Then, we have applied the linear interpolation between the two adjacent recorded bipolar points (+, −) nearest to the zero crossing to estimate the zero-crossing timing position t (denoted as 0). With values of t and the number of recording points between the zero crossings, the estimated time intervals of received data can be obtained. The next step is to calculate the differences between the estimated time intervals and their corresponding ideal timings based on relative centre-position alignment. After that, their small deviations can be projected and recorded as the values of jitters.

Armed with the jitter information from received data, we briefly explain the relationship between jitter and BER in communication channel. According to Li [17], an intrinsic relationship exists between BER and jitter, which has been depicted in Fig. 2. In Fig. 2a, the sampling time (t_s) is the decision moment of the raw received data. For better explanation, let us take the left edge transition as an example. If the edge transition exceeds the sampling time t_s , i.e. the edge transition occurs on the right-hand side of t_s , the system will erroneously determine this bit. Similar situation occurs on the right-hand side. Fig. 2b shows the corresponding probability distribution function (PDF) of the occurrence of the edge transition. Under normal circumstances, the edge transition happens before t_s with high probability. However, there exists possibility of edge transition causing system error due to non-ideal channels characteristics, interferences etc. Then, the error probability is the area of the PDF beyond t_s , which corresponds to the shaded areas in Fig. 2b. By finding this error probability via integral operation, the BER can be estimated. This relationship can be expressed mathematically as shown in (1) based on the statistical principle. Thereby, we can estimate the BER in HBC via jitter characteristics

$$\text{BER} = P_{\text{tr}1} \int_{t_s}^{+\infty} f_{\text{left}}(t) dt + P_{\text{tr}2} \int_{-\infty}^{t_s} f_{\text{right}}(t) dt \quad (1)$$

where $P_{\text{tr}1,2}$ represent the probabilities of edge transitions in the received data stream from '0' to '1' and from '1' to '0'. In general, a 50% probability is used for $P_{\text{tr}1,2}$. Therefore, with sufficient number of jitter samples to assemble an approximate PDF, the BER can be estimated by using (1) in a shorter time than the traditional measurement method which requires large data transmission with long experimental time period for accurate representation of low error characteristics.

To obtain the BER in HBC via (1), jitter PDF should be known in advance. As far as we know, the jitter PDF over HBC has not been published before. In this work, we measured and reported their PDFs based on statistical characteristics. The more the jitter data we measure, the more accurate jitter PDF we can get. However, there is a trade-off between the data sizes and measurement times. To have a compromise of reasonable data size within a short measurement time and acceptable errors with certain confidence interval, (2) was adopted to obtain the data size of jitter [18]

$$N = \frac{4\sigma^2 Z^2}{D^2} \quad (2)$$

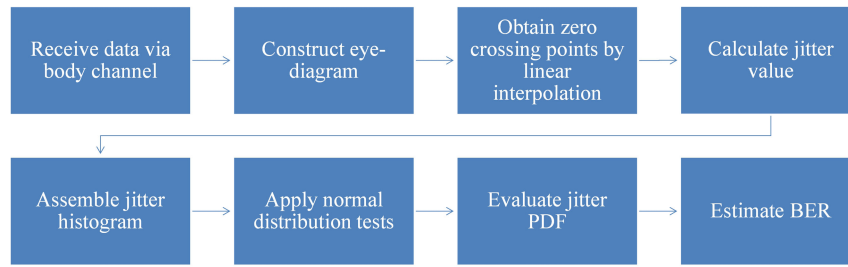


Fig. 4 Flowchart of our proposed BER estimation by using jitter characteristics

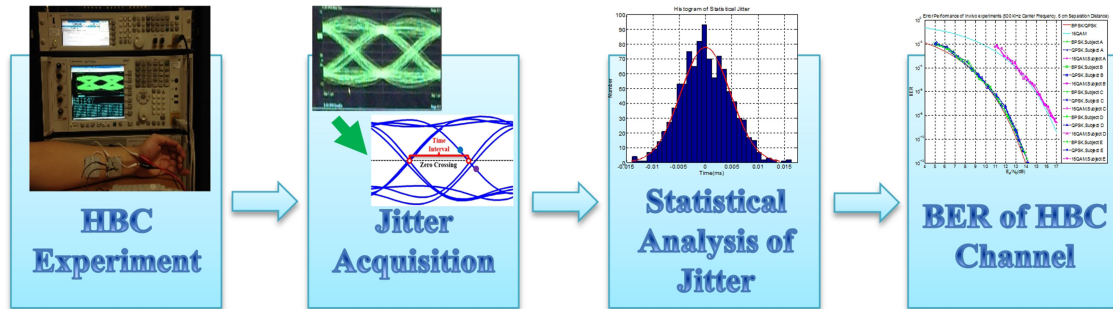


Fig. 5 Major steps for estimating the BER performance in HBC channel

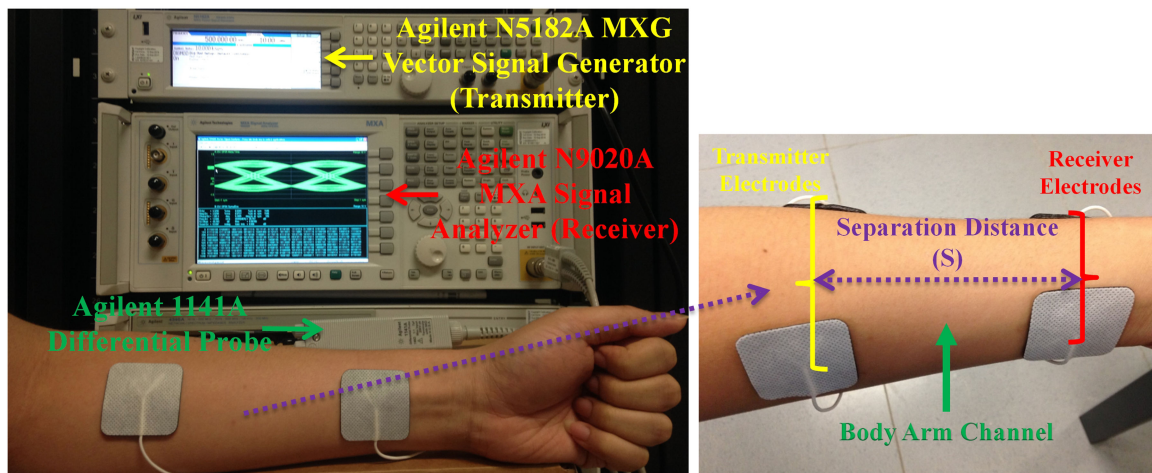


Fig. 6 Measurement setup of human arm channel experiment

where N is the sample size; σ is the standard deviation derived from preliminary study; D is the total width of expected confidence interval; and Z is the standard normal deviate value, which depends on the selected confidence interval. The narrower the total width D , the larger the sample size N . Here, we expect that the measurement of jitter should have 90% confidence interval lies within a width of $\pm 5\%$ of σ , so that the sampling errors of jitter can be restrained. From our preliminary study [19], the estimated σ of jitter is about $7.1 \mu\text{s}$, and then we set the width D to be $\pm 5\%$ of σ (about $0.71 \mu\text{s}$). Besides, Z equals to 1.645 when the confidence interval for the measurement is 90% [18]. Thus, the needed sample size can be calculated as 1082 and this was the approximate number of jitter recorded for each of our measurements in Section 3.

Fig. 4 presents a flowchart that describes our proposed methodology. First, the receiving data via body channel is measured. Then, the corresponding eye diagram is constructed. After that, the zero-crossing points are obtained by linear interpolation, so that the time intervals of received data can be evaluated. Next, the differences between the estimated time intervals and the ideal UI give our empirical jitter values, and hence the approximate jitter histogram can be assembled. Moreover, after applying the normal distribution tests, the statistical characteristics of jitter are analysed and turned out to be primarily normal distributed. With the evaluated jitter PDF and the mathematical relationship between BER and jitter, the BER

performance of HBC can be finally estimated by integral operation.

3 Experiment and statistical analyses

The major steps of *in vivo* experiment and data processing are depicted in Fig. 5. First, *in vivo* HBC experiments are carried out with different parameters and ranges, followed by jitter information acquisition. Next, the bio-jitters are tested for normal distribution via normal probability plot and Kolmogorov–Smirnov (K–S) test. Finally, the BER performances from both measured HBC channel jitters and theoretical AWGN channel characteristics are obtained for discussion.

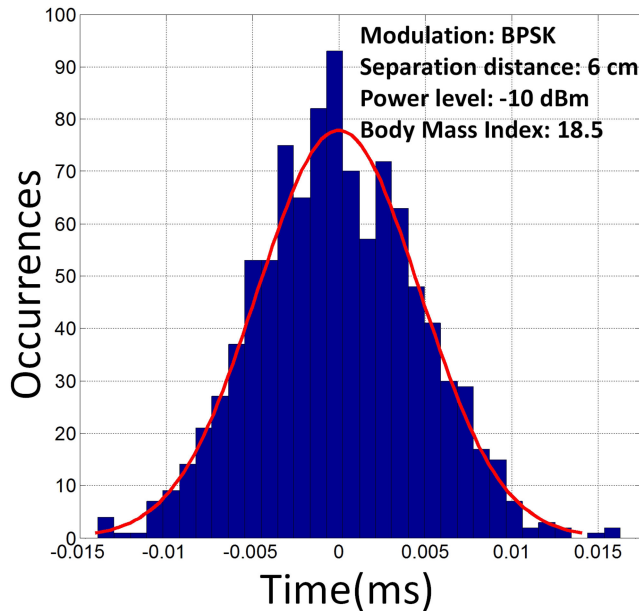
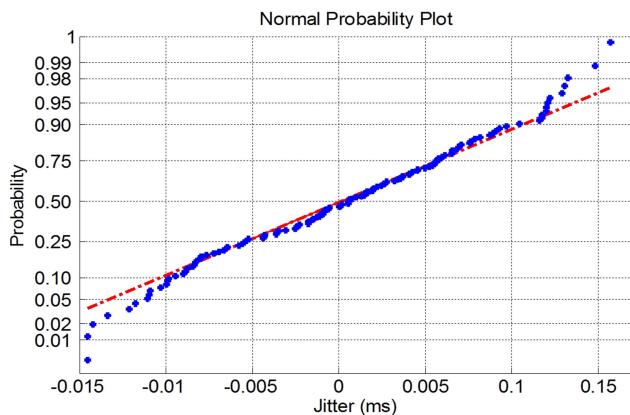
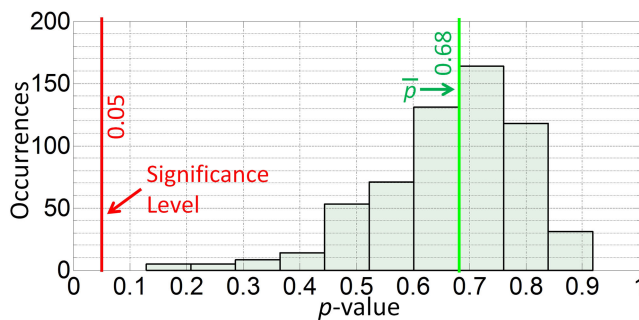
Here, we had recruited five healthy volunteers (three males and two females, with body mass index: 18.5–26.1 and age: 21–30) for our galvanic coupling HBC experiments. Prior to the experiments, all the participants signed an informed consent form after the experimental nature and procedures were explained and their questions were answered.

Fig. 6 shows our *in vivo* experiment measurement setup. Two pairs of physiotherapy electrodes (40 mm × 40 mm, Shanghai Litu, LT-01) were attached to the body arm as the transmitter electrodes and the receiver electrodes, respectively, with certain separation distances, denoted as S . Using the vector signal generator (Agilent, N5182A MXG vector signal generator), the random pattern of digital signals with commonly used modulation schemes [binary

Table 1 Parameters of *in vivo* experiments

Parameter	Range
modulation	BPSK, QPSK, 16-QAM
separation distance (S)	6, 12, 25, 40 cm
power level ^a	-10 to +17 dBm

^aLow enough so that contact current levels over extremities did not exceed safety standard [21].

**Fig. 7** Sample histogram result of statistical jitter from *in vivo* experiments with a fitted curve (red line)**Fig. 8** Normal probability plot of statistical bio-jitter**Fig. 9** Histogram of *in vivo* experimental data with *p*-value from K-S test

phase shift keying (BPSK), quadrature phase shift keying (QPSK), and 16-quadrature amplitude modulation (16-QAM)] were generated with symbol rate of 10 kbps (UI = 0.1 ms), similar to the low demand of biosignal transmission. From our previous work

[20], the carrier frequency was chosen to be 500 kHz for low attenuation over HB arm channel.

At the receiver side on human arm, the signal analyser (Agilent, N9020A MXA signal analyser) was used to pick up the received signal and recovered the data, which can be used for the comparisons of transmitted symbols to obtain the experimental BERs. Besides, all the experiments were carried out warily to avoid the common ground problem by using the battery-powered differential probe (Agilent, 1141A) at the detection site. To obtain comprehensive results, the total number of measurements contained 600 sets of jitter data: 5 healthy subjects, 3 modulation schemes, 4 separation distances (6, 12, 25, and 40 cm), and 10 transmit power levels. Each set of measurement time took around 0.2 s with nearly 40,000 points, which were much shorter than the traditional data measurement method for the same BER. Table 1 summarises the parameters of our experiments.

Next, the records were extracted and processed to acquire the jitter information based on the linear interpolation introduced in Section 2. Fig. 7 presents a sample of jitter histogram assembled by sufficient sample-size data. One could either perform numerical integrations by normalising the histogram data, or fit into a known probability distributions based on observation. Here, the normal distribution curve (red line) was fitted to the experimental jitter histogram. So, we consider that the jitter data of HBC likely to be normal distributed. To further test this hypothesis, two standard and widely used methods for the normal distribution test, namely normal probability plot and K-S test, were employed.

Normal probability plot is one of the commonly used graphical technique to identify the substantive departures from the normal distribution. It is a visual test method with observation of the resulting graph. In normal probability plot, the sorted data will be plotted *versus* the cumulative probabilities. Then, in the resulting graph, if the graph looks close to a straight line pattern, the population is normal consistent, or at least plausibility close to normal distribution. Otherwise, if the testing data is not normal distribution, the results will deviate much from the straight line.

Fig. 8 displays a typical normal probability plot result of statistical bio-jitter. One can observe that most of the testing data located on the resulting straight line and just a small number of data at the two ends deviated from that line. Hence, this plot can imply the bio-jitter data is mainly following the normal distribution.

After the qualitative confirmation, we adopted K-S test to perform a test of probability distribution that can be used to compare a sample with a reference probability distribution. To apply K-S test for the statistical bio-jitter distribution, a hypothesis testing was made, which was shown below:

- H_0 (null hypothesis): The experimental jitter data followed the normal distribution.
- H_1 (alternative hypothesis): The experimental jitter data did not follow the normal distribution.

Before performing the test, a threshold value, also known as significant level (α), was chosen as 5% [22]. If the resulting *p*-value of K-S test was equal or smaller than α (0.05), we should veto the normality of testing jitter data. Otherwise, if the *p*-value was greater than α (0.05), it would suggest that the experimental jitter can be assumed as the normal distribution.

The K-S tests were run for all experimental jitter data to check for their compliance of the normal distribution and the *p*-value histogram was shown in Fig. 9. All the *p*-values were greater than the pre-set significant level α (0.05) and the overall average was about 0.68. Therefore, we can conclude that the jitter data of HBC channel mainly followed the normal distribution.

After obtaining the statistical properties of jitter in HBC channel, we can substitute both $f_{\text{left}}(t_s)$ and $f_{\text{right}}(t_s)$ back into (1) with the normal distribution of mean (μ) and standard deviation (σ) to estimate the BER in HBC channel. Alternately, we also performed the direct numerical integrations using normalised histogram data in (1) to obtain BER values. We found both the direct and indirect ways (fitted to normal distribution) were giving the similar BER results in HBC channel.

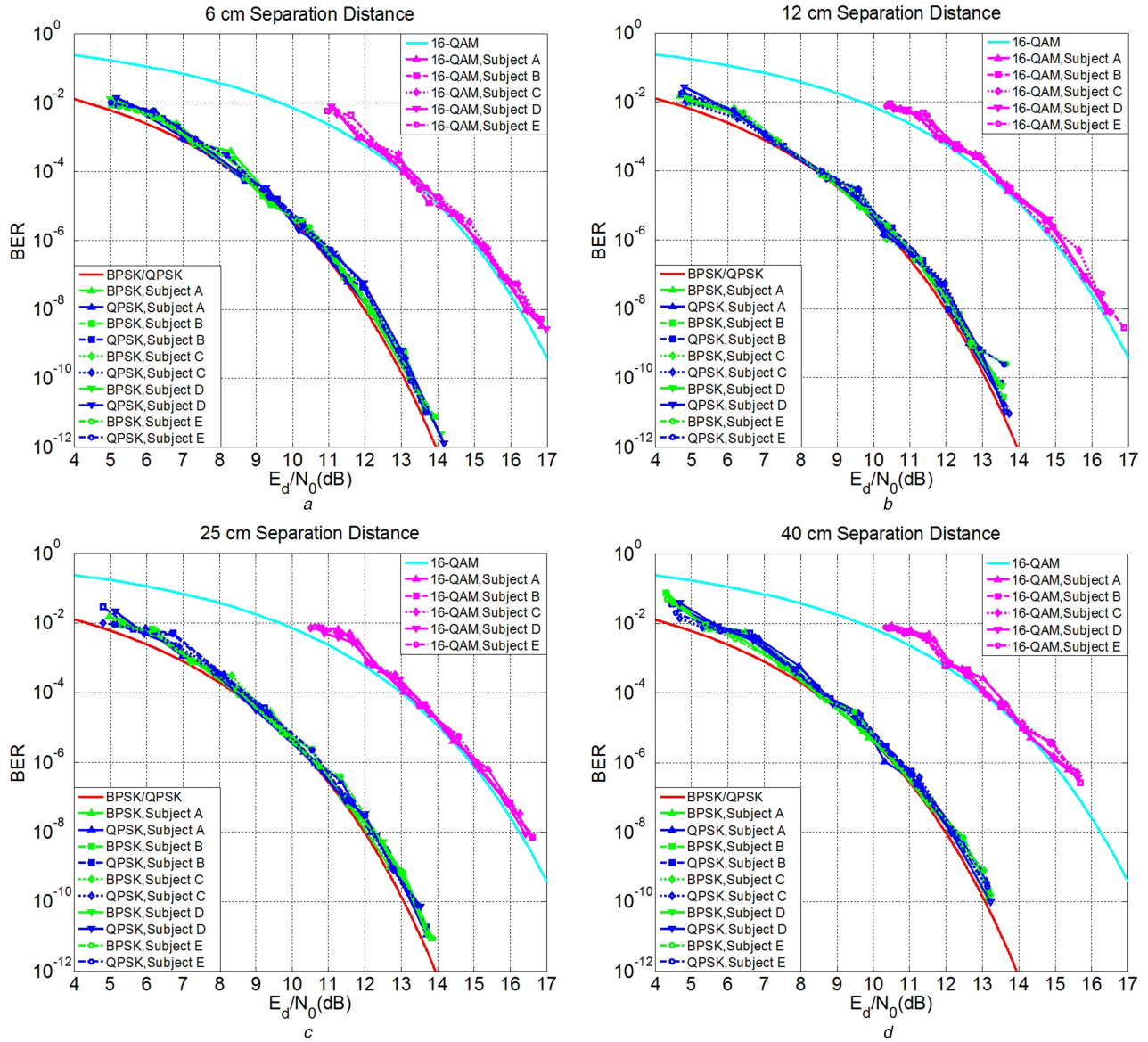


Fig. 10 BER performance in experiments and theoretical calculation based on the AWGN theory for various separations
(a) 6 cm, (b) 12 cm, (c) 25 cm, (d) 40 cm

4 Results and discussion

In Section 4, we discussed the BER performance of HBC channel. In [20], the AWGN channel assumption worked smoothly with HBC. Assuming an AWGN channel, the BER performances in different modulation schemes were theoretically a function of E_b/N_0 (the energy per bit to noise power spectral density ratio), as shown in (3) and (4), where $Q(x)$ is the Gaussian Q-function [23]

$$\text{BER}_{\text{BPSK/QPSK}} = Q(\sqrt{2E_b/N_0}) \quad (3)$$

$$\text{BER}_{16\text{-QAM}} = Q(\sqrt{0.8E_b/N_0}) \quad (4)$$

Fig. 10 shows the BER results for separation distances of 6, 12, 25, and 40 cm using BPSK, QPSK, and 16-QAM, along with the theoretical AWGN calculations. It can be found that the experimental results from jitter characteristics were consistent with the theoretical AWGN calculations over *in vivo* experiments parameters listed in Table 1. This, in turn, can evidently indicate that HBC was not far from the AWGN channel. Errors seemed to be more pronounced in both low and high E_b/N_0 regions. Errors in the low E_b/N_0 region were believed due to the error vector magnitude estimation method in vector signal analyser using a non-data-aided receiver [24]. For high E_b/N_0 region, the errors were mainly due to the limited sample points for each symbol in the

vector signal analyser (or the accuracy of the vector signal analyser). Additionally, the scattering discrepancies occurred could be due to the different body characteristics among human subjects. These results echoed that our proposed technique can estimate the BER over HBC channel with much less measurement time (about 0.2 s for a wide BER range of 10^{-2} – 10^{-11} with 10 kbps on HBC), which can save more times of measurement than the traditional BER testing way, especially in high reliability with low BER (say $< 10^{-5}$).

5 Conclusion

A time-efficient approach for estimating the channel characteristics of low BER in HBC using jitter characteristics had been proposed and implemented here. Adequate sample size of experimental jitters data were analysed based on a 90% confidence interval of jitters located in a $\pm 5\%$ width of σ . We also applied the normal probability plot and K–S test to testify the jitter data in HBC channel mainly followed the normal distribution. In addition, the uniformity of experimental results and theoretical AWGN channel calculations implied that the HBC channel can be modelled as an AWGN channel under the conditions in our experiments. The proposed method via jitter measurement to estimate BER value for HBC was much time-efficient (*in vivo* experimental time within seconds for a wide BER range) than the traditional ones, allowing reliable measurements with little anthropometric changes in HBC.

This approach can be a time-efficient measurement for not only capable of the BER performance in body channel, but also with the flexibility to adapt appropriately in many other low data rate systems with similar time-constraints and low BER requirements.

6 Acknowledgments

This work was supported by the Science and Technology Development Fund of Macau (FDCT) under grant nos. 063/2009/A, 093/2015/A3, 088/2016/A2, the Research Committee of University of Macau under grant nos. MYRG2014-00010-AMSV, MYRG2015-00178-AMSV, MYRG2016-00157-AMSV, the Project of Chinese Ministry of Science and Technology under grant no. 2016YFE0122700, and the National Natural Science Foundation of China under grant U1505251. The authors express faithful thanks to all of the above financial supports.

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