Original Article
Journal of Wellness and Health Care Vol.42 (1)
41～50 2018

Data mining analysis of body movement by low-birth-weight infants

Kaoru Yachi, Tetsu Nemoto[1)], Kazuhiro Ogai[1)], Toshio Kobayashi[2)], Keiko Shimada[1)]

Abstract

Proper management of overall health is critical to provide care for low-birth-weight infants (LBWIs). Clinically, the extent of body movement (BM) is a major indicator of the overall health of LBWIs. The present study was performed to determine the amount of BM that is effective for health management by comparing the quantitative results of amount of BM and weight gain. A bed sensor utilizing a dual piezoelectric element was used for BM measurement. BM was measured throughout the day, and the average amount of BM in a 5-minute period was calculated. In addition, BM data of 33 study subjects were further analyzed to determine the level of BM, i.e., categorized as BM-0 to BM-20, associated with significant weight gain, which was also identified as the coefficients of CA to CE according to the linear and quadratic approximation equations. Statistical analyses between BM-0 to BM-20 and CA to CE were performed by data-mining analysis and multiple linear regression analysis to examine the relations among observed variables and coefficients. The results showed that the amount of BM increased with increasing weight gain of the subjects. Gradual trends were observed between BM-0 to BM-20 and CA to CE, which could be used for routine automatic monitoring of LEWIs.

KEY WORDS

low-birth-weight infant, body movement measurements, body weight gain, data-mining analyses

INTRODUCTION

Approximately10% of all infants born are low-birth-weight infants (LBWI), which have a birth weight of less than 2,500 g. LBWIs exhibit over-reactivity to stimuli due to physiological and neurological immaturity, insufficient movement in the womb, and difficulties adapting to gravity after birth. Therefore, physiological stabilization needs to be considered in postnatal management. A study by Uetani[1)] examined the relationship between birth weight and child development and demonstrated that the developmental prognosis of LBWI is poorer than that of regular term infants. Birth weight is associated with subsequent growth delays and the occurrence of some disorders.

The management of body temperature (heat retention) and nutrition is important for LBWI. However, only few studies have characterized body movement (BM) in LBWIs. Although BM is an objective and important clinical indicator of physiological activity in LBWIs, it has not been analyzed quantitatively. Research on BM in neonates has led to the activity of infants being characterized into seven behavior patterns, and the proportion of each behavior pattern has been investigated[2)]. Previous studies also observed the activity of neonates using actigraphy[3)4)]. Actigraphy is a non-invasive and long-term continuous observation method that measures the activity of a subject per unit of time. The neonatal apnea monitor “Neogard®” has recently been employed for this purpose[5)6)]. Since these studies focused on children, limited information is currently

Kanazawa University Hospital
1) University of Kanazawa
2) University of Miyagi

available on LBWI. Furthermore, it is difficult to collect data over a long period of time with high sensitivity. BM in LBWI may be safely and continuously observed in an incubator using a previously developed method[7]. In the present study, we quantified BM to determine the amount of BM that are associated with weight gain and that can be used as indicators to improve overall health of LBWLs.

MATERIALS & METHODS

1. Subjects

Thirty-three LBWI born at a general perinatal medical care center in the Hokuriku area between November 2011 and October 2013 and admitted to the neonatal intensive care unit were examined. Subjects were born at gestational ages of 28 weeks and 1 day to 37 weeks and 0 days, with an average of 32 weeks and 3 days. The average age at the time of the survey was between 2 to 66 days after birth; therefore, the number of weeks at the time of the survey was between 30 weeks and 0 days and 38 weeks and 2 days, with an average of 34 weeks and 3 days. The number of weeks at the time of the survey is the number of weeks after birth plus the gestation period at birth. LBWI were managed in incubators from immediately after birth. Birth weights were 640 - 2470 g (average, 1686 g), and body weights during the survey were 956 - 2358 g (average, 1681 g). While some of the study subjects had complications such as breathing disorders at birth, all subjects show steady development.

2. Ethical considerations

This research was approved by the Kanazawa University Medical Ethics Committee (approval number 237). General information on this research and an overview of the study were explained to the parents of the children in this study, and consent was obtained both verbally and in writing. Recorded data was saved to a USB drive with security features, strictly stored in a locked shelf, and every effort was made to preserve anonymity, to prevent leaks of information, and to protect confidentiality.

3. BM measurement

As shown in Figure 1, the BM measurement device was composed of piezoelectric elements and two acrylic plates. The piezoelectric effect is a phenomenon in which a polarization (surface charge) voltage proportional to pressure appears when pressure (force) is applied to the ceramic as a material of the piezoelectric body, as described by Nemoto[8]. The voltage signal of the piezoelectric dual sensor was recorded and saved on a computer via a 16-bit A/D interface. In the present study, the sampling period of the A/D converter (Contec ADA 16-32/2 (CB) F, Japan) was set to 50 msec, and observations were continuously performed for 24 hours. Measurements were performed from 12:00 am, and the 24-hour data was collected continuously by creating a new data file automatically on the next day at 11:55 pm. Continuous observations were performed for between 4 and 7 days and all data were automatically saved. Body movements within the days of neonate are an

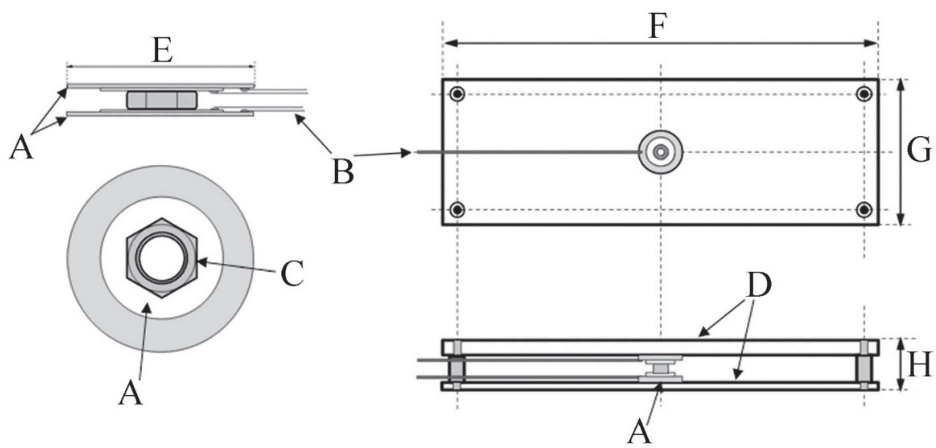

Figure 1 Body movement measurement device
Left side: Two upper and lower piezoelectric elements are sandwiched between two acrylic plates. Right side: The four sides of the acrylic plate are fixed with screws so that the piezoelectric sensors are centered in the acrylic plate.
A: Piezoelectric elements, B: Cable lines, C: Nut, D: Acrylic plates, E: 30 mm, F: 600 mm, G: 200 mm, H: 13 mm.

index of awakening and the sleep. Numbers of body movements fluctuate very varies with daily physical condition of neonate and at the time neonate suckling the milk. Also that occurs on at the time when the nurse changing neonate's diapers. Therefore numbers of the daily body movements are different under the same neonate. Thus, the frequency of each body movements at 0 to 20 body movements for 5 minutes for 3 to 4 days were averaged and intermediate values of the body movements were used in this study.

4. Analysis of BM data

BM data in this survey were analyzed using Origin 8.1 (Light Stone Co., Chiyoda-ku, Tokyo, Japan) for data analysis and graph creation. The upper side of Figure 2 shows the direct voltage waveform recorded by the piezoelectric dual sensor. The recorded voltage waveform included minute vibrations of the breathing component, the heart beat component, and physical activity comprising limb movement. Therefore, a smoothing process was performed at each 5-data point with the recorded voltage waveform, and minute components, namely, respiration components and the waveform of the saturation voltage due to BM, were removed. BM values were collected based on the voltage saturation peak. BM is indicated by circles on the lower side of Figure 2.

Since each infant moved freely and in a random manner, quantification of BM needed to be simplified. This process was performed as follows. The beat number of BM was obtained from a search of peaks in the piezoelectric dual sensor voltage and beat frequency was calculated as a number per minute. The beat number of BM was arranged as a number per 5 min (before and after, 2.5 min each), and was defined as the "BM value". BM values were obtained from the voltage saturation peak, and if the absence of a BM beat was named as BM-0 and maximum beat values as BM-20 for 20 beats in 5 min, then BM was divided into 21 levels (BM-0 to BM-20) defined as the "BM level". There were no records of more than 20 beats in 5 min. The frequencies of the BM value were surveyed over time in one day. BM measurements were performed for a 24-hour period, which we set from 12:00 am to 11:55 pm the next day since the daily measurements had to be recorded in the last 5 minutes before initializing the next cycle. A whole day was defined as 287 (= [24*60/5]-1) divisions of 5 min. Continuous observations of BM values for 4 to 7 days in all subjects were averaged at the same time of day and were defined as the "averaged BM value". In Figure 3, the frequencies of averaged BM values were shown with BM levels, and subjects were divided into four groups based on body weight at the time of the survey. As body weights increased, the frequencies of averaged BM values (vertical axis) between BM-2 and BM-13 became slightly higher.

5. Analysis of data obtained

Data on weight gain in the 33 subjects examined were

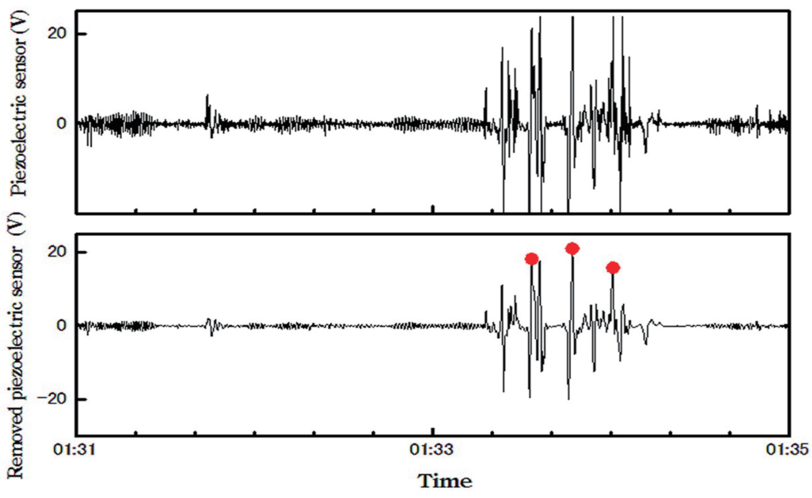

Figure 2 An example of the smoothing process of a waveform.
Upper: A direct voltage waveform of data recorded by the piezoelectric dual sensor, as shown in Figure 1.
Lower: The smoothing process of the waveform was performed at each 5-data point with the voltage waveform recorded. Body movement was indicated by circles.

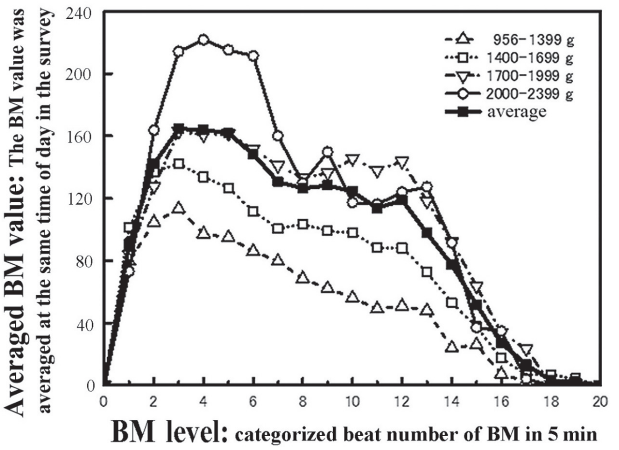

Figure 3 Characteristics of BM observed with different subject weights.
BM: Body movement; BM-0 – BM-20: Categorized BM level, beat number in 5 minutes;
Keys: 4 body weight ranges at the time of the survey.

approximated with linear and quadratic equations and their trends were converted and named into CA to CE, as follows:

$$y = CA^*x + CB \quad (1)$$

$$y = CC^*x^2 + CD^*x + CE \quad (2)$$

where y: body weight (g) of each subject; x: age in days (day).

In Table 1, 5 coefficients of CA to CE, which are the representative values of the body weight gain of subjects, were also displayed in accordance with the same table, i.e. the starting point for further analyses. The physiological BM differences due to corrected gestational ages of subjects are all absorbed and expressed in the coefficients of CA to CE. In addition to the raw data for each subject, weight gain was also categorized in quartiles, from poor (P), below normal less (BN), above normal (AN), and good (G). The quartiles were separated by ±1.5 standard deviation (SD), and the data was presented in the same table. SD score was calculated using " New Calculation File of Birth-Time Body Standard Value By Gestational Period[9] ", in 2010, the Japanese pediatric neonatal committee reported "About introducing a new standard value of birth weight at birth," and recommending the use of its standard value. "New Calculation File of Birth-Time Body Standard Value by Gestational Period" was created by Joint Society of Japan Growth Association, Joint Standard Value Committee of Japan Child Endocrinology Association and Japan Prematurity Neonatology Association in collaboration work.

The degree of the influence of each of the 5 coefficients or standard deviations of growth (GSD) and BM-0 to BM-20 in the two-dimensional table described above was analyzed using data-mining software (IBM-SPSS, Modeler-17; IBM, Armonk, NY, USA). We applied classification and regression tree (C&RT) algorithms[10], which are the most commonly used methods for data-mining processing. This produces a decision tree (Dt), which may be used to analyze and distinguish the roles of BM-0 to BM-20. C&RT optimizes the Gini coefficient,

Table 1 Selected results of related variables by comparing data-mining and MLRA.

target	data	by data-mining: correlation coefficient$	Dt 1st#	Dt 2nd#	by MLRA: representative results
CA	continuous	0.998	BM-15	BM-10, BM-15	BM-10
CD	continuous	0.991	BM-2	BM-2, BM-11	
CE	continuous	0.986	BM-14	BM-15, BM-6	
CB	continuous	0.984	BM-11	BM-11, BM-6	
CC	continuous	0.977	BM-3	BM-1, −	
GSD	continuous	0.997	BM-14	BM-6, BM-2	
GSD	4-NP	0.939	BM-10	BM-7,BM-10	BM-10

MLRA: multiple linear regression analyses; $: predictive accuracy until Dt-5th steps of the decision tree, where Dt: decision tree; #: selected variables with the decision tree; CA - CE: coefficients of linear and quadratic approximating equations as Eqns. 1 and 2; GSD: standard deviation of growth; 4-NP: 4 nominal partitions, based on categories: P<-1.5SD≤BN<0≤AN≤+1.5SD<G, where P: poor, BN: below normal, AN: above normal, G: good, and SD: standard deviation; dark area at ‘by MLRA’: results were useless due to multicollinearity of MLRA.

g(t), which is used in quantitative evaluations of group impurity and is defined at a node t in C&RT, as

$$g(t) = \sum_{j \neq i} p(j|t)p(i|t) \qquad (3)$$

where i and j are categories of explanatory variables, BM-0 to BM-20, dividing subjects into two subsets from left to right according to their data. Therefore, subjects within each subsequent subset are more homogeneous than in the previous subset. The C&RT system is flexible and allows for the consideration of unequal misclassification costs, as opposed to other data-mining processing algorithms. The major advantage is that C&RT is reproducible and delivers only a single selected variable between BM-0 and BM-20 for each step of the constructed Dt.

In addition to data-mining analyses, a multiple linear regression analysis (MLRA), which is the most common form of linear regression analysis, and as a predictive analysis, the multiple linear regression is used to explain the relationship between one continuous dependent variable and two or more independent variables, was performed. Then, MLRA is useful for investigating relationships between many variables, and we used the software IBM-SPSS (Statistics-23; IBM, Armonk, NY, USA). The relationships between CA and CE or 2-GSDs and between BM-0 and BM-20 were analyzed by MLRA.

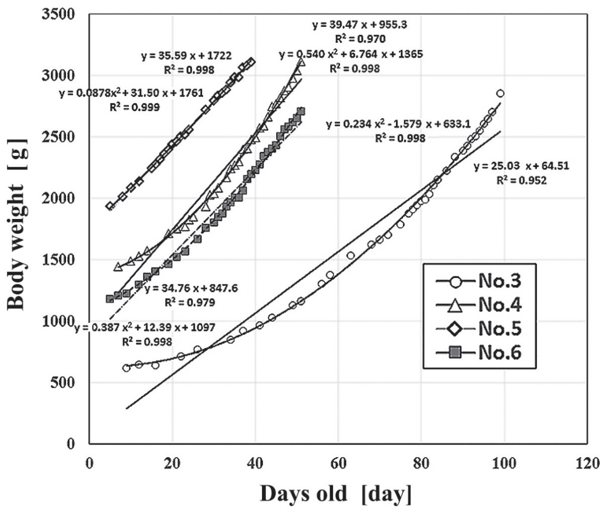

Figure 4 Examples of linear and quadratic approximating equations for body weight gain by subjects.
Equations indicate linear and quadratic equations with the representative coefficients CA to CE as Eqns. 1 and 2; R^2 indicates the coefficient of determination.

RESULTS

1. Results of linear and quadratic equations for weight gain

Examples of linear and quadratic approximating equations for body weight gain were shown in Figure 4 for four subjects. Goodness of fit, as measured by the coefficient of determination or R^2, was different among subjects for linear and quadratic equations. Based on these results, we selected linear and quadratic equations as representative coefficients of weight gain. Among these coefficients, CB and CE, which are the intercepts of the respective equations, correlated with birth weight more strongly than the 3 other coefficients, and the results obtained were shown in the Figure 5 for 33 subjects.

2. Results of data-mining analyses and MLRA

Subsequent analyses were performed using the two-dimensional table with CA to CE, GSDs, and BM-0 to BM-20 on the horizontal axis and 33 subjects on the vertical axis. Data-mining analyses were performed with one target variable (between CA and GSDs) to all explanatory variables (BM-0 to BM-20) in order to clearly identify numeric relationships and select explanatory variables using all data of 33 subjects. An example of the Dt obtained by data mining for CA was shown in Figure 6-1. First, 33 subjects were divided into two groups by g(t) and BM-15, such that 18 subjects were categorized in node-1 and 15 subjects were categorized in node-2. These nodes were further divided into nodes 3-6. This method was used to create Dts with 5 levels; however, the 4th and 5th levels were irrelevant since they were strongly influenced by the data in the

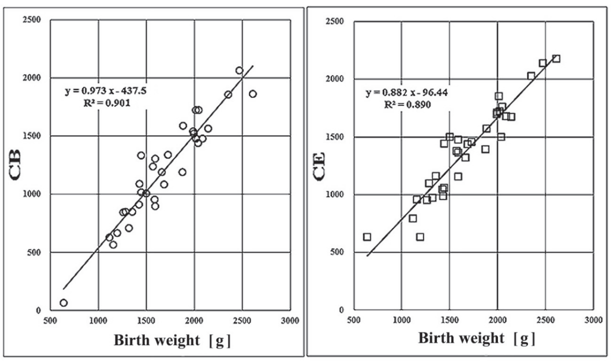

Figure 5 Relationships between birth weight and intercepts of approximating equations for 33 subjects.
CB: Intercept of the linear approximation; CE: intercept of the quadratic approximation, as shown in Figure 4.
The coefficients of determinations (R^2) for CA, CC, and CD correlated weakly with birth weight, with R^2 = 0.31, 0.14, and 0.09 for CA, CC, and CD, respectively.

upper levels. Furthermore, the same processing as that shown in Figure 5 was performed for CB to CE and two GSDs, and analogous and respective results were obtained.

In Table 1, the leftmost vertical term, "target", indicates the objectives of data mining analysis, which is the representative values of weight gain of subjects and is also including the physiological trend of subjects. The terms in the vertical direction of Table 1, "by data-mining" and "by MIRA" show the results of the numerical analysis, which show the close relationship in between BM-0 and BM-20 to "target". As for shadowed terms in "by MIRA", the results were useless due to the effects of multicollinearity, namely, the value of the variance inflation factor (VIF) was generally more than 10. Thus, instead of using all variables for BM-0 to 20, we selected appropriate BM levels for the analysis based on the previously described data-mining analysis. For example, according to Figure 6-1 and 6-7, which were arranged to understand the contents of Table 1, we applied limited explanatory variables, i.e., BM-15, BM-10, BM-5, BM-2, and BM-1 for CA, and the results obtained by MLRA were useful, namely, their VIF values were less than 4.3. BM-10 was identified as the most strongly related variable with CA because its t-value, which represents the magnitude of the influence of explanatory variables on objective variables, and the larger the absolute value, so the stronger the influence, was 2.3 and its p-value, statistical significance probability, was 0.03. According to the same numerical comparisons, BM-1 has the weakest relationship with CA among the 5 variables listed above because its p-value was 0.71.

Table 1 in its 'by date-mining' column shows the analyzed results of BM level, BM-0 to BM-20, that accurately expresses body weight gain by subjects, where CA to CE were arranged in the order of correlation

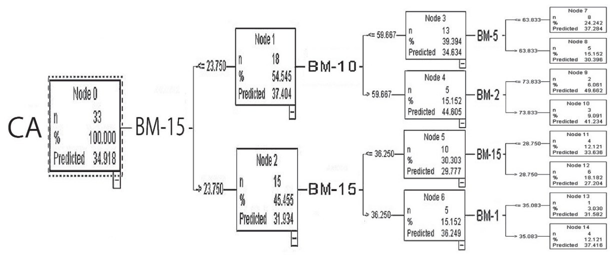

Figure 6-1 Detailed result. An example of a decision tree obtained in data-mining analyses for CA
The BM level most closely related to CA may be identified with the decision tree. The numerical values shown before each Node-N indicate the dividing boundaries optimized by the Gini coefficient; Predicted: estimated from data attributed to each Node.

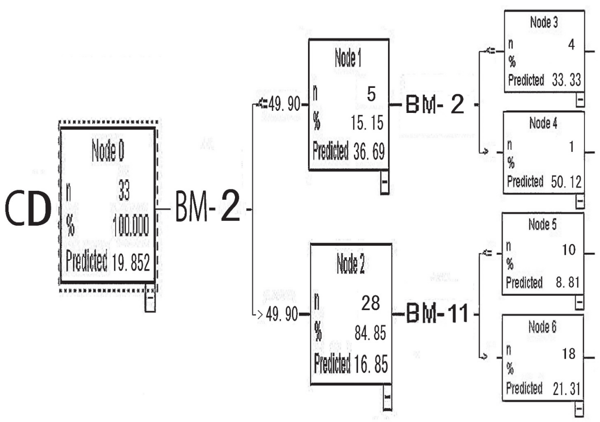

Figure 6-2 Abbreviated results of a decision tree obtained in data-mining analyses for CD.
Displaying order are the same with that of Table 1.

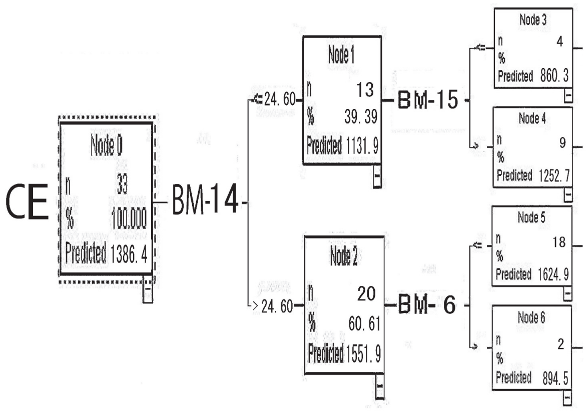

Figure 6-3 Abbreviated results of a decision tree obtained in data-mining analyses for CE.
Displaying order are the same with that of Table 1.

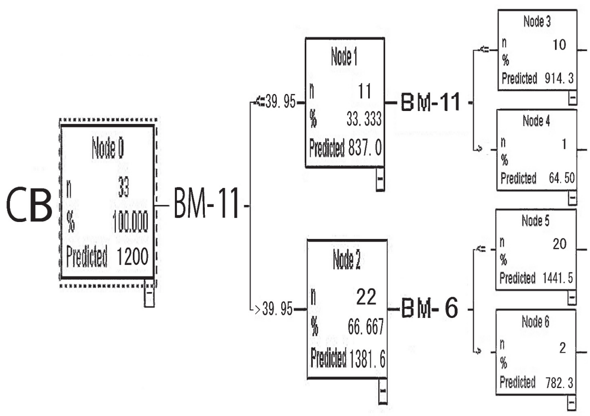

Figure 6-4 Abbreviated results of a decision tree obtained in data-mining analyses for CB.
Displaying order are the same with that of Table 1.

coefficients, reflecting the predictive accuracy of these analyses. The selected BM levels at Dt 1st and 2nd were widely dispersed, and difficulties were associated with concluding which level had the closest relationship with body weight gain by subjects. These findings suggest that the levels of BM are strongly correlated with coefficients CA to CE, and with GSD. CA represented weight gain in the simplest manner, and the BM levels shown in Table 1, in its top and bottom row, agreed with the results 'by MLRA', in which CA and GSD of 4 nominal partitions (4-NP) were obtained. These findings suggest that BM-7 to 15, particularly BM-10, were the strongest indicators of weight gain in the study subjects.

We also noted that MLRA can be used as a complementary tool to validate results from data-mining analysis, regardless of multicollinearities.

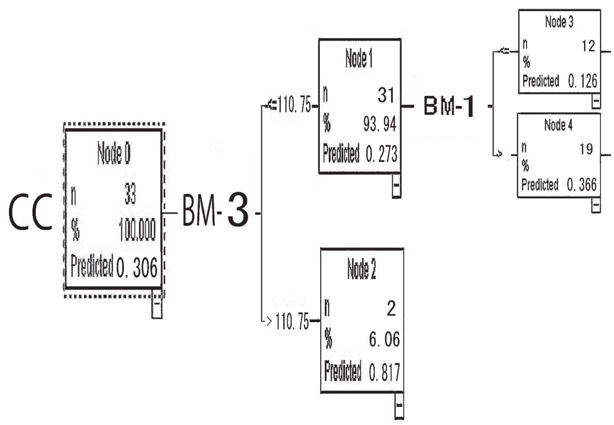

Figure 6-5 Abbreviated results of a decision tree obtained in data-mining analyses for CC.
Displaying order are the same with that of Table 1.

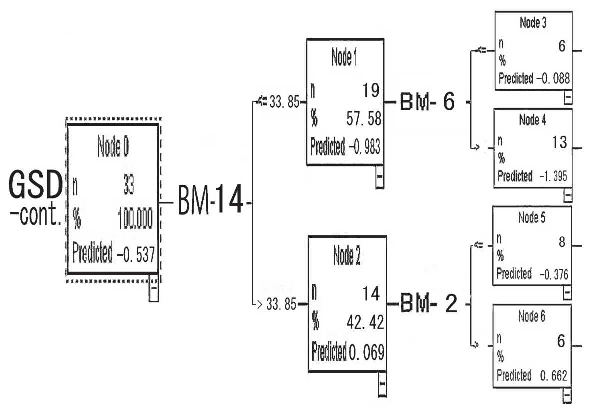

Figure 6-6 Abbreviated results of a decision tree obtained in data-mining analyses for GSD-cont.
Displaying order are the same with that of Table 1.

Discussion

1. BM measurement device

The BM measurement device used in the present study is a bed sensor that utilizes the dual piezoelectric element described by Nemoto et al.[8]. Bed sensors were installed under the bed mattress and detected heart rate, respiration rate, and the number of BM. By comparing electrocardiogram, the nasal cavity thermistor, and acceleration sensor to the abdomen, errors of heart rate and respiratory rate were less than ± 5%, and error of the number of BM was less than 10%. Chen et al.[11] simultaneously installed four bed sensors in different positions during nap times to detect changes in applied pressure due to the heart beating and breathing. Heart rate was detected in all positions, and sensitivity and the positive predictive value were both greater than 97% among the five individuals examined. Regarding its long-term use, Chen et al.[11] reported that a bed sensor is a useful device for monitoring maternal cardiac conditions. A study by Kitamura et al.[12] demonstrated that a slight pressure on the body surface can be detected as the speed of pulse wave velocity (PWV) by placing a double piezoelectric element on top of the arteries in the limbs. On the other hand, Yachi et al.[7] previously reported that the bed sensor was used for BM measurements in LBWI. Yachi et al. also showed that the regression equation for body weight and BM number per day was Y=0.6031x-167.12, which was taken as the "standard value". As described above, the bed sensor allows for continuous and stable measurements for a long period under an environment of approximately 36℃

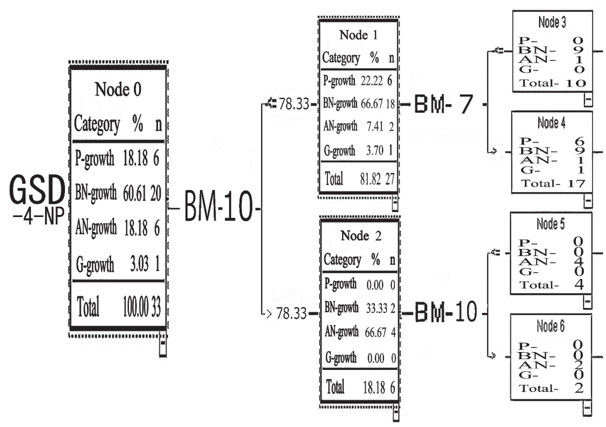

Figure 6-7 Abbreviated results of a decision tree obtained in data-mining analyses for GSD-4-NP.
Displaying order are the same with that of Table 1.
The precise shape of NP analyses differs to those of continues number.

in the incubator. In addition, the bed sensor did not make contact with infants, and, thus, is hygienic and useful for monitoring infants.

2. Practical observations of BM

As already described, the BM of infants in incubators has been suggested to reflect their health condition. However, there is a lack of techniques that enable continuous monitoring of BM in a safe manner, as well as methods to properly organize the observed data. Since neonates are unable to recognize the time of the day despite being able to recognize the intervals between feeding, we observed their BM throughout the day and calculated the daily average. This method can measure body movements conveniently and allowed us to collect highly relevant datasets. In order to numerically arrange the free and random BM of infants, several processes need to be introduced, applied, and quantified in order to represent the natural BM value, which is typically rejected for children and adults. As shown in Figure 3, we applied these processes and demonstrated that the levels of BM can be compared among subjects. These results represent the starting point for numerical analyses.

3. Analyzing various numerical coefficients for our purpose

The purpose of the present study was to clarify the relationship between observed BM levels and body-weight gain by subjects. The practical results of BM values and CA to CE and GSDs representing the weight gain process are shown in Figure 4, and the relationship between these numerical data from 33 subjects were sorted and confirmed as described above. Since the raw data varied widely as shown in Table 1, in its 'by data-mining' column, it could not be estimated directly the relationship between BM levels and weight gain. However, we considered comparative simplifications to be indispensable for the development of concrete technologies, and it is reasonable to conclude that levels in the vicinity of BM-10, i.e., BM-7 to BM-15, is important for our purpose. Conversely, the original BM level with free and random behavior manifested well and are desirable results for understanding the natural BM amounts of infants. To further our understanding of the relationship between BM levels and weight gain, BM levels, particularly around BM-10, should be monitored in a larger cohort of subjects using novel equipment that is safe and easy to use.

4. Viewpoint from the field of neonatal nursing

The BM of LBWI have not been standardized as observation items. Thoman[13] observed behaviors of term infants between 2 to 5 weeks after birth, and demonstrated that infants with inconsistent behavioral patterns exhibited developmental disorders. Another study used a health monitoring system (HMS) to monitor sleep in infants on the day of their birth and demonstrated correlation between sleep and development[14]. The findings of the study suggested that premature infants with developmental disorders exhibit abnormalities in their sleep cycle before signs of developmental disorders become apparent. The present study further indicated that the change in the BM of infants detected in a 24-hour cycle is another important variable. Therefore, it is desirable to develop tracking observations to elucidate the relationship between infant development and BM and develop more accurate body motion measurement equipment.

Limitations of this study

Because the subjects of this research were limited to one facility and due to an inadequacy in the number of subjects, the results of this research cannot be generalized. In addition, there is also the possibility that the body movements in this study included not only spontaneous body movements but also artificial body movements due to treatment from medical staff, nurses, etc.

ACKNOWLEDGEMENTS

We deeply appreciate NICU hospitalized children, their families, and the medical staff of the NICU for their cooperation. The Arteriosclerosis Research Foundation of Japan supported the statistical processing of this work financially, which was approved by Miyagi University.

REFERENCE

1) Uetani Y: The prognosis of very low-birth-weight infants as viewed from a nationwide survey. Journal of Japan Society of Perinatal and Neonatal Medicine 41(4): 758-760, 2005 (In Japanese)
2) Brandon DH, Holditch-Davis D, Beylea M: Nursing care and the development of sleeping and waking behaviors in preterm infants. Research in Nursing & Health 22: 217-229, 1999
3) Korte J, Hoehn T, Siegmund R: Actigraphic recordings of activity-rest rhythms of neonates born by different delivery modes. Chronobiology International 21: 95-106, 2004
4) Sung M, Adamson TM, Home RS: Validation of actigraphy for determining sleep and wake in preterm infants. Acta Paediatrica 98(1): 52-57, 2009
5) Minosaki Y, Oku K, Yamanami S, et al.: Shinseijiyou Mukokyu monitor [Neogard®] no Shiyou Keiken. Perinatal Care 20(1): 72-79, 2001 (In Japanese)
6) Inoue M: Apnea monitor for infants. The Japanese Journal of Medical Instrumentation 83(4): 362-365, 2013 (In Japanese)
7) Yachi K, Nemoto T, Shimada K: Quantification of body movement measurements in low-birthweight infants. Journal of the Tsuruma Health Science Society Kanazawa University 49(1): 11-19, 2016
8) Nemoto T, Ogai K, Kitamura K, et al.: Development of vibration measurement equipment of each body part under the sleep. Proc. of the 48th Annual Conference of Japanese Society for Medical and Biological Engineering 48: 23-25, 2009
9) The Japanese Society for Pediatric Endocrinology. New Calculation File of Birth-Time Body Standard Value By Gestational Period. http://jspe.umin.jp/medical/files/taikakubirthlongcrossv1.xlsx/ (accessed 2016-6-13)
10) IBM SPSS, Modeler-17-Manual, Algorithms Guide-p59, pp62-63, 2015
11) Chen W, Zhu X, Nemoto T: A New Sensory Device and Optimal Position for Monitoring HR/RR during sleep. Proc. of the World Congress on Medical Physics and Biomedical Engineering 25: 126-129, sept 7-12, 2009
12) Kitamura K, Takeuchi R, Ogai K, et al.: Development of a novel pulse wave velocity measurement system: Using dual piezoelectric elements. Medical Engineering & Physics 36: 927-932, 2014
13) Thoman EB: Early communication as the prelude to later adaptive behaviors. In Begab MJ, Haywood HC, & Garber HL: Psychosocial Influences in Retarded Performance, Vol. Ⅱ . Strategies for Improving Competence: Baltimore University Park Press, 219-244, 1981
14) Freudigman KA, Thoman EB: Infant Sleep During the First Postnatal Day: an Opportunity for Assessment of Vulnerability. Pediatrics 92(3): 373-379, 1993

低出生体重児の体動の測定とデータマイニング解析

谷内　　薫、根本　　鉄[1]、大貝　和裕[1]、小林登史夫[2]、島田　啓子[1]

要　　旨

低出生体重児のケアを提供する上で、全身状態の適切な管理が重要である。臨床において、体動は低出生体重児の全身管理の指標の一つである。本研究では、低出生体重児の体動を定量化し、体重増加との関係を比較することにより、全身管理の指標となる体動量を明らかにすることを目的とした。体動計測装置は、デュアル圧電素子を用いたベッドセンサを用いた。33 名の低出生体重児を調査対象とし、体動を 24 時間測定し、5 分間の平均体動量を算出した。統計解析にはデータマイニング解析および多変量解析を用いて統計学的分析を行った。調査の結果により、低出生体重児の体重を区分してみた結果、体重が大きい児の方が体動が大きいことが示された。また、BM- 0 ～ BM-20 と CA ～ CE の間には一定の傾向が認められ、体動計測装置は低出生体重児の体動を自動的にモニタリングできるルーチンの手法として用いることができる。