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A model for automatic identification of human pulse signals*

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Abstract: This paper presents a quantitative method for automatic identification of human pulse signals. The idea is to start with the extraction of characteristic parameters and then to construct the recognition model based on Bayesian networks. To identify depth, frequency and rhythm, several parameters are proposed. To distinguish the strength and shape, which cannot be represented by one or several parameters and are hard to recognize, the main time-domain feature parameters are computed based on the feature points of the pulse signal. Then the extracted parameters are taken as the input and five models for automatic pulse signal identification are constructed based on Bayesian networks. Experimental results demonstrate that the method is feasible and effective in recognizing depth, frequency, rhythm, strength and shape of pulse signals, which can be expected to facilitate the modernization of pulse diagnosis.

Key words: Pulse signal identification, Feature extraction, Bayesian network, Quantitative diagnosis, Wavelet transform

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INTRODUCTION

In traditional Chinese medicine (TCM), pulse signals are considered carrying important information that can reflect the health state of human body. Pulse diagnosis in TCM has been validated for more than 2000 years, which is inexpensive, painless, convenient and non-invasive. The identification of pulse signals is the purpose of pulse diagnosis. In traditional pulse diagnosis, doctors diagnose patients using the fingertips to feel the pulse beating at the measuring point of the radial artery, which requires long experiences and a high level of skill. The diagnostic process is subjective and deficient. Much effort is being made on pulse analysis for quantitative identification of pulse signals (Lee *et al*., 1993; Lu *et al.*, 1996; Nakayama *et al.*, 2000; Xu *et al.*, 2006; Tsui *et al.*, 2007; Wang and Zhang, 2007; Shu and Sun, 2007; Zhang and Wang, 2008). In pioneer work, multi-variable statistical analysis (MSA) was mostly utilized to construct pulse diagnostic models (Fu and Lai, 1989; Yoon *et al*., 2000; Shu and Sun, 2007; Tyan *et al*., 2008). In these studies, the thresholds of pulse parameters were determined mostly through try-and-error, which is often unreliable and difficult to operate. And MSA is a linear model, which cannot reflect the complex relationships between pulse signals and pulse types. Many studies have been carried out to construct non-linear models for pulse recognition. A self-organizing classification system using an adaptive resonance theory based neural network was constructed in (Chiu *et al.*, 2000) to evaluate the signs of abnormal and normal autonomic control, where only two parameters were used for extracting the minimal cardiac cycles, which is not enough for pulse recognition of the complex pulse signals. Another work (Hu *et al.*, 1997) was based on artificial neural network, in which the features used were very simple and the extraction procedure was not described. This method did not experiment on a pulse signal sample database and the effectiveness was not validated. In

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addition, such models were mostly built under the assumption that the pulse signal features are independent, which is not always the truth. In fact, there are complex dependency relationships among pulse para- meters (Fei, 2003; Zhang and Wang, 2008). Xu *et al.* (2006) detected arrhythmic pulses using Lempel-Ziv complexity analysis and classified the pulse signals according to rhythms. However, other pulse features, such as pulse shape, were not considered.

In pulse diagnosis, fuzziness and uncertainty are inherent issues. An attractive tool for managing various forms of uncertainty is Bayesian networks (BNs) (Pearl, 1986; Heckerman *et al*., 1995). As compared with other methods that can also handle uncertainty quite adequately, such as fuzzy logic (Dubois *et al*., 1997) and belief functions (Spiegelhalter, 1991), BNs may be particularly well-suited for modeling pulse diagnosis. Firstly, BNs are grounded on a solid statistical theory, which makes it suitable to deal with stochastic and non-linear characteristics of pulse signals in a natural way. Secondly, BNs describe causal relationships in graphics mode, which is easy to comprehend and can be used to predict the consequences of intervention. The graph structure can help explain the diagnostic results and analyze the interrelationships between pulse signals and pulse types visually. Thirdly, BNs can deal with incomplete data and are often insensitive to imprecision in the numerical probabilities. Finally, expert knowledge can be incorporated to meliorate the model. As a rigorous probabilistic model, BNs can dispose small sample sizes. In pulse diagnosis, it is difficult to collect enough samples for each pulse type. In our previous work (Wang and Cheng, 2005), we constructed a diagnostic model for pulse diagnosis, but the system was incomplete—the detailed procedures of feature extraction and model construction were not reported, and the database was not well established, i.e., some pulse types, such as float pulse and knotted pulse, had less than 20 samples.

In this paper, we improve the feature extraction method and develop a framework for automatic identification of pulse signals based on BNs. The detailed procedure of feature extraction is presented first; then taking the characteristic parameters as the input, the pulse signal recognition models are built; lastly, the proposed method is tested by a renewed pulse signal database.

TIME-DOMAIN CHARACTERISTICS OF PULSE SIGNALS

Fig.1 presents a period of a pulse waveform of a healthy volunteer, which is obtained by a pulse transducer. Fig.2 illustrates the pulse signal acquisition system. The sampling rate is 100 Hz. The pulse transducer is belt-mounted and fixed on the radial pulse at the wrist. We can regulate the pressure gradually from 0 to 250 g through a vertical position regulator screw. This system can record a series of pulse signals under different contact pressures. The pulse signal whose modulus reaches the maximum is selected as the investigated subject. As the contact pressure of the pulse transducer increases, the amplitude of the pulse signal first increases, reaching a maximum point and then decreases. One period of the pulse waveform is usually composed of three waves: percussion wave, tidal wave, and dicrotic wave (Fig.1). The main time-domain characteristic parameters, which have been testified to be important for diagnosis, are marked in Fig.1: h_{sp}, h_{ee}, h_{ef}, h_{ff}, h_{fg} and T_1. These parameters all have physiological, pathologic and psychological significance (Fei and Zhang, 1995; Hu *et al*., 1998; Fei, 2003; Xie and Zhao, 2003).

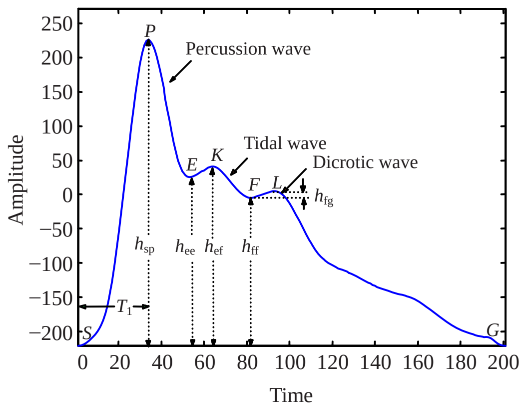


Fig.1 Time-domain characteristic parameters of a pulse signal from a healthy volunteer

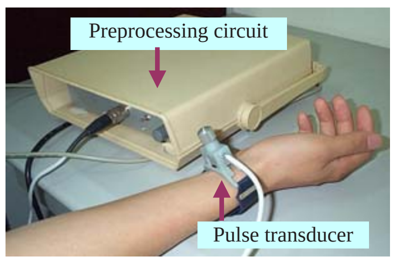


Fig.2 Pulse signal acquisition system, which consists of a preprocessing circuit and a pulse transducer

FEATURE EXTRACTION OF PULSE SIGNALS

Generally pulse signals consist of seven elements (Fei, 2003): depth, width, length, frequency, rhythm, strength, and shape, according to which, clinical pulse signals are classified.

In TCM, physicians recognize pulse types by placing their index, middle and ring fingers on the patient's wrist to feel the pulse beating at the measuring point of the radial artery (Fei, 2003; Wu *et al*., 2007), i.e., cun, guan, chi (Fig.3). As shown in Fig.3, lines *b*, *c*, *d* and *e* are boundaries, inside which pulse beat can be felt but not outside. Pulse length can be expressed by the distance between lines *b* and *c*; pulse width can be represented by the distance between lines *d* and *e*. The pulse transducer we used is a single-point pressure transducer and can only record the pulse signal at one point. In this study, we recorded merely the pulsation at the guan point, and thus the acquired signals cannot reflect the information of width and length of human pulse. Therefore, we discuss the pulse signal identification based on the other five factors.

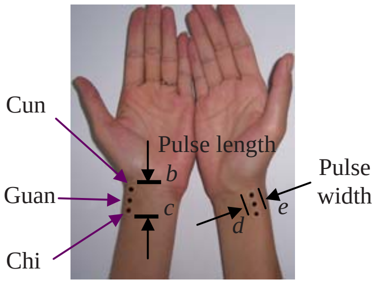


Fig.3 Measuring positions for pulse diagnosis and illustration of pulse length and pulse width

Pulse depth

Pulse depth represents the pressure magnitude to feel the pulse and can determine the classification of pulse signals into floating pulse (FL-pulse), sinking pulse (SI-pulse) and normal depth pulse (ND-pulse). An FL-pulse signal is palpable by light touch and grows faint under firm pressure, while an SI-pulse signal can only be felt by firm pressure. Hence, we selected the contact pressure P_1, under which the modulus of the pulse signal reaches the maximum, as a characteristic parameter to identify the pulse depth.

Pulse frequency

Pulse frequency is the times of pulse beats per minute, which indicates the pulse wave velocity. According to pulse frequency, pulse signals can be grouped into slow pulse (SL-pulse, <60), moderate pulse (M-pulse, 60~90), and rapid pulse (R-pulse, >90). To determine the pulse frequency, two characteristic parameters, i.e., the period of the pulse signal (C_1) and the number of periods in one minute (N_m), were computed. These two parameters were calculated grounded on one characteristic point of the pulse signal, such as the crest of the percussion wave (CPW, marked as P in Fig.1). Pulse frequency can be detected accurately based on wavelet transform (Quddus and Fahmy, 1999; Sun *et al*., 2004; Tu and Hwang, 2005; Wang and Zhang, 2007).

Fig.4 shows one periodicity-detection example. Fig.4a is a pulse signal sample, Fig.4b is the characteristic detection result obtained by our method, and Fig.4c shows the positions of CPWs. The interval between two consecutive CPWs was read as period C_1. We recorded pulse signals in 1 min and counted the number of CPWs in this time slice as N_m. Hence, C_1 is computed by

$$C_1=60/N_m. \tag{1}$$

It can be seen that the proposed approach can not only detect the periodicity of the pulse signal correctly but also judge the uniformity of pulse rhythm. For arrhythmic pulse (A-pulse), the period is not constant.

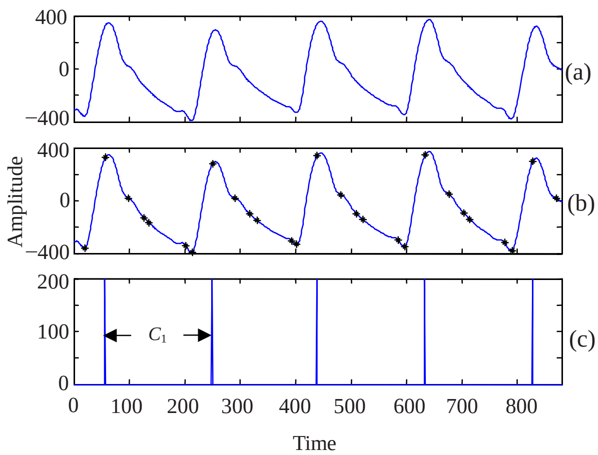


Fig.4 Calculation of period of a pulse signal based on characteristic detection using wavelet transform. (a) Pulse signal sample; (b) Characteristic points detection result; (c) Positions of crests of percussion waves and illustration of period C_1

Pulse rhythm

Pulse rhythm denotes regularity of a pulse signal, grounded on which pulse signals can be sorted into rhythmic pulse (T-pulse) and A-pulse. Spacing between consecutive CPWs is uniform in T-pulse, but uneven in A-pulse. Thus, we can differentiate T-pulse from A-pulse according to the position distribution of CPWs. Uniformity of distribution can be measured by distance standard deviation (DSD). Let S_0 denote the pulse signal recorded in one minute and P represent the position distribution of CPWs in S_0. The number of CPWs in S_0 is N_d. The DSD of P is given by

$$S_\mathrm{d}=\sqrt{\frac{1}{N_\mathrm{d}-1}\sum_{i=1}^{N_\mathrm{d}-1}(d_i-\bar{d})^2}, \qquad (2)$$

where d_i denotes the distance between the ith and (i+1)th CPWs, i=1, 2, …, N_d−1, and $\bar{d}$ is the mean of these N_d−1 distances. S_d is small for T-pulse, while large for A-pulse.

Intermittent pulse (I-pulse) and knotted pulse (K-pulse) are two typical A-pulses. K-pulse is a slow pulse pausing at irregular intervals, where the irregularity and slowness are due to blood obstruction. Fig.5a illustrates a K-pulse signal sample, from which it can be seen that the pulse waveform is irregular and CPWs are unequally spaced. I-pulse, comparatively relaxed and weak, pauses at regular intervals. I-pulse usually occurs in the exhaustion of viscera organs, severe trauma, or horror (Dharmananda, 2000; Fei, 2003). I-pulse periodically loses a beat after two, three or five but less than six pulse periods, which are called bigeminy, trigeminy, and pentalogy, respectively (Fei, 2003). Fig.5b shows an I-pulse sample, which is a trigeminy, and demonstrates that the distribution of pulse waveforms is inerratic. To distinguish I-pulse from K-pulse, we define three characteristic parameters, i.e., S_d2, S_d3, and S_d5.

Suppose $A=\{a_1, a_2, ..., a_i, a_{i+1}, ..., a_{N_\mathrm{d}-1}\}$ is the set of CPWs in P.

S_d2: If the subscript i satisfies i mod 2=1, retain the point a_i; otherwise, delete a_i. Then we obtain a new set $A_2=\{a_1, a_3, a_5, ..., a_{N_2}\}$. Let P_2 be the position distribution of A_2. Compute the DSD of P_2, which we call S_d2. If the pulse signal is a bigeminy, S_d2 is small.

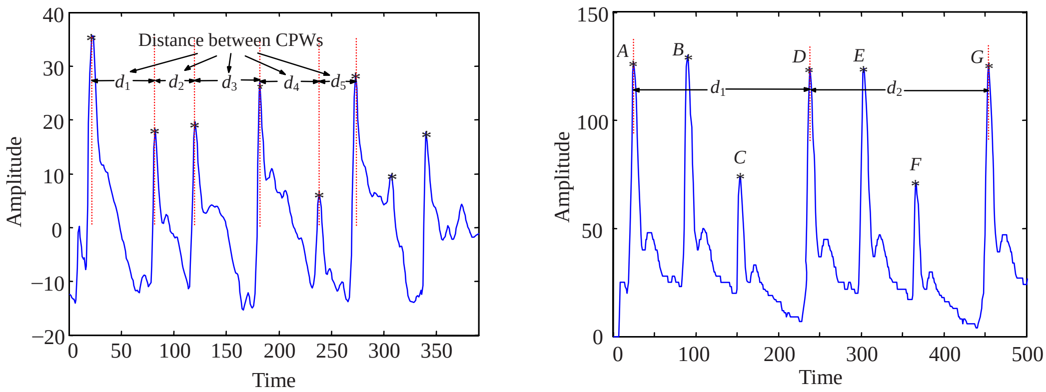
S_d3: If i satisfies i mod 3=1, retain point a_i; or else, delete a_i. Then we obtain a new set $A_3=\{a_1, a_4, a_7, ..., a_{N_3}\}$. We denote the new position distribution of A_3 by P_3. Compute the DSD of P_3, which is called S_d3. If the pulse signal is a trigeminy, S_d3 is small.

S_d5: If i satisfies i mod 5=1, retain point a_i; in other ways, delete a_i. Then a new set $A_5=\{a_1, a_6, a_{11}, ..., a_{N_5}\}$ is gained. P_5 is the position distribution of A_5. Compute the DSD of P_5, which is called S_d5. If the pulse signal is a pentalogy, S_d5 is small.

From the above discussion, the four parameters S_d, S_d2, S_d3 and S_d5 are utilized to identify the pulse rhythm. We can recognize the pulse rhythm according to the following rules:

Rule 1 If S_d, S_d2, S_d3 and S_d5 are all small, the pulse signal is a T-pulse. For example, for the pulse signal shown in Fig.4, S_d=2.87, S_d2=3.86, S_d3=2, S_d5=1.23.

Rule 2 If S_d is large, but any one of S_d2, S_d3 and S_d5 is small, then the pulse signal is an I-pulse. For example,



(a) (b)

Fig.5 (a) K-pulse signal sample and corresponding distances between CPWs in *P*; (b) Trigeminy I-pulse sample and corresponding distances between CPWs in P_3

for the pulse signal shown in Fig.5b, S_d=9.19, S_{d2}=10.5, S_{d3}=1.5, S_{d5}=10.78.

Rule 3 If S_d, S_{d2}, S_{d3} and S_{d5} are all large, the pulse signal is a K-pulse. For example, for the pulse signal shown in Fig.5a, S_d=16.03, S_{d2}=24.04, S_{d3}=35.76, S_{d5}=33.33.

Pulse strength and pulse shape

Pulse strength is the synthetic reflection of pulse force and tendency. Pulse signals can be sorted into normal strength pulse (NS-pulse), replete pulse (E-pulse) and feeble pulse (B-pulse). A pulse that feels vigorous and forceful on both light and high pressure is named E-pulse (Dharmananda, 2000; Fei, 2003), while B-pulse is a pulse that feels feeble and void, occurring when qi (Nie, 1984) and blood are deficient or body fluid is impaired (Fei and Zhang, 1995; Fei, 2003).

Pulse shape signifies the contour characteristic of a pulse signal. Based on the pulse shape, pulse signals commonly encountered in clinic can be sorted into slippery pulse (P-pulse), hesitant pulse (H-pulse) and wiry pulse (W-pulse). P-pulse, like beads rolling on a plate, is a fluent pulse and often present in normal persons, pregnant women, and patients who are phlegm-damp or food stagnation (Dharmananda, 2000; Fei, 2003). H-pulse, like a knife scrapes across bamboo, is a choppy pulse, and denotes that the blood circulation is slow as a result of blood deficiency or qi and blood stagnation (Fei, 2003; Yue, 2006). W-pulse is a pulse that feels straight and long, like a musical instrument string. This pulse type is often found in normal persons or patients whose liver and gallbladder are in disorder or have severe pains (Hu *et al.*, 1998; Fei, 2003).

As can be seen from the above discussion, the features of these pulse types are characterized by one or several characteristic parameters and hard to quantify. Accordingly, the recognition of E-, B-, P-, H- and W-pulse is more complicated. To identify them, we computed the main time-domain characteristic parameters, which are h_{sp}, h_{ef}, h_{ff}, h_{fg} and T_1 (Fig.1), C_1 (Fig.3), r_{fp}, r_{es} and r_{fs}. Thereinto, $r_{es}=h_{ef}/h_{sp}$, $r_{fp}=h_{ff}/h_{sp}$ and $r_{fs}=h_{fg}/h_{sp}$. These parameters are endowed with physiological, pathologic and psychological significance and have been validated to be significant for diagnosis (Fei, 2003; Zhang and Wang, 2008). For example, r_{es} reflects the resilience and peripheral resistance of the vascular wall. The parameter h_{ee}, which has the same physiological significance as h_{ef}, is not considered in this paper. We assume that these nine parameters are equally important in pulse diagnosis.

PULSE SIGNAL RECOGNITION MODEL

The outline of the model for automatic pulse signal identification based on BNs is illustrated in Fig.6. Note that pulse signals can be easily contaminated by background noises, such as the uncontrollable movements of body limbs, respiration, and so on. Hence, the preprocessing of pulse signals is needed, which includes noise reduction and baseline wander removal. The preprocessing method has been studied in our previous work (Zhang and Wang, 2008) and proved effective. The ultimate goal of our model is to recognize pulse types automatically. We constructed five BNs to identify the depth, frequency, rhythm, strength, and shape of pulse signals, respectively.

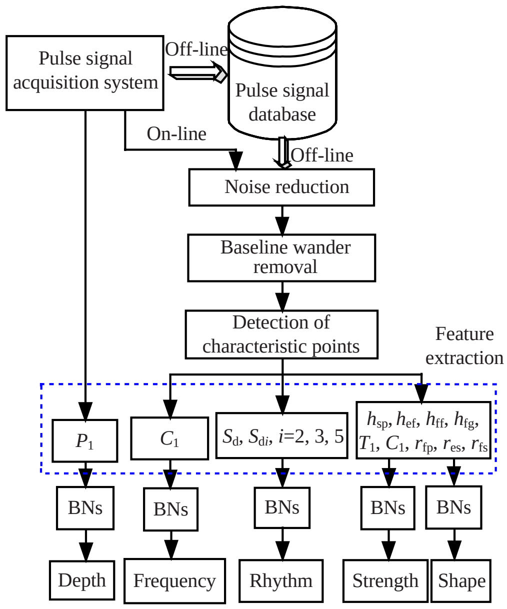


Fig.6 Outline of the model for automatic identification of pulse signals

In almost all medical diagnosis, uncertainty is an inherent issue. BNs, also known as 'directed graphical models', can represent knowledge with uncertainty and perform reasoning tasks efficiently. Specifically, a graphical model denotes the joint probability distribution (JPD) of n random variables $X=\{X_1, X_2, \ldots, X_n\}$ by a directed acyclic graph (DAG) M. In a BN, each node i corresponds to a variable X_i, and an arc from nodes A to B indicates that A is the cause of B. X_i is conditionally independent of its ancestors given its parent set Π_i. The BN decomposes the JPD as

$$p(X \mid M, \theta) = \prod_{i=1}^{n} p(X_i \mid \Pi_i, \theta), \tag{3}$$

where θ is the set of all parameters in the graphical model M.

Learning BNs involves structure learning and parameter learning. Structure learning is to find the most appropriate DAG by searching through the space of possible DAGs. The learning algorithms can be classified into two main groups (Spirtes and Meek, 1995; Nicandro *et al*., 2006): constraint-based methods and scoring metrics based methods. In the first group, conditional independence tests may lead to unreliable results if the amount of data is not enough. In the second group, DAGs are evaluated by a specific scoring metric and the DAG that maximizes this score is selected. However, the search space is often very large, making the learning procedure slow. The local optimal solution, not the global one, may be found. To improve algorithms of these two categories, hybrid learning algorithms are developed, among which a greedy Bayesian pattern search algorithm (Spirtes and Meek, 1995) is the most effective one and includes two steps. Firstly, the PC algorithm (Spirtes *et al*., 1993) is utilized to generate an initial pattern (significance level is set to 0.05 in our model). Secondly, a greedy pattern search is performed to search for the best DAG according to a scoring metric. However, this algorithm ignores one possibility: If there is no edge to be deleted or added in DAG construction, the reversion of a directed edge can also change the pattern. Wang *et al*.(2004) proposed a new algorithm by adding one step to deal with the possibility. This new method was applied to build the DAG in our model. The Bayesian information criterion (BIC) is selected as the scoring function, defined as

$$BIC = \log p(X \mid M, \theta) - \frac{d}{2}\log n, \tag{4}$$

where d is the dimension of M. The BN with the highest BIC is selected as the identification model.

We used discrete BNs to build the model. Time-domain characteristic parameters utilized to construct the model are all numeric features. Discretization is a popular approach to handling numeric variables. Using discretized data can usually engender more accurate results than using continuous values (Liu and Wang, 2005). Equal frequency discretization (EFD) (Yang and Webb, 2002) was used and the number of intervals was set to 10. This method divided the sorted values to make each interval contain approximately the same number of instances.

EXPERIMENTS AND RESULTS

Experiments were carried out to verify that: (1) the characteristic parameters we extracted are useful; (2) the proposed model can identify pulse signals effectively. A pulse signal database was employed, in which a total of over 500 pulse signals were gathered from several hospitals of TCM. The diagnostic results were given by one group of clinical physicians with three members. The samples whose characteristic points were detected and labeled incorrectly (Zhang and Wang, 2008) were picked out. After that, 468 samples survived and were utilized to validate the proposed model. A stratified κ-fold cross validation (κ=10) was used to evaluate the accuracy.

We trained five BNs based on the characteristic parameters in Fig.6, which are called D-BNC, F-BNC, R-BNC, T-BNC, and H-BNC, respectively. The graphical structures of the five learned BNs are shown in Fig.7. The identification results given by our model are reported in Tables 1~6, where the numbers in the parentheses represent the actual numbers of samples. Tables 1~6 indicate that the depth, frequency, rhythm, strength, and shape of pulse signals can all be identified effectively. The average accuracy reaches 92.14%. For pulse strength and pulse shape, which are difficult to comprehend and diagnose for beginners, the accuracies reach 89.74% and 89.32%, respectively. These results demonstrate that the features we extracted are useful for diagnosis and the method we proposed is feasible and effective.

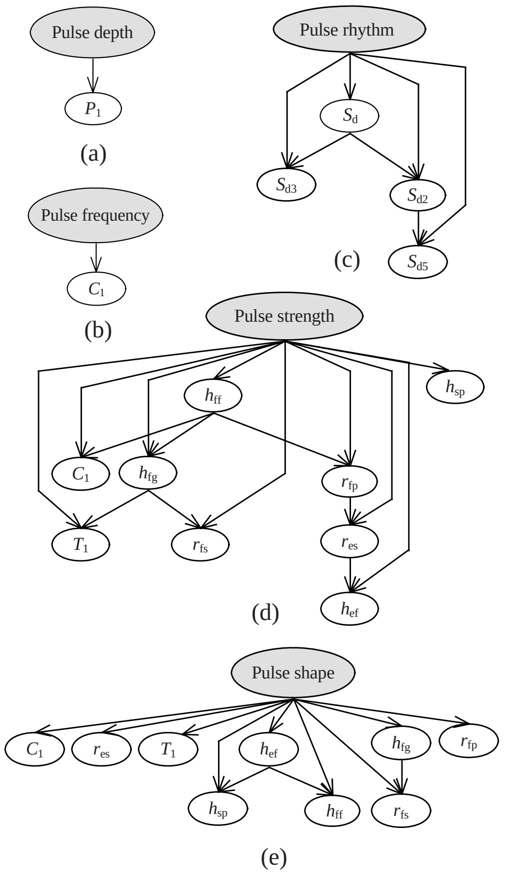


Fig.7 Graphical structures of five learned Bayesian networks. (a) D-BNC; (b) F-BNC; (c) R-BNC; (d) T-BNC; (e) H-BNC

Table 1 Confusion matrix of pulse depth

	FL-pulse	SI-pulse	ND-pulse
FL-pulse	40 (44)	0	4
SI-pulse	1	218 (219)	0
ND-pulse	0	18	187 (205)

Table 2 Confusion matrix of pulse frequency

	SL-pulse	M-pulse	R-pulse
SL-pulse	132 (132)	0	0
M-pulse	8	173 (181)	0
R-pulse	0	17	138 (155)

Table 3 Confusion matrix of pulse rhythm

	T-pulse	K-pulse	I-pulse
T-pulse	343 (350)	5	2
K-pulse	0	63 (66)	3
I-pulse	5	4	43 (52)

Table 4 Confusion matrix of pulse strength

	E-pulse	B-pulse	NS-pulse
E-pulse	188 (198)	4	6
B-pulse	8	132 (146)	6
NS-pulse	10	14	100 (124)

Table 5 Confusion matrix of pulse shape

	P-pulse	W-pulse	H-pulse
P-pulse	172 (188)	16	0
W-pulse	10	160 (184)	14
H-pulse	0	10	86 (96)

Table 6 Accuracy of the proposed model

Pulse type	Accuracy (%)
Depth	95.09±3.56
Frequency	94.66±6.21
Rhythm	91.88±1.96
Strength	89.74±0.77
Shape	89.32±2.23
Average	92.14

CONCLUSION AND FUTURE WORK

In this paper, we presented a model to realize the automatic identification of human pulse signals. We first detected the characteristic points based on wavelet transform, then extracted the features based on the detected characteristic points, and then constructed the identification model based on Bayesian networks. Experimental results showed that our method is feasible and effective in recognizing depth, frequency, rhythm, strength, and shape of pulse signals.

Further work is needed to explore new pulse transducers which can collect multidimensional information of pulse signals. More information should be gathered to improve the predictive ability. For example, new acquisition systems need to be developed to gain such information as width and length of pulse signals. At the same time, more representative features of pulse signals are expected to be found.

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