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Heart Rate Pattern Classification based on a Binary Classification Scheme

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Abstract. This paper explores to search for the best classification scheme of autonomic states based on the heart rate variability(HRV). Six drug induced distinct states are artificially created and classified by the multi-layer perceptron(MLP). 14 healthy male subjects aged 19-38 were volunteered to be subject of study. 5minutes heart rate data in different autonomic states are collected for the classification. Optimized binary classification scheme has been utilized and the classification accuracy of sensitivity 0.861 and specificity 0.970 has been achieved.

Keywords: Heart Rate Variability, State Classification, Artificial Neural Networks, Biosignal Analysis, Autonomic Nervous System, Power Spectral Analysis, Entropy Bandwidth

1. Introduction

Yet heart rate variability (HRV) has been a well-known source of information to probe the autonomic nervous activity[1], a large Individual variation in HRV properties prevents from making them standardized indices for the clinical diagnoses and other application areas. Authors demonstrated in the previous report[2] that the introduction of individualized relative heart rate spectra to correctly classifies the physiologically well-defined autonomic states. This paper improved its classification accuracy by setting adequate physiological states to be classified.

2. Methods

2.1. Data acquisition

The instantaneous heart rate signals of 14 normal subjects aged 19-38 years old reconstructed by Burger's method[3] from ECG recordings are collected under drug induced physiologically well-defined autonomic states. Distinct states are control (C), parasympathetic blockade by Atropine (A), sympathetic blockade by propranolol (P) and double blockade (D), Data are collected in supine (S) and upright (U) posture for each autonomic states resulted in eight states altogether. The data collection scheme has been documented in [4]. Power spectra have been estimated by averaging 256 point FFT (Δf=0.012Hz).

2.2. State Classification

Features for the state classification: As the basic features for the state classification, signal variance, incremental HF, LF and LF/HF are adopted. Additional features incremental MF (0.04-0.11Hz) is considered for the classification. Those indices are obtained from the heart rate power spectra. The standard half overlapped running Hanning windows are applied to the data and FFT (N=256) frequency power were averaged to yield the power spectra estimates. Frequency resolution is 0.0156 (Hz). The coefficient of variation of estimated power spectra is 0.408 with averaging six FFT frequency powers. Then all indices are normalized to ones obtained for the control supine condition. We call them incremental parameters. For example, the incremental LF/HF (ILF/HF) is defined as:

$$ILF / HF = 10\log\frac{LF / HF}{LF / HF_0}$$

In this way incremental indices IHF, ILF, IHF/LF, IMF are defined and utilized for the following state classification.

2.3. Classification Scheme

Fig.1 shows the HRV binary classification scheme adopted here. Binary decision tree to separate(A+D) and (C+P) at the beginning showed the best classification results. Here sign"+"shows OR operation of the data set. Careful examination of raw data and spectral patterns of each state leads us to combine the state PU, DS. Those state are shown to be indistinguishable from the HRV spectral data.

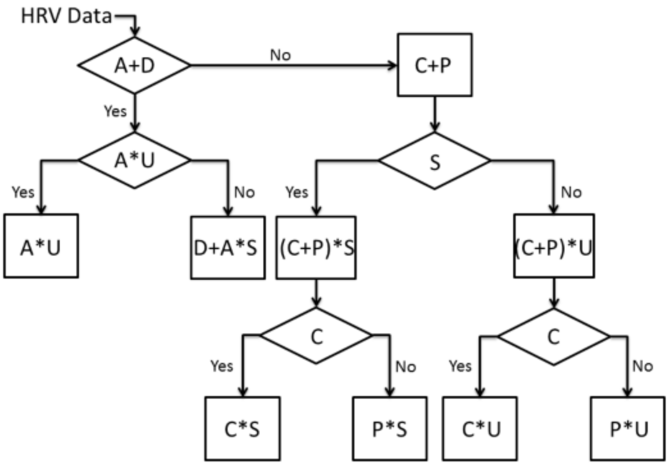

Figure 1. Heart Rate Pattern Classification Scheme

3. Results

3.1. State Classification

For each binary classification shown in Fig. 1, three layered ANN has been utilized. The number of hidden layers and the learning coefficients have been empirically adjusted to get the best classification accuracy. Leave one out cross validation has been applied for evaluating the classification accuracy. The basic indices utilized for the classification are HF, LF/HF, average and variance of the heart rate.

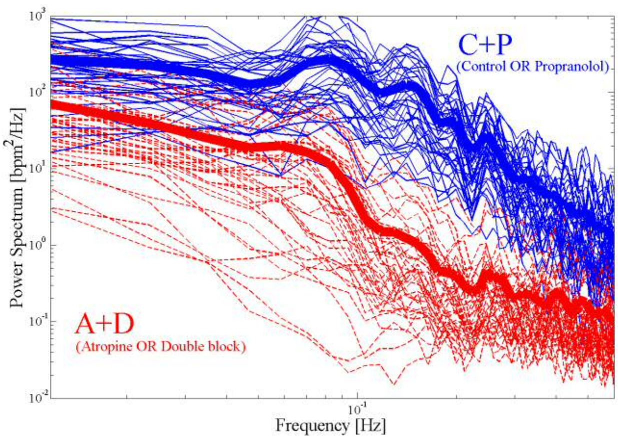

Fig. 2 Power spectra Comparison between C+P and A+D Cases

3.2. Classification of A+D and C+P cases

Fig. 2 shows the power spectra for C+P (Blue: Control or Propranolol) and A+D (Red: Atropine or Double blockade) cases. Even eye inspection confirms the good pattern separation in frequency domain. This validates our classification scheme (Fig. 1) put this classification at the very beginning.

3.3. Classification Results

Table 1 shows the classification results. Overall sensitivity and specificity were shown to be 0.861 and 0.970 respectively. Reasonable classification accuracy has been achieved except for PU. PU his tend to be classified as CS or PS for this data set.

TABLE 1 Autonomic State Classification Results

	CS	CU	PS	PU	AU	D
CS	**1.000**	0.000	0.000	0.000	0.000	0.000
CU	0.071	**0.858**	0.000	0.000	0.071	0.000
PS	0.143	0.000	**0.857**	0.000	0.000	0.000
PU	0.143	0.000	0.286	**0.571**	0.000	0.000
AU	0.000	0.000	0.000	0.000	**1.000**	0.000
D	0.000		0.000		0.118	**0.882**

3.4. Classification of A*U and D+A*S cases

Among five binary classifications in the scheme shown in Fig. 1, all but A*U case use the basec indices mentioned abovel. For A*U classification case, MF and LF/HF has been adopted as input indices. Fig. 3 shows overlapped and mean power spectra for A*U and D+A*S cases. It is apparent that LF and MF takes higher values for A*U cases.

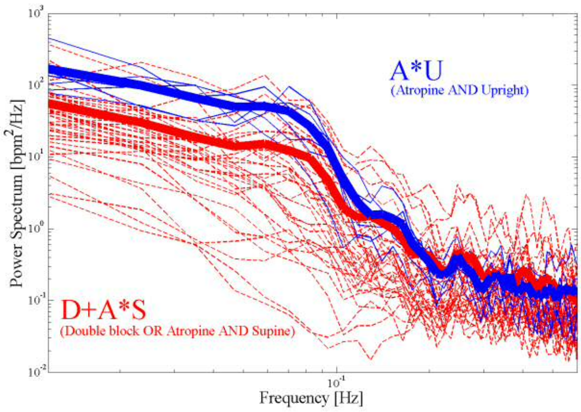

Fig. 3 Power spectra Comparison between A*U and D+A*S Cases

To see this more clearly box plots (Fig. 4) for MF (left) and LF/HF (right) have been shown. Even one of those indices alone would give a good classification accuracy.

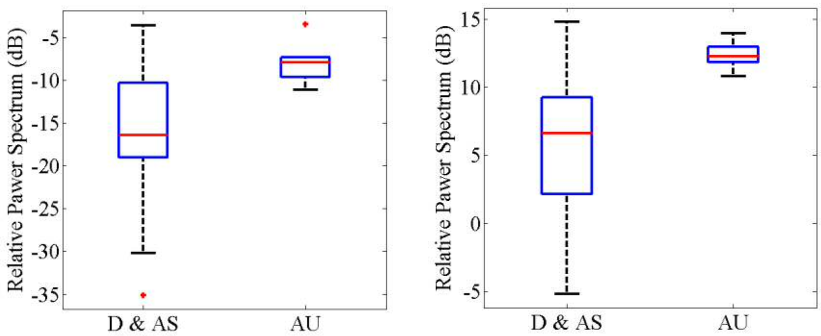

Fig. 4 Distribution of Indices: (MF: right; LF/HF: left)

4. Conclusion

Combining states PU, DU and DS improved the HRV classification accuracy. Since upright posture suppresses the parasympathetic activity, it is reasonable to assume PU is the same as state D where both sympathetic and parasympathetic activities are suppressed. The overall classification accuracy is satisfactory for many practical applications except for PU separation, which needs further methodological improvement.

Acknowledgements

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References

[1] Saif Ahmad, Anjali Tejula et al., "A review and analysis of heart rate variability and the diagnosis and prognosis of infection," Crinical Care, Vol 13, pp. 232-238, 2009.

[2] S. Kaneko, S. Yamashita, K. Yana(2013), "Individualized Autonomic State Classification based on Changes in Heart Rate Variability Indices", EMBC2013 Short Paper No. 3381., 2013.

[3] R.D. Berger, S. Akselrod, D.Gordon and R.J. Cohen, "An efficient algorithm for spectral analysis of heart rate variability," IEEE Trans. BME. Vol. 33, pp.900-904, 1989.

[4] K.Yana, J.P. Saul, R.D. Berger, M. H. Perrott and R. J. Cohen, "A time domain approach for the fluctuation analysis of heart rate related to instantaneous lung volume," IEEE Trans. BME, Vol. 40, No .1, pp. 74-81, 1993.