HUMAN STRESS LEVEL COMPUTATION USING MULTIPLE PHYSIOLOGICAL SIGNALS - BASED ON FUSION TECHNIQUE THROUGH DYNAMIC BAYESIAN NETWORK

by

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LIST OF ABBREVIATION

AAD	Average absolute deviation
ANOVA	Analysis of variance
ANS	Autonomic nervous system
AR	Auto regressive
ARMA	Auto regressive moving average
ATH	Adrenal hypothalamus
BMI	Body mass index
BP	Blood pressure
BVP	Blood volume pulse
CA	Approximation coefficient
CAD	Coronary artery disease
CD	Detailed coefficient
CPD	Conditional probability distribution
CWT	Continuous wavelet transform
DAG	Directed acyclic graph
DASS	Depression anxiety stress scale
DBN	Dynamic Bayesian network
DBP	Diastolic blood pressure
DFA	Detrended fluctuation analyses
DST	Dempster Shaffer theory
DFT	Discrete Fourier transform
DWPT	Discrete wavelet packet transform
DWT	Discrete wavelet transform
ECG	Electrocardiogram

EDA	Electro dermal activity
EEG	Electroencephalogram
EMD	Empirical mode decomposition
EMG	Electromyography
ENATF	European and north American task force
FD	Frequency domain
FFT	Fast Fourier transform
FN	False negative
FOD	First order difference
FP	False positive
FPM	Fisher projection matrix
GAS	General adaptation syndrome
GSR	Galvanic skin response
HHT	Hilbert Huang transform
HMM	Hidden Markova model
HOS	Higher order statistics
HPF	High pass filter
HR	Heart rate
HRV	Heart rate variability
HRVTI	HRV Triangular Index
IAV	Integral of absolute value
IBI	Inter-beat-interval
IBS	Irritable bowel syndrome
ICA	Independent component analysis

IDWPT	Inverse discrete wavelet packet transform
IDWT	Inverse discrete wavelet transform
IIR	Infinite impulse response
VLF	very low frequency
WPC	wavelet packet coefficients
WPT	wavelet packet transform
IS	Introductory segment
KNN	K nearest neighbor
LDA	Linear discriminate analysis
LF	Low frequency
LPD	Low pass differential
LPF	Low pass filter
LS	Lomb-Scargle
MAD	Median absolute deviation
MAT	Mental arithmetic task
MF	Mid-frequency
MLE	Maximum likelihood Estimation
MLP	Multi-layer perceptron
MSE	Mean square error
NLP	Natural language processing
PD	Pupil diameter
PDF	Probability density function
PN	Probabilistic network
PNN	Probabilistic neural network

PNS	Parasympathetic nervous system
PSD	Power spectral density
QP	Quadratic programming
QCD	Quartile coefficient of dispersion
RBF	Radial-bias function
RMSSD	Root mean square of the standard deviation
RR	Respiration rate
RS	Resting segment
SAIL	Smart assisted in living
SAQ	Self-analysis questionnaire
SBN	Static Bayesian networks
SBP	Systolic blood pressure
SCL	Skin conductance level
SE	Standard error
SNR	Signal-to-noise ratio
SNS	Sympathetic nervous system
SRR	Skin resistance response
ST	Skin temperature
STFT	Short-term Fourier transform
SURE	Steins unbiased risk estimator
SV	Stroke volume
SVM	Support vector machine
TD	Time domain
TP	True positive

VLF	very low frequency
TSST	Trier social stress test
WLPD	Weighted low pass differential
WPC	wavelet packet coefficients
WT	Wavelet transform
ZC	Zero cross

Pengiraan Aras Tekanan Manusia Menggunakan Pelbagai Isyarat Fisiologi - Berdasarkan Teknik Fusion melalui Rangkaian Dynamic Bayesian

ABSTRAK

Tesis ini mengkaji untuk meningkatkan pengiraan aras tekanan dan kebolehpercayaan dengan menggunakan pelbagai isyarat fisiologi. Dalam tesis ini, penginduksian tekanan, pengambilalihan isyarat fisiologi, prapemproses, pengekstrakan ciri, klasifikasi, pengoptimuman ciri-ciri dari pelbagai isyarat fisiologi, anggaran ciri penting, pengoptimuman keputusan sempadan dan gabungan adalah langkah-langkah penting yang terlibat. Tugas mental aritmetik rangsangan telah digunakan untuk mendorong tekanan pada 60 subjek yang sihat dengan umur purata 22.5 ± 2.5 tahun. Lima jenis isyarat fisiologi diambilkira dalam penyiasatan ini (elektrokardiogram (ECG), eelectromyogram (EMG), response kulit galvani (GSR), suhu kulit (ST) , kepelbagaian kadar jantung (HRV)) untuk mengukur kesan dorongan tekanan pada subjek. Isyarat ECG dan EMG yang diperoleh telah dipraproses dengan menggunakan kaedah 'wavelet denosing' untuk menyingkirkan bunyi dalam keseluruhan julat frekuensi isyarat dan penapis perintah keempat eliptik digital digunakan untuk menyingkirkan bunyi dalam isyarat GSR dan ST. Algoritma penyikiran ektopik digunakan untuk menghapuskan kehadiran puncak bunyi dan artifak dalam isyarat HRV. Dalam pengekstrakan ciri, ciri-ciri isyarat ECG dan EMG dikira menggunakan diskret wavelet packet transform (DWPT) dan Lomb-Scargle (LS) periodogram telah digunakan untuk mengeluarkan spectrum kuasa rendah dan jalur frekuensi yang tinggi dalam isyarat istilah pendek HRV. Algoritma pengesanan ketakutan telah dilaksanakan untuk mengeluarkan dan menganalisis ciri-ciri yang berkaitan dengan GSR tonik tindak balas, dan akhirnya ciri-ciri suhu kulit diekstrak secara langsung dalam rantau masa. Ciri-ciri yang diperolehi telah dikelaskan kedalam empat tahap tekanan termasuk tahap normal dengan menggunakan tiga pengelas linear (K paling hampir neighbor (KNN), rangkaian neural berkebarangkalian (PNN), dan mesin vektor sokongan (SVM)). Kadar klasifikasian purata dan skor F_1 melebihi 50% dan 0.5 dianggap sebagai ciri dominan dalam kerja ini. Keputusan menunjukkan 20 ciri sebagai dominan dikalangan 244 ciri-ciri yang disiasat dalam pelbagai jalur frekuensi lima isyarat fisiologi. Purata maksimum ketepatan klasifikasi empat peringkat telah diperoleh 74.20% dalam ciri min ECG, 74.75% dalam ciri cumulant ketiga HRV, 74.67% dalam min EMG, 66.84% dalam cirri kekerapan ketakutan daripada GSR, dan 63.63% dalam ciri min ST dalam kajian hal bebas. Bagi meningkatkan kadar klasifikasi tahap tekanan dan kebolehpercayaanya, pengoptimuman sempadan keputusan dan ciri fisiologi penting vector anggaran diperlukan. Pemboleh ubah-perintah tersembunyi Markova model (HMM) berdasarkan rangkaian Bayesian dinamik (DBN) telah dibina untuk mendapatkan perubahan dinamik setiap ciri isyarat fisiologi dan berupaya untuk mengenalpasti vektor ciri penting dan sempadan keputusan sepadan dengan pelbagai tahap tekanan. Rangkaian DBN yang mengamkan tiga sempadan keputusan yang terdiri daripada 20 ciri-ciri berbeza yang diproses, dan hasilnya menunjukkan bahawa purata kebarangkalian Bayesian maksimum untuk setiap sempadan adalah 0,544, 0.61 dan 0.75 dalam semua keadaan berkenaan kepada keadaan normal. Akhirnya, vektor ciri-ciri yang dioptimumkan ini menjadi milik sempadan yang berbeza dan telah digabungkan untuk membuat keputusan global dengan ketepatan pengesanan yang lebih baik dan boleh dipercayai.

Human Stress Level Computation Using Multiple Physiological Signals-Based on Fusion Technique through Dynamic Bayesian Network

ABSTRACT

This study investigates to improve the stress levels computation and its reliability using multiple physiological signals. In which, stress inducement, physiological signal acquisition, preprocessing, feature extraction, classification, optimization of features from multiple physiological signals, significant feature estimation, decision boundary optimization, and fusion are the major process. Mental arithmetic task stimulus is used to induce stress on the subjects and sixty healthy subjects with a mean age of 22.5 ± 2.5 years were used. This investigation considered the five physiological signals (electrocardiogram (ECG), heart rate variability (HRV) signal, electromyogram (EMG), galvanic skin response (GSR), and skin temperature (ST)) to measure the effect of stress induced on the subject. The acquired ECG and EMG signals were preprocessed using wavelet denoising method to remove the noises in the frequency range of signals and 4^{th} order IIR elliptic filter to remove the noises in GSR and ST signals. The ectopic beat removal algorithm was used to eliminate the presence of noise peaks and artifacts in HRV signal. In the feature extraction, ECG and EMG signals features were computed using discrete wavelet packet transform (DWPT), Lomp-Scargle (LS) periodogram is used to extract the low and high frequency band's power spectrum in the short- term HRV signal. The startle detection algorithm was implemented to extract and analyze the feature related to GSR tonic response, and finally the skin temperature features were extracted directly in the time domain. The obtained features classified in to four levels of stress including normal using three nonlinear classifiers (K nearest neighbor (KNN), probabilistic neural network (PNN), and support vector machine (SVM)). Average classification rate and F_1 score above 50% and 0.5 are considered as the dominant features respectively in this work. Result indicates that, 20 features as dominant features among the 244 features investigated over various frequency bands of five physiological signals. The maximum average classification accuracy of four levels was obtained as 74.20% in mean feature of ECG, 76.69% in third cummulant feature of HRV, 74.67% in mean of EMG, 66.84% in startle frequency feature of GSR, and 63.63% in mean feature of ST in subject-independent study. The results also indicate a significant improvement of classification results in the four class of subject-independent study over the earlier highly subject-dependent studies. In order to improve the classification rate on stress levels and its reliability, the optimization of decision boundary based on physiologically significant feature vectors estimation is required. The variable-order hidden Markov model (HMM) based-dynamic Bayesian network (DBN) was constructed to extract the dynamic changes of each physiological signal feature and capable to identify the significant feature vectors and decision boundaries corresponding to the different levels of stress. The DBN networks generalized the three decision boundaries of the 20 different dominant features processed, and the result shows that the maximum average Bayesian probability of each boundary is 0.544, 0.61, and 0.75 in all the states with respect to normal state. Finally, these optimized feature vectors belongs to different boundaries fused to make the global decision to ensure the reliability. The result shows that, an excellent agreement of reliability measure with improved classification accuracy while the significant components only presents in the fusion.