



Bio-Inspired Sensor Data Fusion for Herbal Tea Flavour Assessment

by

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LIST OF ABBREVIATIONS

| | |
|----------|--|
| AD | Anderson-Darling |
| BP | Back propagation |
| CDA | Canonical discriminant analysis |
| CDF | Computable document format |
| D.O.E | Design of experiment |
| E.I | Electron-ionization |
| EEG | Electroencephogram |
| E-nose | Electronic nose |
| E-tongue | Electronic tongue |
| FE | Features extraction |
| FID | Flame ionisation detector |
| FDA | Linear Discriminant Analysis with fisher criterion |
| FS | Features selection |
| FTIR | Fourier transform IR spectroscopy |
| GC | Gas Chromatography |
| GC-O | GC-Olfactometry |
| GDA | Generalized Discriminant Analysis |
| GRNN | General regression neural network |
| HLDF | High Level Data Fusion |
| HPLC | High performance liquid chromatography |
| HS | Headspace |
| ILDF | Intermediate Level Data Fusion |
| KNN | K-nearest neighbour |

| | |
|------|------------------------------|
| KS | Kolmogrov-Smirnov |
| LDA | Linear discriminant analysis |
| LF | Lilliefors |
| LLDF | Low Level Data Fusion |
| LS | Least Squares |
| MLP | Multi-Layer Perceptron |
| MOS | Metal oxide semiconductor |
| MS | Mass Spectrometry |
| MSDF | Multi sensor data fusion |
| MSE | Mean squared error |
| MVA | Multivariate analysis |
| NMR | Nuclear magnetic resonance |
| NN | Neural network |
| OAA | One against all |
| OAO | One against one |
| PCA | Principal component analysis |
| PEN3 | Portable electronic nose |
| PH | Pureherb |
| PLS | Partial least square |
| PNN | Probabilistic neural network |
| POL | Polens |
| QP | Quadratic programming |
| RBF | Radial basis fuction |
| RH | Rainhill |
| RTD | Ready To Drink |

| | |
|-------|---------------------------------|
| SIM | Selective ion monitoring |
| SMO | Sequential Minimal Optimization |
| SOM | Self-organizing map |
| SPME | Solid phase microextraction |
| SVM | Support vector machine |
| SW | Shapiro-Wilk |
| TIC | Total Ion Chromatography |
| V.F.C | Volatile flavour compound |

LIST OF SYMBOLS

| | |
|--------------|--------------------------|
| $\mu_1\mu_2$ | Mean vector |
| C | Box constraint |
| C_1C_2 | Covariance matrices |
| G/G0 | Ratio of conductance |
| M/Z | Mass/charge |
| V | Voltage |
| α_i | Inequalities |
| β | Linear model coefficient |
| ξ_i | Slack variable in SVM |

Bio-Inspirasi Gabungan Data Sensor Untuk Penilaian Perasa Teh Herba

ABSTRAK

Produk-produk berasaskan herba menjadi amalan pengeluaran meluas di kalangan pengeluar untuk pasaran antarabangsa dan tempatan. Memandangkan bertambahnya pengeluaran bagi memenuhi permintaan pasaran, adalah sangat penting bagi pengeluar supaya memastikan produk mereka telah memenuhi kriteria dan kualiti tertentu yang telah ditetapkan oleh pengawal kualiti. Salah satu produk berasaskan herba yang terkenal ialah teh herba. Tesis ini mengkaji penilaian-penilaian rasa berdasarkan inspirasi bio dalam konteks gabungan data melibatkan e-hidung dan e-telinga. Objektif kajian ini adalah untuk mendapatkan pengelasan yang tepat bagi pelbagai jenis dan jenama teh herba, pengelasan beberapa agen ‘masking’ rasa dan yang terakhir pengelasan berdasarkan perbezaan kepekatan teh herba. Dalam penyelidikan ini, dua tahap gabungan data dimanfaatkan iaitu gabungan data tahap rendah (LLDF) dan gabungan data tahap pertengahan (ILDF). Empat teknik pengelasan; ‘Fisher Linear Data Analysis (FDA)’, ‘Support Vector Machine (SVM)’, ‘k-Nearest Neighbour (KNN)’ dan ‘Probability Neural Network (PNN)’ telah diuji dalam mencari pengelas terbaik bagi mencapai objektif penyelidikan. Dalam menilai prestasi pengelas, penganggar ralat berdasarkan pengesahan silang ‘k-fold’ dan ‘leave-one-out’ (LOO) telah digunakan. Pengelasan berdasarkan data GC/MS TIC turut disertakan sebagai satu perbandingan kepada prestasi klasifikasi menggunakan pendekatan-pendekatan gabungan. Secara umumnya, melalui gabungan data tahap rendah dan gabungan data tahap pertengahan, KNN mengatasi teknik pengelasan yang lain untuk tiga penilaian rasa. Bagaimanapun, keputusan-keputusan pengelasan berdasarkan data GC/MS TIC adalah berubah-ubah bagi aplikasi yang berbeza. Memandangkan KNN dapat memberikan keupayaan pengelasan yang tinggi, sistem automatik pengredan dibina berdasarkan algoritma teknik tersebut.