Taste Recognition in E-Tongue using Local Discriminant Preservation Projection

Lei Zhang, *Member, IEEE*, Xuehan Wang, Guang-Bin Huang, *Senior Member, IEEE*, Tao Liu and Xiaoheng Tan

***Abstract*—Electronic tongue (E-Tongue), as a novel taste analysis tool, shows a promising perspective for taste recognition. In this paper, we constructed a voltammetric E-Tongue system and measured 13 different kinds of liquid samples, such as tea, wine, beverage, functional materials, etc. Owing to the noise of system and a variety of environmental conditions, the acquired E-Tongue data shows inseparable patterns. To this end, from the viewpoint of algorithm, we propose a local discriminant preservation projection (LDPP) model, an under-studied subspace learning algorithm, that concerns the local discrimination and neighborhood structure preservation. In contrast with other conventional subspace projection methods, LDPP has two merits. On one hand, with local discrimination it has a higher tolerance to abnormal data or outliers. On the other hand, it can project the data to a more separable space with local structure preservation. Further, support vector machine (SVM), extreme learning machine (ELM) and kernelized extreme learning machine (KELM) have been used as classifiers for taste recognition in E-Tongue. Experimental results demonstrate that the proposed E-Tongue is effective for multiple tastes recognition in both efficiency and effectiveness. Particularly, the proposed LDPP based KELM classifier model achieves the best taste recognition performance of 98%. The developed benchmark data sets and codes will be released and downloaded in http://www.leizhang.tk/tempcode.html**

***Index Terms*—Electronic tongue, taste recognition, subspace learning, extreme learning machine.**

I. Introduction

In recent years, electronic tongue (E-Tongue), as a kind of promising bionic systems for five basic biological tastes including sourness, saltiness, bitterness, sweetness and umami, is playing an increasingly important role in automatic food and pharmaceutical assessment, etc. E-Tongue owns some inherent merits such as easy measurement procedure, low cost and portability. The E-Tongue system was defined by Vlasov *et al.* [1] as a multi-sensor system, consisting of an array of nonspecific, low selective and high cross-sensitive sensors and a multivariate data analysis module.

A. Development in Application Level

The applications of E-Tongue have pervaded in many areas, such as food analysis [2]–[10], pharmaceutical manufacture [11]–[14] and environmental monitoring [15], [16]. For food analysis, there are numerous research work in automatic recognition of tea [2], beer [3], [4], wine [5], [6], milk [7] and olive oil [8]. Besides, Kutyła *et al.* [9] proposed to analyze extracts obtained from raw and dried apples. Apetrei *et al.* [10] proposed to discriminate and evaluate freshness of beef. For pharmaceutical manufacture, Eckert *et al.* [11] proposed to control quality of complex herbal mixture. Ciosek *et al.* [12] proposed to differentiate pharmaceutical samples. Yaroshenko *et al.* [13] proposed to explore bitterness in traditional Chinese herbal medicine. Wesoły *et al.* [14] proposed to assess drug dissolution profiles and detect modified release effect. For environmental monitoring, Kirsanov *et al.* [15] proposed to assess toxicity in urban waters. Facure *et al.* [16] proposed to detect concentrations of organophosphate pesticides. Other applications are referred as protein biosynthesis control [17], explosives detection [18] and medical diagnosis [19], etc.

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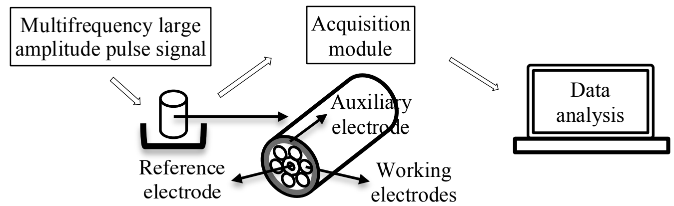


Fig. 1. The framework of a MLAPV E-Tongue system, which includes pulse signal input, electrodes sensor array, data acquisition module and data analysis.

B. Development in System Level

Different sensing principles can be exploited in different E-tongue systems, such as potentiometric E-Tongue [20], voltammetric E-Tongue [21], [22], etc. The E-Tongue system based on potentiometric sensor is one of the most popular system. ToKo *et al.* [20] first proposed the taste sensor composed of potentiometric electrodes with lipid-polymeric membranes in 1989. Also, voltammetric sensor, owing to its high sensitivity, versatility, simplicity and robustness, is also widely used in E-Tongue systems. The first type of voltammetric E-Tongue proposed by Winquist *et al.* [21] employed an array of noble metal working electrodes with small amplitude pulse voltammetry (SAPV) or large amplitude pulse voltammetry (LAPV). Tian *et al.* [22] developed a voltammetric E-Tongue system by combining working electrodes with multifrequency large amplitude pulse. Other electrochemical sensors applied in E-Tongue include acoustic sensors [23] and bioelectronic sensors [24]. A review of the existing E-Tongue work is referred as [25]. In this paper, we integrate the multifrequency large amplitude pulse voltammetry (MLAPV) in our E-Tongue system. Fig. 1 shows a general framework of the MLAPV E-Tongue system, which mainly includes four parts: pulse signal, sensor array, data acquisition module and data analysis.

C. Development in Algorithm Level

The multivariate data analysis module is composed of data processing, analysis and recognition. Generally, due to the random perturbation of electronic devices, the acquired sensing data usually contains noise and distortion, that causes clutter background and inseparability. Therefore, subspace projection methods, such as principal component analysis (PCA) [26], linear discriminant analysis (LDA) [27], locality preserving projections (LPP) [28], locality preserving discriminant projections (LPDP) [29] and other subspace learning models [30], [31], have been widely studied for feature abstract. PCA is an unsupervised statistical learning algorithm, which aims to maximize the information of the data with dominate principal components. LDA is a supervised learning algorithm, which aims to maximize the separability between classes and the compactness within classes. LPP is an unsupervised neighborhood structure preservation algorithm based on manifold assumption, which supposes that neighborhood data should be with similar class. LPDP was proposed with manifold and Fisher criterion which was an intuitive combination of LDA and LPP. However, LPDP only considers the global discrimination, which is easily distorted by local outliers.

To this end, to overcome the noise caused by implicit outliers in E-Tongue data, in this paper, a local discriminant preservation projection (LDPP) model is proposed, in which the local between-class separability, local within-class compactness and local structure preservation are simultaneously exploited. Additionally, classifiers in LDPP subspace should be learned for taste recognition. In view of the high scalability and low computational complexity of extreme learning machine (ELM) proposed by Huang, *et al.* [32], [33], ELM plus LDPP is intuitively utilized for taste recognition. Briefly, ELM is a fast learning algorithm for single-hidden layer feedforward neural network (SLFN), which tends to achieve the smallest training error as well as the smallest norm of prediction weights. Other improved versions of ELM for odor recognition, image recognition, and robotics are referred as [34]–[48]. To the best of our knowledge, there are few report of ELM application for taste recognition in E-Tongue systems.

D. Paper Contribution

In terms of the descriptions above, the contributions of the paper can be summarized as four folds:

- A feasible E-Tongue system is designed based on inert metal electrode sensors, aiming at implementing bionic taste recognition. The E-Tongue system is constructed with high efficiency, high effectiveness, high portability and low-cost.
- A benchmark dataset of 114 samples of tea, wine, beverage and functional materials collected by our E-Tongue system will be shared around the world, which, to our best knowledge, is the first released dataset in E-Tongue.
- A novel local discriminant preservation projection (LDPP) model by maximizing the local separability and local compactness is proposed for discriminative feature subspace learning. The taste recognition performance achieves 98%, which is greatly improved over state-of-the-arts.
- Extreme learning machine, to our best knowledge, is the first attempt for taste recognition in E-Tongue field and achieves the best performance, which provides new application perspectives and insights for ELM community.

E. Paper Organization

The rest of this paper is organized as follows. Section II enumerates the related work of algorithms in E-Tongue. Section III illustrates the preliminary of our E-Tongue system. Section IV describes the model formulation and optimization of the proposed LDPP model. Section V introduces the briefs of SVM, ELM and KELM classifiers in this paper. The experiments and results are presented in Section VI and further discussion is given in Section VII. Finally, Section VIII concludes this paper.

II. Related Works

In E-Tongue community, the data analysis algorithms are generally divided into two categories: feature extraction and pattern recognition, which are summarized as follows.

A. Feature Extraction Algorithms

In E-Tongue applications, the subspace learning methods for dimensionality reduction are widely used. The most popular ones are PCA and LDA. Lenik *et al.* [49] employed PCA to evaluate taste masking effect of diclofenac with a potentiometric E-Tongue. Also, Wesoły *et al.* [50] proposed an E-Tongue system to analyze taste masking effects in pharmacy with PCA. Nery *et al.* [51] applied PCA to discriminate and analyze beer and wine samples measured by the paper-based potentiometric E-Tongue. Queiroz *et al.* [52] utilized PCA to treat the capacitance data for discriminating ethanol/water mixtures. Buratti *et al.* [53] classified Barbera wines based on the E-Tongue and LDA. Ceto *el al.* [54] used LDA to discriminate the geographical region of wine based on voltammetric E-Tongue. Veloso *et al.* [55] classified olive oils based on a potentiometric E-Tongue and LDA. Panchuk *et al.* [56] developed a potentiometric E-Tongue with LDA to analyze microcystins in water samples. Ítala *et al.* [57] applied LDA to verify the performance of the potentiometric E-Tongue for distinguishing aqueous standard solutions. To our best knowledge, LPP has never been reported in E-Tongue application, which also demonstrates the novelty of our LDPP for taste recognition.

B. Pattern Recognition Algorithms

Classifiers are commonly used to recognize or classify taste samples. In E-Tongue analysis, the most popular classification methods are support vector machine (SVM), artificial neural networks (ANN) and partial least squares regression (PLS). Dominguez *et al.* [58] developed a voltammetric E-Tongue to

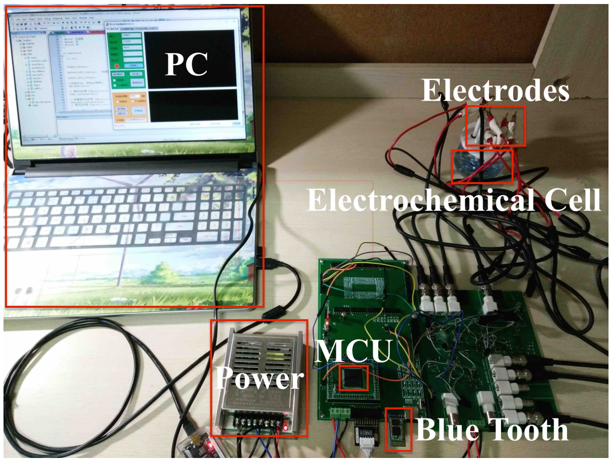


Fig. 2. The platform of our E-Tongue system, in which the MCU is the central processing unit, the Power is for electricity supply, the Blue Tooth is for data transfer, the Electrodes denote the sensor array, the Electrochemical cell is the liquid container, and the PC is for data acquisition and analysis.

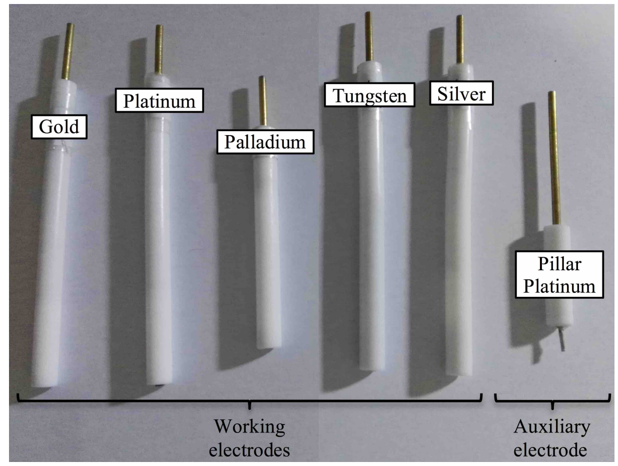


Fig. 3. The electrodes used in this work, in which 5 working electrodes and 1 auxiliary electrode are included.

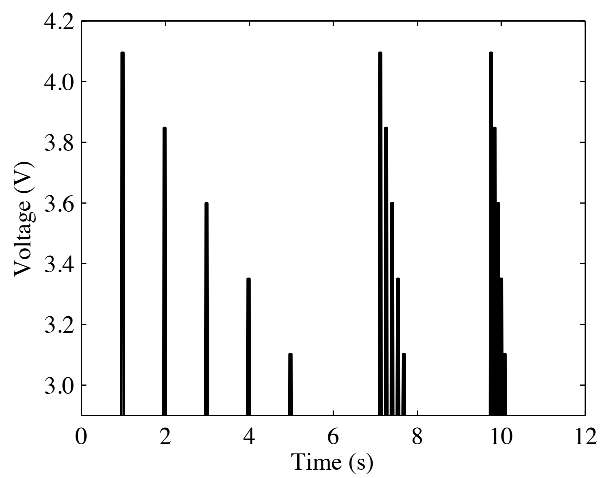


Fig. 4. Multifrequency large amplitude pulse signal, which contains three frequencies, i.e. 1 Hz, 3 Hz, 5 Hz.

recognize distinctive features of coffee samples by using SVM. Teye *et al.* [59] applied the E-Tongue and SVM to discriminate seven categories of cocoa beans from Ghana. Cartas *et al.* [60] proposed an E-Tongue system based on ANN for quantifying the electroactive substances. Gil-Sánchez *et al.* [61] applied ANN to analyze salt samples obtained by an E-Tongue. Gonzalez-Calabuig *et al.* [62] constructed a voltammetric E-Tongue with ANN to determine nitro-containing and peroxide-based explosive compounds. Kang *et al.* [63] designed an E-Tongue system to differentiate Korean rice wines brewed from nine cultivars of rice by using PLS method. Lin *et al.* [64] also evaluated the bitterness of Traditional Chinese Medicines with the E-Tongue and PLS. Pérez-Ràfols *et al.* [65] analyzed the mixture of the metal ions by a screen-printed voltammetric E-Tongue with process of PLS. To our best knowledge, there are few report of ELM application in E-Tongue field. Therefore, inspired by existing works mentioned above, in this paper, PLS, SVM and ELMs are chosen as classifiers, and their performance in taste recognition are compared.

III. Our E-Tongue System Preliminary

The E-Tongue system used in our experiment is designed based on the MLAPV (multi-frequency large amplitude pulse voltammetry) principle. The experimental platform including E-Tongue system, personal computer (PC), and electrochemical cell is shown in Fig. 2. The pulse signal excitation and acquisition modules are controlled by a microcontroller unit. The response (perception) signal (output) is then transmitted to the computer by a blue-tooth module.

A. Electrodes Setup

Electrodes, as sensor array of E-Tongue, play a key role for taste recognition. By following the electrodes setup as Tian et al. [5], in our E-Tongue, five electrodes, such as the gold, platinum, palladium, tungsten and silver, are chosen as working electrodes. The pillar platinum is used as the auxiliary electrode and the Ag/AgCl is used as the reference electrode. The electrodes selected in our E-Tongue system are shown in Fig. 3. The experiments indicate that the electrodes sensor array shows different patterns to different kinds of substances in the electrochemical cell, which preliminarily shows the feasibility of our E-Tongue.

B. Multi-frequency Large Amplitude Pulse Signal Setup

MLAPV is adopted as the measuring technique in our system. The multiple frequency pulse signal used in our E-Tongue is shown in Fig. 4. The pulse signal (excitation) comprises of three individual frequencies: 1 Hz, 3 Hz and 5 Hz, and five amplitudes of voltage: 4.10V, 3.85V, 3.60V, 3.35 and 3.10V for each frequency. Thus, the system is termed as multi-frequency large amplitude pulse voltammetry (MLAPV) based E-Tongue.

IV. The Proposed Local Discriminant Preservation Projection Model

A. Notations

In this paper, the data matrix is denoted as $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N] \in \Re^{D\times N}$, where D is the dimensionality, $N = N_1 + N_2 + \cdots + N_C$ is the number of samples, C is the number of classes. The label vector of data is denoted as $\mathbf{y} = [y_1, y_2, \ldots, y_N]^{\mathrm{T}} \in \Re^N$. Let $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_d] \in \Re^{D\times d}$ represent the projection matrix that maps the original data from the space $\Re^D$ to a new lower-dimensional subspace $\Re^d$. The symbol $\|\cdot\|_{\mathrm{F}}$ and $\|\cdot\|_2$ denotes the Frobenius norm and l_2-norm respectively. $Tr(\cdot)$ denotes the trace operator and $N_k(\cdot)$ denotes the k nearest neighbors operator. Throughout this paper, matrix is written in capital bold face, vector is shown in lower bold face, and variable is written in italics.

B. Linear Discriminant Analysis

The main idea of LDA [27] is to enhance the global class discrimination after projection, hence it maximizes the between-classes separability and within-class compactness. The objective function of LDA can be formulated as

$$\max_{\mathbf{W}} \frac{Tr\left(\mathbf{W}^{\mathrm{T}}\mathbf{S}_B\mathbf{W}\right)}{Tr\left(\mathbf{W}^{\mathrm{T}}\mathbf{S}_W\mathbf{W}\right)} \tag{1}$$

where $\mathbf{S}_B$ is the between-class scatter matrix and $\mathbf{S}_W$ is the within-class scatter matrix. The model pursuits for a discriminative subspace projection $\mathbf{W}$ that can maximize the trace of between-class scatter matrix and simultaneously minimize the trace of within-class scatter matrix.

C. Locality Preserving Projections

With the manifold assumption, LPP [28] aims to optimally preserve the neighborhood structure of data. Generally, the LPP model can be formulated as

$$\begin{aligned} &\min_{\mathbf{W}} Tr\left(\mathbf{W}^{\mathrm{T}}\mathbf{X}\mathbf{L}\mathbf{X}^{\mathrm{T}}\mathbf{W}\right) \\ &s.t\ \mathbf{W}^{\mathrm{T}}\mathbf{X}\mathbf{D}\mathbf{X}^{\mathrm{T}}\mathbf{W} = \mathbf{I} \end{aligned} \tag{2}$$

where $\mathbf{L} = \mathbf{D} - \mathbf{A}$ is the Laplacian matrix, $D_{ii} = \sum_j A_{ij}$ is a diagonal matrix, and $\mathbf{A} \in \Re^{N\times N}$ is the sparse affinity matrix, and $A_{ij} = 0$ only if x_i and x_j are not adjacent. By learning a projection $\mathbf{W}$, the objective function minimizes the distance between those data points with neighborhood relation in the raw data space (i.e. locality preservation).

D. Locality Preserving Discriminant Projections

LPDP [29] inherits the characters of locality preservation and global discrimination. The LPDP model is formulated as

$$\begin{aligned} &\min_{\mathbf{W}}\ Tr\left(\mathbf{W}^{\mathrm{T}}\mathbf{X}\mathbf{L}\mathbf{X}^{\mathrm{T}}\mathbf{W}\right) \\ &-\left(Tr\left(\mathbf{W}^{\mathrm{T}}\mathbf{S}_B\mathbf{W}\right) - \mu\cdot Tr\left(\mathbf{W}^{\mathrm{T}}\mathbf{S}_W\mathbf{W}\right)\right) \\ &s.t\ \mathbf{W}^{\mathrm{T}}\mathbf{X}\mathbf{D}\mathbf{X}^{\mathrm{T}}\mathbf{W} = \mathbf{I} \end{aligned} \tag{3}$$

where μ is the regularization (trade-off) coefficient. This model can be viewed as a combination of LDA and LPP.

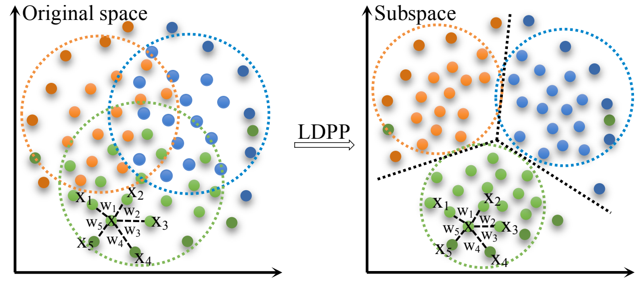


Fig. 5. Illustration of the proposed LDPP model. The circles denote the local part of each class, which show the between-class overlap and within-class outliers. After LDPP, the local discrimination with implicit outliers excluded and the locality structure preservation are expected to be achieved.

E. The Proposed LDPP: Formulation and Optimization

The proposed LDPP pursues neighborhood structure preservation and local discrimination. The former inherits the manifold assumption that neighbor data points are with similar labels and tends to find an low-dimensional affinity structure embedded in the raw data space. The latter aims to enhance the local discriminative property which is not sensitive to implicit outliers. The model is motivated by two intuitions: geometric intuition and attribution intuition. Geometric intuition is that if the interior data can be distinguished well, exterior data should be naturally distinguished. Attribution intuition is that exterior data has a higher probability to be abnormal or outlier data. Therefore, we modify the Fisher criterion by imposing locality constraint which is important for small size E-Tongue data. Additionally, manifold regularization is also used for local similarity preservation. The main idea of the model is shown in Fig. 5, in which the data points with lighter color represents the local part for between-class matrix, and the data points in the dashed blue, green and orange circles represent the local part of three classes for within-class matrix.

We construct the local between-class scatter matrix $\mathbf{S}_{LB}$ with the k_m nearest neighbors to the center $\mathbf{m}$, and the local within-class scatter matrix $\mathbf{S}_{LW}$ with the k_{mc} nearest neighbors to the class center $\mathbf{m}_c$. The local numbers k_m and k_{mc} can be determined as

$$k_m = [r_b \cdot N] \tag{4}$$

$$k_{mc} = [r_w \cdot N_c] \tag{5}$$

where r_b and r_w are local ratio coefficients. N and N_c are the number of samples. $[\cdot]$ is the rounding operator. The $\mathbf{S}_{LW}$ and $\mathbf{S}_{LB}$ are defined as

$$\mathbf{S}_{LB} = \sum_{c=1}^{C} N_{lc}(\mathbf{m}_{lbc} - \mathbf{m}_{lb})(\mathbf{m}_{lbc} - \mathbf{m}_{lb})^{\mathrm{T}} \tag{6}$$

$$\mathbf{S}_{LW} = \sum_{c=1}^{C} \sum_{\substack{i=1,\\ \mathbf{x}\in N_{k_{mc}}(\mathbf{m}_c)}}^{k_{mc}} \left(\mathbf{x}_i^{(c)} - \mathbf{m}_{lwc}\right)\left(\mathbf{x}_i^{(c)} - \mathbf{m}_{lwc}\right)^{\mathrm{T}} \tag{7}$$

where $\mathbf{m}_{lb} = \frac{1}{k_m}\sum_{i=1,\mathbf{x}\in N_{k_m}(\mathbf{m})}^{k_m} \mathbf{x}_i$ is the center of local part for $\mathbf{S}_{LB}$ computation, $\mathbf{m}_{lbc} = \frac{1}{N_{lc}}\sum_{i=1,\mathbf{x}\in N_{k_m}(\mathbf{m})}^{N_{lc}} \mathbf{x}_i^{(c)}$ is the center of the c-th class in local part for $\mathbf{S}_{LB}$ computation, N_{lc} is the number of the c-th class in local part, and

$\mathbf{m}_{lwc} = \frac{1}{k_{mc}} \sum_{i=1,\mathbf{x}^{(c)} \in N_{k_{mc}}(\mathbf{m}_c)}^{k_{mc}} \mathbf{x}_i^{(c)}$ is the center of the c-th local class for $\mathbf{S}_{LW}$ computation.

Additionally, the locality preservation regularization term is shown as follows.

$$\begin{aligned} &\min_{\mathbf{W}} \sum_{i=1}^{N} \sum_{j=1}^{N} A_{ij} \left\| \mathbf{W}^{\mathrm{T}} \mathbf{x}_i - \mathbf{W}^{\mathrm{T}} \mathbf{x}_j \right\|^2 \\ &= Tr \left(\mathbf{W}^{\mathrm{T}} \sum_{i=1}^{N} \sum_{j=1}^{N} A_{ij} (\mathbf{x}_i - \mathbf{x}_j)(\mathbf{x}_i - \mathbf{x}_j)^{\mathrm{T}} \mathbf{W} \right) \\ &\Leftrightarrow Tr \left(\mathbf{W}^{\mathrm{T}} \sum_{i=1}^{N} \sum_{j=1}^{N} A_{ij} \left(\mathbf{x}_i \mathbf{x}_i^{\mathrm{T}} - \mathbf{x}_i \mathbf{x}_j^{\mathrm{T}} \right) \mathbf{W} \right) \\ &= Tr \left(\mathbf{W}^{\mathrm{T}} \left(\sum_{i=1}^{N} D_{ii} \mathbf{x}_i \mathbf{x}_i^{\mathrm{T}} - \sum_{i=1}^{N} \sum_{j=1}^{N} A_{ij} \mathbf{x}_i \mathbf{x}_j^{\mathrm{T}} \right) \mathbf{W} \right) \\ &= Tr \left(\mathbf{W}^{\mathrm{T}} \left(\mathbf{X}\mathbf{D}\mathbf{X}^{\mathrm{T}} - \mathbf{X}\mathbf{A}\mathbf{X}^{\mathrm{T}} \right) \mathbf{W} \right) \\ &= Tr \left(\mathbf{W}^{\mathrm{T}} \mathbf{X}\mathbf{L}\mathbf{X}^{\mathrm{T}} \mathbf{W} \right) \end{aligned} \tag{8}$$

where $\mathbf{L}$ is the Laplacian matrix defined as $\mathbf{L} = \mathbf{D} - \mathbf{A}$. $\mathbf{D}$ is diagonal matrix with entries $D_{ii} = \sum_j A_{ij}$. $\mathbf{A}$ is the affinity matrix, calculated in the following two manners [66].

1) Simple-minded (S):

$$A_{ij} = \begin{cases} 1, \; if \; \mathbf{x}_i \in N_k(\mathbf{x}_j) || \mathbf{x}_j \in N_k(\mathbf{x}_i) \\ 0, \; others \end{cases} \tag{9}$$

2) Heat kernel (H):

$$A_{ij} = \begin{cases} e^{-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|^2}{t}}, \; if \; \mathbf{x}_i \in N_k(\mathbf{x}_j) || \mathbf{x}_j \in N_k(\mathbf{x}_i) \\ 0, \; others \end{cases} \tag{10}$$

where t is the kernel parameter. A_{ij} will be assigned a large value if $\mathbf{x}_i$ is the neighborhood of $\mathbf{x}_j$.

With Eqs.(6), (7), and (8), the proposed LDPP model can be formulated as

$$\begin{aligned} &\max_{\mathbf{W}} \; Tr \left(\mathbf{W}^{\mathrm{T}} \mathbf{S}_{LB} \mathbf{W} \right) - \mu \cdot Tr \left(\mathbf{W}^{\mathrm{T}} \mathbf{S}_{LW} \mathbf{W} \right) \\ &- \gamma \cdot Tr \left(\mathbf{W}^{\mathrm{T}} \mathbf{X}\mathbf{L}\mathbf{X}^{\mathrm{T}} \mathbf{W} \right) \end{aligned} \tag{11}$$

where μ and γ represent the regularization (trade-off) coefficients. It can be seen that LDPP aims to maximize the trace of local between-class scatter matrix and minimize the trace of the local within-class scatter matrix, and simultaneously, the local preservation is exploited. With equality constraint, Eq.(11) can be further transformed into the following problem,

$$\begin{aligned} &\max_{\mathbf{W}} Tr \left(\mathbf{W}^{\mathrm{T}} \mathbf{S}_{LB} \mathbf{W} \right) \\ &s.t. \; \mu \cdot \mathbf{W}^{\mathrm{T}} \mathbf{S}_{LW} \mathbf{W} + \gamma \cdot \mathbf{W}^{\mathrm{T}} \mathbf{X}\mathbf{L}\mathbf{X}^{\mathrm{T}} \mathbf{W} = \eta \cdot \mathbf{I} \end{aligned} \tag{12}$$

where η is a constant, and the equality constraint can ensure the unique solution of $\mathbf{W}$. By introducing Lagrange multiplier λ, the objective function of model (12) can be written as

$$\begin{aligned} &L(\mathbf{W}, \lambda) = \mathbf{W}^{\mathrm{T}} \mathbf{S}_{LB} \mathbf{W} \\ &- \lambda \cdot \left(\mu \cdot \mathbf{W}^{\mathrm{T}} \mathbf{S}_{LW} \mathbf{W} + \gamma \cdot \mathbf{W}^{\mathrm{T}} \mathbf{X}\mathbf{L}\mathbf{X}^{\mathrm{T}} \mathbf{W} - \eta \cdot \mathbf{I} \right) \end{aligned} \tag{13}$$

By computing the partial derivative of $L(\mathbf{W}, \lambda)$ with respect to $\mathbf{W}$, and let it be zero, there is

Algorithm 1. The proposed LDPP

Input: The data matrix $\mathbf{X} \in \Re^{D \times N}$, the regularization coefficients μ and γ, the local ratio coefficient r_b and r_w, the dimension d of the new subspace.

Procedure:

1. Compute the center $\mathbf{m}$ and $\mathbf{m}_c$;
2. Compute the local numbers k_m and k_{mc} via (4) and (5);
3. Compute the local center $\mathbf{m}_{lb}$ of the $\mathbf{x} \in N_{k_m}(\mathbf{m})$;
4. Compute the center of the c-th local class $\mathbf{m}_{lbc}$ of the $\mathbf{x}^{(c)} \in N_{k_m}(\mathbf{m})$ and $\mathbf{m}_{lwc}$ of the $\mathbf{x}^{(c)} \in N_{k_{mc}}(\mathbf{m}_c)$;
5. Compute the local between-class scatter matrix $\mathbf{S}_{LB}$ and the local within-class scatter matrix $\mathbf{S}_{LW}$ via (6) and (7);
6. Construct the affinity matrix $\mathbf{A}$ via (9) or (10);
7. Compute the diagonal matrix $\mathbf{D}$, $D_{ii} = \sum_j A_{ij}$;
8. Compute the Laplacian matrix $\mathbf{L}$, $\mathbf{L} = \mathbf{D} - \mathbf{A}$;
9. Solve the projection matrix $\mathbf{W}$ via the eigenvalue decomposition problem (14);

Output: The projection matrix $\mathbf{W} \in \Re^{D \times d}$.

$$\left(\mu \cdot \mathbf{S}_{LW} + \gamma \cdot \mathbf{X}\mathbf{L}\mathbf{X}^{\mathrm{T}} \right)^{-1} \mathbf{S}_{LB} \mathbf{W} = \lambda \cdot \mathbf{W} \tag{14}$$

where the projection matrix $\mathbf{W}$ that maximizes the objective function can be easily computed as the eigenvectors corresponding to the first d maximum eigenvalues λ_1, λ_2,..., λ_d, by solving the above generalized eigenvalue problem Eq.(14).

Actually, the $\mathbf{W}$ is spanned by the eigenvectors. For easy following the proposed LDPP model in implementation, the algorithm is summarized in **Algorithm 1**.

V. Classification Models

Subspace learning methods merely map the data to a more separable space, to achieve the final taste recognition task, classifier learning is necessary. In this paper, as described above, off-the-shelf classifiers such as SVM, ELM and KELM are used after LDPP. For readers' convenience, the principle of ELM is briefly introduced in the following sections.

A. Extreme Learning Machine

1) Basic case: ELM [32], as a single layer feed-forward neural network, is solved by minimizing the squared loss of prediction and the norm of the output weights for classification and regression. The hidden layer output matrix $\mathbf{H}$ with L hidden neurons can be computed as

$$\mathbf{H} = \begin{bmatrix} h(\mathbf{w}_1^{\mathrm{T}} \mathbf{x}_1 + b_1) & h(\mathbf{w}_2^{\mathrm{T}} \mathbf{x}_1 + b_2) & \cdots & h(\mathbf{w}_L^{\mathrm{T}} \mathbf{x}_1 + b_L) \\ h(\mathbf{w}_1^{\mathrm{T}} \mathbf{x}_2 + b_1) & h(\mathbf{w}_2^{\mathrm{T}} \mathbf{x}_2 + b_2) & \cdots & h(\mathbf{w}_L^{\mathrm{T}} \mathbf{x}_2 + b_L) \\ \vdots & \vdots & \ddots & \vdots \\ h(\mathbf{w}_1^{\mathrm{T}} \mathbf{x}_N + b_1) & h(\mathbf{w}_2^{\mathrm{T}} \mathbf{x}_N + b_2) & \cdots & h(\mathbf{w}_L^{\mathrm{T}} \mathbf{x}_N + b_L) \end{bmatrix} \tag{15}$$

where $h(\cdot)$ is the activation function of hidden layer, such as sigmoid function. $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_L] \in \Re^{d \times L}$ and $\mathbf{b} = [\mathbf{b}_1, \mathbf{b}_2, \ldots, \mathbf{b}_L]^{\mathrm{T}} \in \Re^L$ are randomly generated input weights and bias, respectively. With such a hidden layer output matrix $\mathbf{H}$, ELM model can be formulated as follows.

$$\begin{aligned} &\min_{\boldsymbol{\beta}\in\Re^{L\times C}} \frac{1}{2}\|\boldsymbol{\beta}\|^2 + \tau\cdot\frac{1}{2}\sum_{i=1}^{N}\|\boldsymbol{\xi}_i\|^2 \\ &s.t.\ h(\mathbf{x}_i)\boldsymbol{\beta} = \mathbf{t}_i^{\mathrm{T}} - \boldsymbol{\xi}_i^{\mathrm{T}}, i = 1,2,\ldots,N \end{aligned} \tag{16}$$

where the label $\mathbf{t}_i \in \Re^C$. Note that if $\mathbf{x}_i$ belongs to the c-th class, only the c-th element of $\mathbf{t}_i$ is 1, others are set to 0. $\boldsymbol{\beta} \in \Re^{L\times C}$ denotes the output weights between hidden layer and output layer. $\boldsymbol{\xi}_i = [\xi_{i1}, \xi_{i2}, \ldots, \xi_{iC}]^{\mathrm{T}}$ is the training error vector, and τ is a penalty constant on the training errors.

The closed-form solution of $\boldsymbol{\beta}$ is shown as follows.

$$\boldsymbol{\beta}^* = \begin{cases} \left(\mathbf{H}^{\mathrm{T}}\mathbf{H} + \frac{\mathbf{I}_{L\times L}}{\tau}\right)^{-1}\mathbf{H}^{\mathrm{T}}\mathbf{T},\ if\ N \geq L \\ \mathbf{H}^{\mathrm{T}}\left(\mathbf{H}^{\mathrm{T}}\mathbf{H} + \frac{\mathbf{I}_{N\times N}}{\tau}\right)^{-1}\mathbf{T},\ if\ N < L \end{cases} \tag{17}$$

where label matrix $\mathbf{T} = [\mathbf{t}_1^{\mathrm{T}}; \mathbf{t}_2^{\mathrm{T}}; \ldots; \mathbf{t}_N^{\mathrm{T}}] \in \Re^{N\times C}$.

Then the output function of ELM can be computed as

$$f(\mathbf{x}) = h(\mathbf{x})\boldsymbol{\beta}^* \tag{18}$$

2) Kernel case: The kernel matrix of ELM [33] is defined as $\boldsymbol{\Omega} = \mathbf{H}\mathbf{H}^{\mathrm{T}}$, where $\Omega_{ij} = h(\mathbf{x}_i)\cdot h(\mathbf{x}_j) = k(\mathbf{x}_i, \mathbf{x}_j)$ and $k(\cdot)$ is the kernel function. Generally, radial basis function (RBF) is used as kernel function, where $k(\mathbf{u},\mathbf{v}) = e^{-\frac{\|\mathbf{u}-\mathbf{v}\|^2}{t}}$. Then the Kernelized ELM (KELM) output can be computed as

$$\begin{aligned} \mathbf{y} &= h(\mathrm{x})\boldsymbol{\beta}^* \\ &= h(\mathrm{x})\mathbf{H}^{\mathrm{T}}\left(\mathbf{H}^{\mathrm{T}}\mathbf{H} + \frac{\mathbf{I}_{N\times N}}{\tau}\right)^{-1}\mathbf{T} \\ &= \begin{bmatrix} k(\mathbf{x},\mathbf{x}_1) \\ \vdots \\ k(\mathbf{x},\mathbf{x}_N) \end{bmatrix}\left(\boldsymbol{\Omega} + \frac{\mathbf{I}_{N\times N}}{\tau}\right)^{-1}\mathbf{T} \end{aligned} \tag{19}$$

Owing to the kernel matrix $\Omega \in \Re^{N\times N}$, the number L of hidden neurons is not explicit in KELM.

B. Classification

After projecting the data $\mathbf{X}$ to the new subspace $\mathbf{Z}$ by LDPP, the classifier is trained on the projected data $\mathbf{Z}$ and label $\mathbf{Y}$. The classification procedure is summarized in **Algorithm 2**. An overview of the taste recognition paradigm is shown in Fig. 6. The training and test phases in our E-Tongue system are described in two branches, respectively, including data preprocessing, feature selection, subspace learning (projection by $\mathbf{W}$), and classifier learning (decision by $f(\cdot)$).

VI. Experiments

A. Experimental Setup

1) Data Measurement: The data measurement process includes sample preparation, signal perception, signal acquisition and electrodes cleaning. All the measurements were performed at room temperature (25 ± 1°C) and the electrochemical cell was exposed to ambient air without any treatment. The experimental steps are presented as follows.

Algorithm 2. Classification

Input: The data matrix $\mathbf{X} \in \Re^{D\times N}$, the label $\mathbf{Y}$, the projection matrix $\mathbf{W} \in \Re^{D\times d}$.

Procedure:

1. Compute the projected data $\mathbf{Z} = \mathbf{W}^{\mathrm{T}}\mathbf{X} \in \Re^{d\times N}$;
2. Train a classifier using $\{\mathbf{Z}, \mathbf{Y}\}$;

Output: the classification model.

Step 1: Liquid sample preparation. The solid state analytes are dissolved in distilled water. Then, the prepared liquid sample is placed in the electrochemical cell.

Step 2: Electrodes pre-cleaning. Clean the electrodes by using polishing cloth and polishing powder until the electrodes surface becomes mirror-polished, then clean the electrodes with distilled water.

Step 3: Signal perception. Place the electrodes in the electrochemical cell, then exert the multi-frequency large amplitude pulse to the electrodes for taste signal.

Step 4: Signal acquisition. The signal is transmitted to the personal computer by a blue tooth module.

Step 5: Electrodes post-cleaning. Repeat Step 2, and then dry the electrodes by the filter paper.

Step 6: Dilute the liquid sample with distilled water to obtain a different concentration, then repeat Step 3-5.

2) Feature Selection: As described, each liquid sample is measured by the E-Tongue system with 5 electrode sensors. For each sensor, 2050 points are observed, and results in a 5×2050 data matrix for each observation. The raw signal of 5 sensors is shown in Fig. 7(a). For further denoising, in this paper, a sliding window based smooth filter is considered. The filtered signal of 5 sensors is shown in Fig. 7(b). The signal fragment with respect to three frequencies is shown in blue boxes in Fig. 7(a). Each frequency has five sub-pluses of different amplitudes. For feature selection, the maximum and minimum values in the 1st filtered sub-pluse indicated by red circles in Fig. 7(b) are extracted. Therefore, $5 \times 2 \times 3 \times 5 = 30 \times 5 = 150$ points are extracted as features for each sample. Totally, 114 samples of 13 kinds of liquid including beer, red wine, white spirit, black tea, Mao Feng tea, Pu'er tea, oolong tea, coffee, milk, cola, vinegar, medicine and salt are acquired. The detail of 5-fold sample partition is presented in Table I.

3) Cross-Validation: To evaluate the taste recognition ability of our E-Tongue system, in our experiment, 5-fold cross-validation (CV) strategy is used. 4 folds are used as training set and the remaining 1 fold is used as test set. The average accuracy of the five folds is reported. Specifically, the 5-fold CV strategy is illustrated in Fig. 8.

B. Parameter Setting

In LDPP model, to achieve the optimal performance, the kernel parameter t for constructing the affinity matrix $\mathbf{A}$ is tuned from the given set $\{10^{-4}, 10^{-3}, \ldots, 10^4\}$; the subspace dimension d is tuned from the given set $\{20, 25, \ldots, 150\}$; the regularization coefficients μ and γ are adjusted from the given

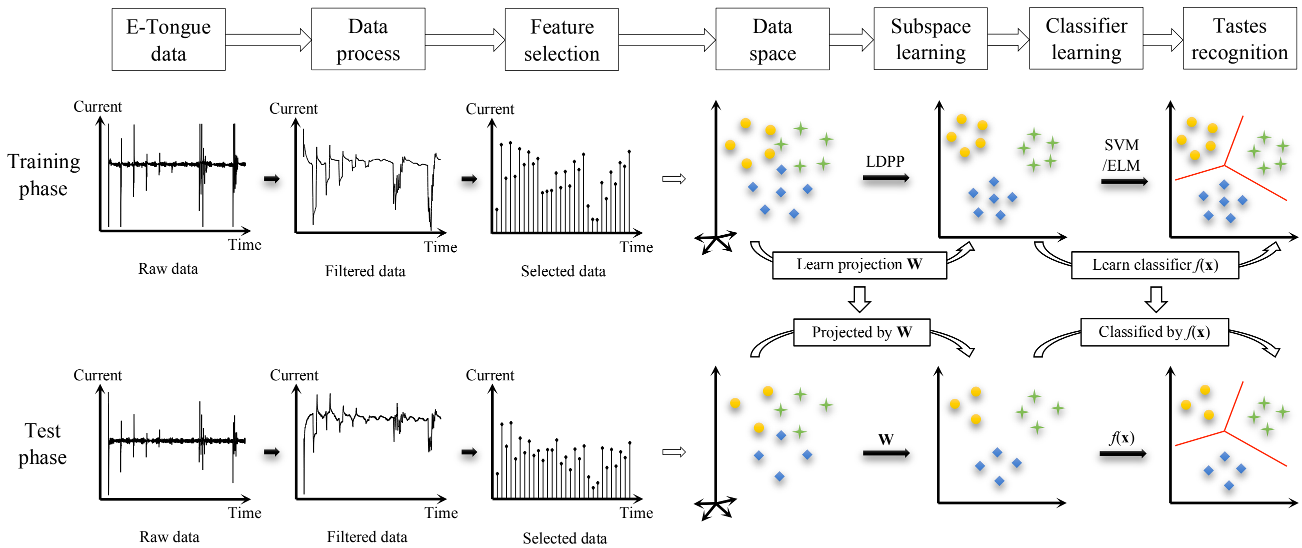
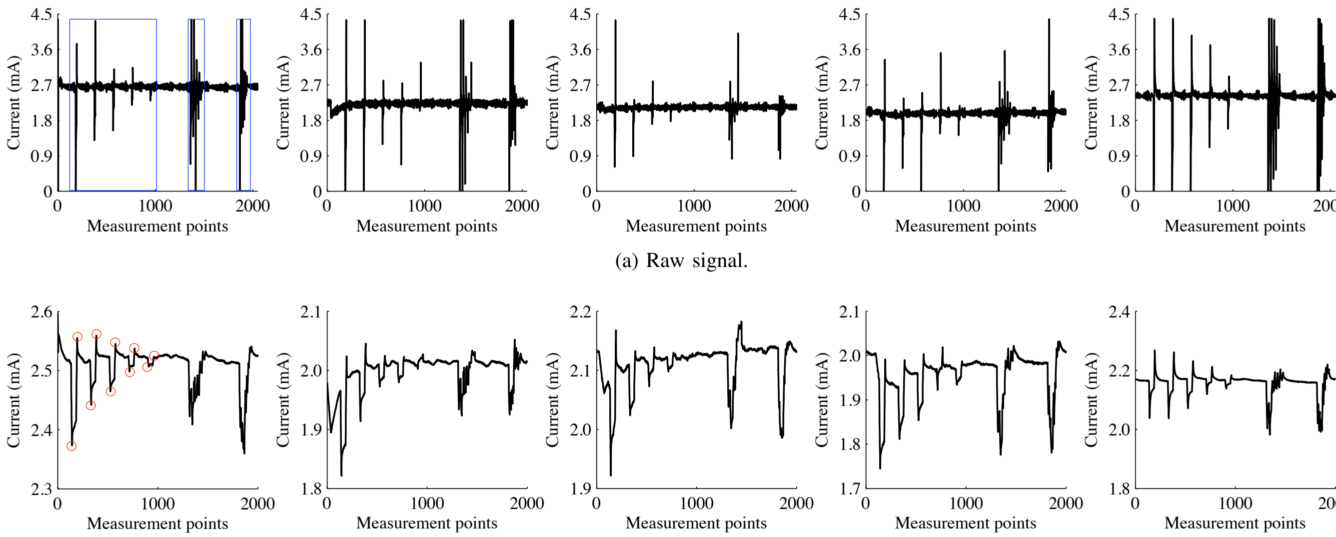


Fig. 6. Overview of the proposed LDPP based recognition framework in E-Tongue system, which contains data processing, feature extraction, subspace learning and classifier learning. In training phase, the projection $\mathbf{W}$ and classifier f are learned, which will be used for taste recognition in testing phase.



(a) Raw signal.

(b) Filtered signal.

Fig. 7. The illustration of feature selection. (a) denotes the raw signal of 5 sensors (gold, platinum, palladium, tungsten, and silver); (b) denotes the filter signal from which 10 features in red circles of the 1st frequency are selected, and totally 30 features (10×3) are obtained for each electrode sensor.

set $\{10^{-4}, 10^{-3}, \ldots, 10^{4}\}$; the local ratio coefficients r_b and r_w are empirically set as 0.9 in this paper.

In classifier learning, empirically, the penalty coefficient τ of all classifiers (SVM/ELM/KELM) is set as 10^5, the hidden neurons L of ELM is set as 5000 and sigmoid function is used for the hidden layer activation. For KELM, RBF function is used as the kernel function and the kernel parameter t is set as 100. For SVM, both linear/RBF kernel is considered. Note that, for each method, the best performance is tuned and reported. Further, the discussion of parameter sensitivity in LDPP and classifiers is presented in the Section VII.

C. Compared Methods

To evaluate the recognition performance of proposed LDPP based classifier models, we compare our model with the off-the-shelf subspace learning methods such as PCA, KPCA, LPP, LDA and LPDP. Additionally, the performance of different baseline classifiers such as PLS, SVM, ELM and KELM with different subspace learning methods is also compared. Notably, for our LDPP model, LDPP-S and LDPP-H are differentiated, where -S and -H denotes that the affinity matrix $\mathbf{A}$ is constructed with the simple-minded rule in Eq.(9) and the heat kernel rule in Eq.(10), respectively.

D. Experimental Results

With the experimental setup and parameter setting mentioned above, the average recognition accuracy of 5-fold cross-validation for all methods are reported in Table II, Table III and Table IV, respectively. In Table II, III and IV, PLS, SVM, ELM, and KELM denote the classifier learning on the raw

TABLE II
RECOGNITION ACCURACY (%) OF DIFFERENT SUBSPACE PROJECTION METHODS BASED ON SVM CLASSIFIER. "RAW" DENOTES THE RAW DATA SPACE

Class	PLS (raw)	SVM (raw)	PCA	KPCA	LPP-S	LPP-H	LDA	LPDP-S	LPDP-H	**LDPP-S**	**LDPP-H**
Beer	85	90	90	88.33	90	90	90	95	95	95	95
Red wine	100	100	100	100	100	100	100	100	100	100	100
White spirit	100	100	100	100	100	100	100	100	100	100	100
Black tea	70	80	80	70	80	80	80	80	80	80	80
Mao Feng tea	80	80	80	70	80	100	100	100	100	100	100
Pu'er tea	80	90	90	80	90	90	100	100	100	90	100
Oolong tea	20	90	90	100	100	100	90	100	100	100	100
Coffee	60	80	80	70	80	80	80	80	100	100	100
Milk	100	100	100	90	100	100	100	100	100	100	100
Cola	60	90	90	100	90	90	90	90	90	100	100
Vinegar	90	100	100	80	100	100	100	100	100	100	100
Medicine	70	100	100	100	100	100	100	100	100	100	100
Salt	100	100	100	100	100	100	100	100	100	100	100
Average	77.27	93.00	93.00	89.49	93.87	94.74	94.74	96.48	97.35	**97.35**	**98.22**

TABLE III
RECOGNITION ACCURACY (%) OF DIFFERENT SUBSPACE PROJECTION METHODS BASED ON ELM CLASSIFIER. "RAW" DENOTES THE RAW DATA SPACE

Class	ELM (raw)	PCA	KPCA	LPP-S	LPP-H	LDA	LPDP-S	LPDP-H	**LDPP-S**	**LDPP-H**
Beer	97.5	93.5	84	97	98.5	94.5	99	100	98.5	100
Red wine	100	100	100	100	100	100	100	100	100	100
White spirit	100	100	99	100	100	100	100	100	100	100
Black tea	74	70	70	82	80	80	98	86	88	88
Mao Feng tea	100	100	90	100	100	100	100	90	100	100
Pu'er tea	97	99	100	100	98	97	96	100	100	100
Oolong tea	79	80	90	80	78	79	80	92	84	88
Coffee	84	87	80	90	88	90	96	98	96	98
Milk	98	96	90	98	96	99	100	94	99	100
Cola	100	100	98	100	100	100	90	100	100	100
Vinegar	90	86	80	88	98	96	80	86	94	94
Medicine	100	100	70	100	100	100	100	100	100	100
Salt	100	100	80	100	100	100	100	100	100	100
Average	94.05	93.18	87.35	94.94	94.84	94.50	95.48	96.51	**96.69**	**97.56**

data without subspace projection. For other subspace based classifier methods, such as PCA, KPCA, LDA, LPP, LPDP, and LDPP, SVM/ELM/KELM are used as the off-the-shelf classifiers. From these Tables, we observe that:

- In Table II, the average accuracy of our LDPP model reaches 98.22%, which is significantly higher than PLS (77.27%) and SVM (93.00%). The importance of subspace learning is well shown. Notably, PLS obtains the lowest accuracy. One reason might be that PLS is a probabilistic classier which is more suitable for the task of large amount of samples. Another reason is that PLS is a linear regression model which may perform well when variables and observations are with linear relationship. Additionally, the proposed LDPP based SVM method outperforms other popular subspace projection based SVM classifiers (e.g. LPDP with 97.35% ranks the second best) about 1%. This demonstrates the effectiveness of the LDPP model.
- In Table III, with the ELM as the generic classifier, the proposed LDPP model still achieves the best average accuracy of 97.56%, which is also 1% higher than the second best LPDP method (96.51%). Similarly, after subspace projection, the performance is significantly better than ELM (94.05%). Note that considering the random generation of input weights and biases in ELM, the results in Table III is the average of 10 times runs.
- In Table IV, with KELM as the generic classifier, similar findings can be concluded that the proposed LDPP based classifier also turns out to be the best recognition performance (98.22%), which is always 1% higher than the second best LPDP method (97.35%). Another finding is that the recognition performance of other methods is also upgraded with KELM classifier. The superiority of

TABLE IV
RECOGNITION ACCURACY (%) OF SUBSPACE PROJECTION METHODS BASED ON KELM CLASSIFIER. "RAW" DENOTES THE RAW DATA SPACE

Class	KELM (raw)	PCA	KPCA	LPP-S	LPP-H	LDA	LPDP-S	LPDP-H	**LDPP-S**	**LDPP-H**
Beer	95	100	83.33	95	95	100	95	100	100	100
Red wine	100	100	100	100	100	100	100	100	100	100
White spirit	100	100	100	100	100	100	100	100	100	100
Black tea	80	80	70	80	80	80	70	80	80	80
Mao Feng tea	100	100	100	100	100	100	100	100	100	100
Pu'er tea	100	100	100	100	100	100	100	100	100	100
Oolong tea	90	90	100	80	90	90	90	80	90	90
Coffee	80	90	60	90	80	90	100	100	100	100
Milk	100	90	100	100	100	100	100	100	100	100
Cola	100	100	90	100	100	100	100	100	100	100
Vinegar	100	100	80	100	100	100	100	100	100	100
Medicine	100	100	100	100	100	100	100	100	100	100
Salt	100	100	100	100	100	100	100	100	100	100
Average	95.61	96.48	91.23	95.61	95.61	97.35	96.48	97.35	**98.22**	**98.22**

TABLE I
EXPERIMENTAL DATA PARTITION OF 5-FOLDS

Class	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5	*Total*
Beer	4	3	4	4	4	19
Red wine	1	2	2	2	1	8
White spirit	1	1	1	2	1	6
Black tea	1	2	2	2	2	9
Mao Feng tea	2	1	2	2	2	9
Pu'er tea	2	2	1	2	2	9
Oolong tea	2	2	2	1	2	9
Coffee	2	2	2	1	2	9
Milk	2	2	1	2	2	9
Cola	1	1	2	1	1	6
Vinegar	2	1	2	2	2	9
Medicine	1	2	1	1	1	6
Salt	2	1	1	1	1	6

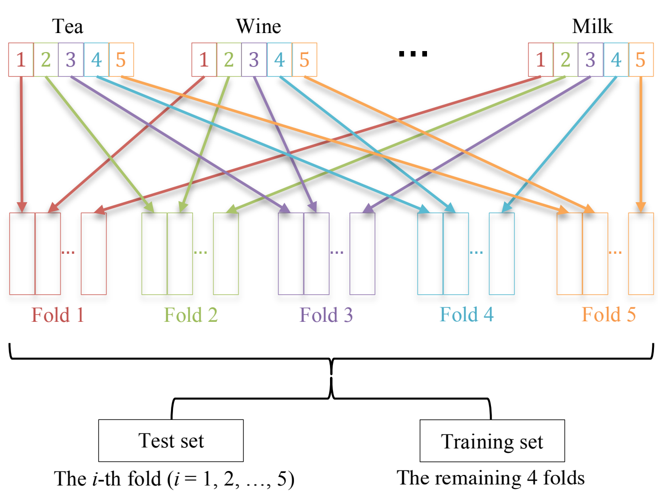
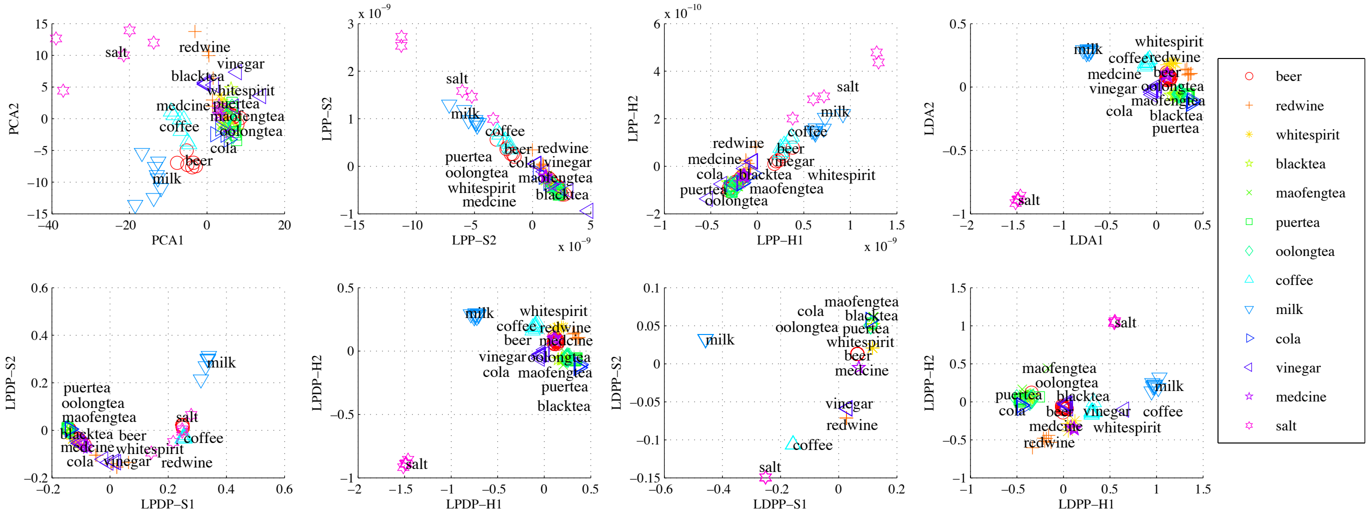


Fig. 8. 5-fold cross-validation for taste samples.

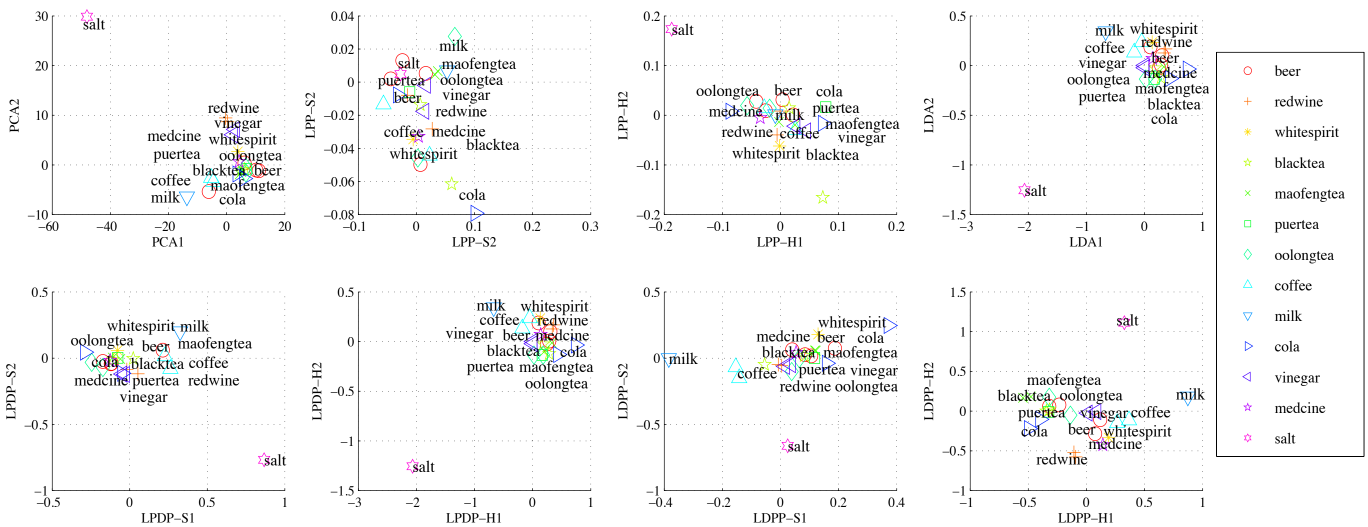
KELM is demonstrated by comparing to SVM and ELM.

- By comparing the Table II, Table III and Table IV, ELM achieves 94.05% that is better than SVM (93.0%), but becomes worse than SVM when subspace projection is used. The overall performance of KELM is better than both SVM and ELM. Additionally, the proposed LDPP based methods always show the best taste recognition performance by comparing to other methods. Another observation is that KPCA shows worse results than other linear subspace projection methods, and the reason may be that with nonlinear kernel transformation, the data is distorted. Therefore, linear subspace projection is beneficial to taste recognition.
- We have also done the statistical test based on Table II, Table III and Table IV by using the popular $Friedman$ test method which is a non-parametric statistical test method. The significance level is set as 0.05. Based on the $Friedman$ principle, the calculated p-value in Friedman's ANOVA for each test on the results is lower than 0.05, which clearly demonstrates the statistical significance of the classification results.

Further, for visualization of the projected data based on different subspace learning methods, the 2D scatter points of the first two dominates in training set and test set are shown in Fig. 9(a) and Fig. 9(b), respectively. From the Fig. 9(a), we can observe that the scatter points based on the proposed LDPP model are more separable with clearer clusters. The projected data based on LDA and LPDP shows a similar distribution with LDPP, but more overlaps can be clearly observed. From the test data shown in Fig. 9(b), the LDPP model shows more significant clusters than that of LDA and LPDP methods. Therefore, the properties of locality, discrimination and affinity preservation of the proposed LDPP can better promote the taste recognition performance.

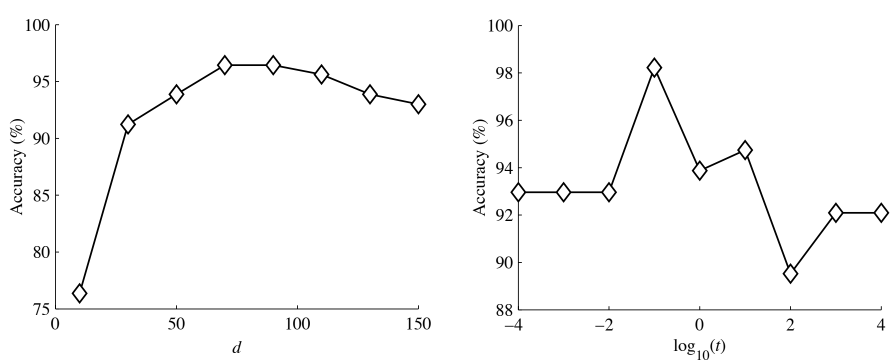


(a) Training set.



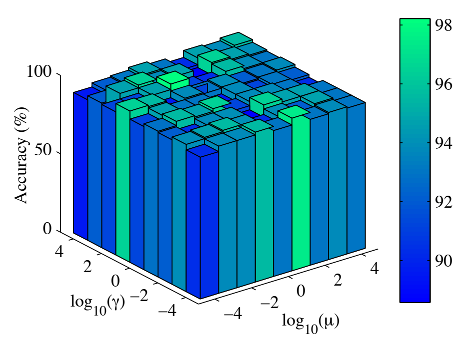
(b) Test set.

Fig. 9. The scatter points of the first two components for all methods.



(a) New subspace dimension d.

(b) Kernel parameter t.



(c) Regularization coefficients μ and γ.

Fig. 10. Parameter sensitivity analysis of LDPP-H.

VII. Discussion

A. Analysis of LDPP Parameters

The proposed LDPP-H has four parameters: the new subspace dimension d, the kernel parameter t and the regularization coefficients μ and γ. For observing the performance variation with respect to these parameters, the sensitivity of which has been shown in Fig. 10 (a), (b), and (c), respectively.

First, with the increase of the dimension d, the accuracy has a rising trends and then becomes stable. In experiments, when $d = 60$, the performance of LDPP achieves the best. Second, the kernel parameter t is closely related to the affinity matrix in local manifold preservation. Specially, when t approaches infinity, the LDPP-H model degenerates into the LDPP-S model. For different tasks, the parameter t can be tuned for better performance. The regularization coefficients μ and γ provide a trade-off between the local discrimination term and the manifold preservation term, which can be easily tuned via an alternative strategy. In experiments, when $\mu = 0.1$ and $\gamma = 100$, the optimal performance can be achieved.

B. Analysis of Classifier Parameters

For SVM/ELM/KELM, the performance with penalty coefficient τ is shown in Fig. 11(a), from which we can see that with the increase of τ, the performance is improved. Therefore, $\tau = 10^5$ is set for each classifier.

For ELM classifier, the number of hidden neurons L is an important parameter. For better insight of the L, we have presented the performance variation w.r.t. L for each method in Fig. 11(b). We observe that a larger L can help improve the recognition performance. Therefore, after a trade-off between accuracy and time, $L = 5000$ is set in this work. The computational time analysis of ELM w.r.t. L is discussed later.

For KELM classifier, the performance with kernel parameter t is shown in Fig. 11(c), from which the optimal t is clearly observed. Therefore, $t = 100$ is empirically set.

C. Analysis of Computational Time

First, we present the computational time analysis of ELM in Fig. 12 by increasing the number of hidden neurons L. We can observe that when L is larger than 10000, the running time of ELM is dramatically increased. By joint analysis of Fig. 12 and Fig. 11(b), there is an easy trade-off between time and accuracy, and $L = 5000$ is picked for ELM.

Further, the average computational time of training and test for 5 folds by using different classifiers is provided in Table V. We can observe that KELM classifier is several times faster than both ELM and SVM. Therefore, KELM shows better efficiency and effectiveness in our E-Tongue system.

From the perspective of subspace learning methods, we can observe that the running time of classifiers with subspace learning methods seems to be shorter than that of basic classifier. This demonstrates that subspace learning not only improves the recognition ability of classifier, but also speed up the training process for classifiers. Notably, all the procedures are implemented in a MacBook Air computer of Intel Core i5 CPU, 1.3GHz, and 4GB RAM.

D. Further Discussion of the LDPP

From the above comparisons with other popular methods in recognition accuracy and computational time, our proposed LDPP model shows excellent performance for taste recognition. The superiority and importance of LDPP that suit for the E-Tongue data analysis can be summarized as follows.

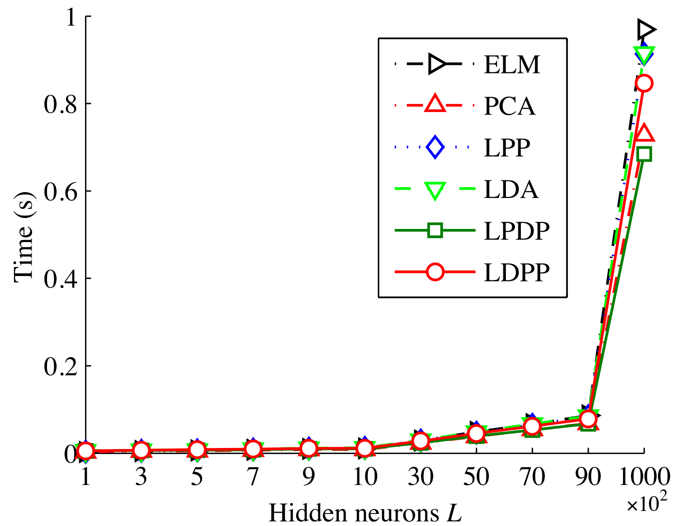
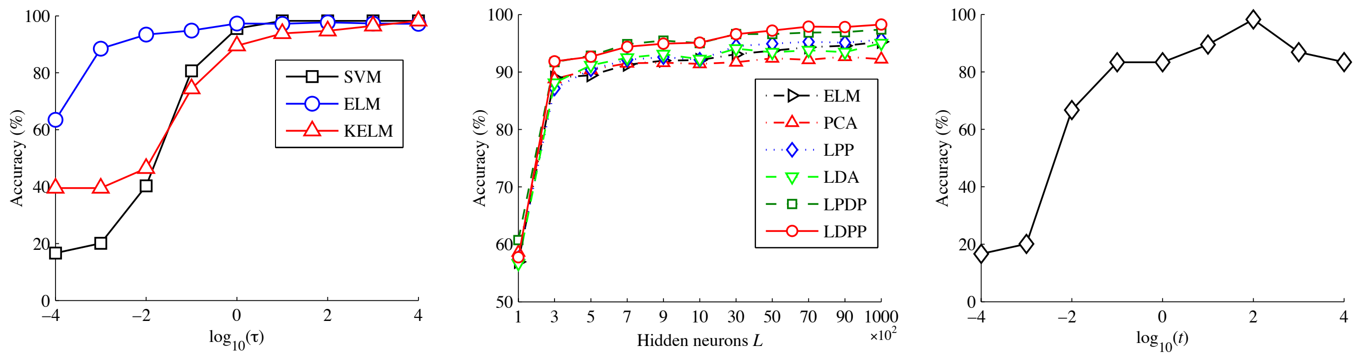


Fig. 12. Time analysis with increasing number L of hidden neurons in ELM.

- The regularization coefficients of LDPP play an important role in learning process. For different datasets, the local between-class scatter matrix, the local within-class scatter matrix and the neighborhood affinity preservation show different contribution, which is geometric distribution specific. Therefore, by introducing the regularization, the model flexibility as well as scalability is improved.
- The presence of outliers may cause the computational bias of the between-class and within-class scatter matrix. Therefore, the Fisher criterion with locality constraint is first formulated. Then the potential abnormal samples (outliers) can be automatically excluded, and the class discrimination is improved. Note that, the locality ratio is a tunable parameter, which may be different for distinctive recognition tasks. The possible reason is that the number of outliers in real application is different. It denotes that the ratio of the locality is problem specific.
- Actually, the provided E-Tongue benchmark dataset in this work is small sized. Due to the cost-ineffectiveness, collecting a very number of data by using one E-Tongue system may not be realistic, especially for labeled data. The local manifold structure constraint preserves the affinity of the possible similar data, which can be easily extended to semi-supervised learning scenarios in E-Tongue. Also, based on the local regularization in LDPP, overfitting is avoided.
- The proposed LDPP is specially formulated for taste recognition in E-Tongue. First, the size of E-Tongue data cannot be very large due to the cost-ineffective essence, and therefore simple but effective algorithm is necessary. Second, the labeled data acquisition is time consuming, and locality constrained discriminant model is needed. Third, feature extraction is another important aspect in bionic data analysis, and feature learning is important. Fourth, the outliers can be easily implied in E-Tongue data due to manual operation in experiment, and local data construction can effectively achieve outlier removal.



(a) Penalty coefficient. (b) Hidden neurons L of ELM. (c) Kernel parameter t of KELM.

Fig. 11. Parameter sensitivity analysis of classifiers.

TABLE V
COMPARISON OF COMPUTATIONAL TIME ($\times 10^{-3}$s)

Classifier	None	PCA	KPCA	LPP-S	LPP-H	LDA	LPDP-S	LPDP-H	**LDPP-S**	**LDPP-H**
SVM	10.66	8.63	5.927	19.36	18.18	24.46	26.82	25.91	28.79	25.85
ELM	53.57	39.15	40.30	49.64	48.49	49.92	39.97	40.14	44.59	46.30
KELM	1.820	1.145	1.279	1.215	1.205	1.388	1.613	1.255	1.178	1.044

VIII. CONCLUSION

In this paper, we have designed an E-Tongue system and a novel local discriminant preservation projection (LDPP) model for bionic taste recognition. The LDPP aims at enhancing the tolerance to abnormal samples or implicit outliers from E-Tongue system. Therefore, the locality constraint for discrimination and the local structure preservation are integrated. For taste recognition, off-the-shelf classifiers such as SVM, ELM and KELM are exploited. Finally, 98.22% recognition accuracy on 13 kinds of liquids is achieved and it outperforms other popular methods in E-Tongue community.

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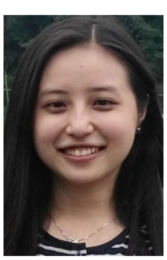

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