One-class Classification-based Acoustic Inspection Method for Canned Foods

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Abstract. It is significant to inspect whether the vacuum degree of food container meets the standard. This paper proposes to treat it as a one-class classification problem. And for this, we present a one-class classification algorithm based on semi-non-negative matrix factorization: the classifier only needs to be learned from the dataset of qualified products, and then it can be used to judge whether the vacuum of the detected product is qualified or not. The detection results show that the proposed method can not only acquire the highest detection accuracy, but also correctly distinguishes the unqualified types that are easy to be misjudged by traditional methods.

Introduction

The three-piece steel cans are widely used as packaging containers to store food. Generally the food containers required to be vacuum for preventing the stored food from premature deterioration. It is significant to inspect whether the vacuum degree of food container meets the standard. The vacuum degree of the container is closely related to its internal pressure. Furthermore, the sound generated from the forced vibration of the container cover reflects the stress of the container cover. This inspired people to analyze the vacuum degree of the container by the sound produced by the vibration of the container cover. Hence the acoustic technology has been widely applied to detect the vacuum degree of canned foods in recent years [1,2,3]. At present, acoustic-based vacuum inspection technology for canned food mainly adopts spectrum peak method [1,2], that is to judge the vacuum of the product is qualified or unqualified according to whether the spectral peak frequency of the sound generated from the vibration of the container cover is within the appropriate range. The traditional method relies on the artificial experience to extract spectral peak frequency as the feature for inspecting the quality of canned foods. However, the sound emitted by the vibration of an object is usually a composite signal composed of many components with multiple frequencies [4], which may result in the fact that the spectral peak frequency does not afford sufficient discrimination between abnormal and normal cans. It was found from the practical application that the spectral peak frequencies of some unqualified canned foods are close to that of the qualified ones. These cause the misjudgment of the spectrum peak method.

Actually the purpose of the inspection is only to distinguish whether a product is qualified or unqualified, without having to distinguish the specific types of disqualification. Therefore this paper proposes to treat the inspection as a one-class classification problem [5]. One-class classification is the task of discerning unusual samples in data. Typically, it is treated as an unsupervised learning problem where the anomalous samples are not known a priori and it is assumed that the majority of the training dataset consists of normal data [6]. The purpose then is to learn a model that accurately describes the “normality”. Deviations from this description are then deemed to be anomalies. It is widely used in text classification, spam detection, outlier images, video anomalies, machine fault detection, and so on [9]. The common classical one-class classification methods include the support vector machine-based one-class classifier (OneClass-SVM) [7], the auto-encoder-based one-class classifier (OneClass-AutoEncoder) [8].
Non-negative matrix factorization (NMF) is a feature extraction method that has the property of intuitive part-based representation of the original features [10]. It focuses on the decomposition of non-negative multivariate data matrix into features matrix and coefficients matrix that are also nonnegative [11]. Furthermore, semi-non-negative matrix factorization (SNMF) relaxes the non-negativity constraint of NMF and allows the data matrix and the features matrix to have mixed signs [12], which is more suitable for acoustic signals. In this work, we introduce a novel approach to inspect canned foods. Our method builds a one-class classification network based on SNMF (OneClass-SNMF), and only the data of qualified products are needed for training. During the training phase, it trains the network by continuously decreasing the decomposition error of qualified sample data to obtain the final features matrix of the SNMF. In the subsequent inspection stage, the reconstruction error of the test data is calculated in the case of fixed features matrix to determine whether the test object is qualified or not.

Related Work

In this work, we assume that our data is provided in a matrix form \( X \in \mathbb{R}^{n \times p} \), i.e., \( X = [x_1, x_2, \ldots, x_n]^T \) is a collection of \( n \) data vectors as rows, each with \( p \) features. Matrix factorization aims at finding factors of \( X \) that satisfy certain constraints. In SNMF [12], we factorize \( X \) into two factors: the features matrix \( F \in \mathbb{R}^{k \times p} \) and the coefficients matrix \( G \in \mathbb{R}^{n \times k} \). SNMF allows the data matrix and the features matrix to have mixed signs, while restricting the coefficients matrix to comprise of strictly non-negative components, thus approximating the following factorization:

\[
X \approx GF
\]

The cost function we optimize for approximating the SNMF factors is indeed:

\[
\min \Gamma(G,F) = \|X - GF\|_F^2, \text{s.t. } G \geq 0
\]

We optimize \( \Gamma(G,F) \) via an alternate optimization of \( F \) and \( G \); we iteratively update each of the factors while fixing the other, imposing the non-negativity constrains only on the coefficients matrix \( G \):

\[
F = \left(G^T G\right)^{-1} G^T X
\]

where \( G \) is the Moore–Penrose pseudo-inverse of \( F \), and

\[
G = \frac{\left[X F^T\right]_{\text{pos}} + G\left(F F^T\right)_{\text{neg}}}{\left(X F^T\right)_{\text{neg}} + G\left(F F^T\right)_{\text{pos}}}
\]

where \( A_{\text{pos}} \) is a matrix that has the negative elements of matrix \( A \) replaced with 0, and similarly \( A_{\text{neg}} \) is one that has the positive elements of \( A \) replaced with 0:

\[
\forall i, j, A_{i,j}^{\text{pos}} = \frac{|A_{i,j}| + A_{i,j}}{2}, \quad A_{i,j}^{\text{neg}} = \frac{|A_{i,j}| - A_{i,j}}{2}
\]

Proposed Method

![Figure 1. Overview of the proposed algorithm](image-url)
The proposed method is in Fig. 1. The time-domain sound signal \( S = [s_1, s_2, \ldots, s_n]^T \) \((i = 1, 2, \ldots, n)\) transformed to frequency domain with the FFT to compute the Fourier spectrum \( P = [p_1, p_2, \ldots, p_n]^T \). The amplitudes of the Fourier spectrum are then normalized to the range of 0~1 by the Eq. 6. And the normalized spectrum \( X = [x_1, x_2, \ldots, x_n]^T \) used as the input of our proposed one-class classification network to train or test.

\[
x_i = \frac{p_i - \min(p_i)}{\max(p_i) - \min(p_i)}
\]  

(6)

| Algorithm 1: OneClass-SNMF Algorithm |
|--------------------------------------|
| **Training Phase**                   |
| **Input:** Qualified products' dataset \( X \)  |
| **Initialize:** Features matrix \( F \) is a weight with its elements in the range of -1~1.  |
| **Repeat:**                          |
| \( G \leftarrow \) Compute the coefficient matrix using the Eq.4.  |
| \( F \leftarrow \) Update the weight according to the loss function and the corresponding error back propagation rule.  |
| **Until:**                           |
| Stop condition is satisfied.         |
| **Output:** Features matrix \( F \)    |
|**Testing Phase**                     |
| **Input:** Test product' data \( X \), features matrix \( F \), threshold value \( \delta \)  |
| **Initialize:** Each element of coefficients matrix \( G \) is a random value in the range of 0~1.  |
| **Repeat:**                          |
| Compute the coefficients matrix \( G \) according to the Eq.4.  |
| **Until:**                           |
| Stop condition is satisfied.         |
| **Output:** Test product is qualified if \( RE \leq \delta \); test product is unqualified if \( RE > \delta \) |

The training and testing phases of the proposed method is in Algorithm 1. The task that detecting the unqualified objects is conducted a semi-supervised framework, using only data of qualified instances for training the one-class classification network based on SNMF. First, the features matrix \( F \) is obtained by training the classification network with the data of qualified products. Then the data of the test object is decomposed based on SNMF to obtain its coefficient matrix under circumstance of fixing the feature matrix. And the reconstruction error \( RE \) of the test data that is calculated is the scoring criteria to judge the test object is qualified or unqualified. In our algorithm, the loss function the training process is the standard SNMF model as shown in the Eq.2, and the stopping condition of iteration is that the number of iterations reaches the maximum iterations.

\[
RE = \| X - \hat{X} \|^2
\]  

(7)

**Experiments**

**Experiment System**

We construct a detection system for canned foods, as shown in Fig. 2, to verify the proposed algorithm. The working procedure of this system is as follows: 1) when the photoelectric sensor detects a canned food on the conveyor belt, the control & processing module drives the electromagnetic motivation probe through the electromagnetic signal generation unit to make the
canned lid vibrate and make a sound; 2) the sound acquisition unit collects the sound through a microphone; 3) the control & processing module invokes the pre-trained detection model to distinguish whether the current product is qualified or unqualified. In our system, the sampling frequency of sound signal is 48 kilohertz, the number of quantization bits is 32 bits, and the corresponding sound duration of each canned food is 18.67 ms.

Experiment Datasets

The inspection objects are the Wong Lo Kat Herbal Tea packed by the three-piece steel cans. We have 35 qualified samples and 11 unqualified samples. The unqualified types include leaky cans, dented cans, empty cans and damaged cans. The experiment data come from their sound recordings collected by the experiment system. Fig.3 and Fig.4 show the sound signal and frequency spectrum of the qualified and unqualified (leaky and dented) products.

Scoring Criteria

Experimental scoring criteria are shown in Tab.1. As described in Section 3, the proposed OneClass-SNMF algorithm takes $RE$ as the criterion for judging whether the tested object is qualified or not. In addition, the OneClass-AutoEncoder algorithm is also applicable to this judgment criterion [13].

| Scoring Criteria | Applicable Methods                                                                 |
|------------------|------------------------------------------------------------------------------------|
| $RE$             | OneClass-AutoEncoder$^{[10]}$, OneClass-SNMF                                      |
| $Acc$            | Spectrum Peak Algorithm$^{[1]}$, OneClass-SVM$^{[9]}$, OneClass-AutoEncoder$^{[10]}$, OneClass-SNMF |

In general, accuracy ($Acc$) is an indispensable indicator for evaluating each detection system. We also select the $Acc$ as the evaluative criteria. The $Acc$ is in Eq.8, where the $True$ is the number of test objects correctly predicted, and the $Total$ is the total number of test objects.

$$Acc = \frac{True}{Total} \tag{8}$$

Results

In the experiment, the number of training samples is 24, and the maximum iterations of SNMF are
The 24 qualified samples were randomly selected for training, and the remaining samples were used for testing, which were repeated 10 times. The results of RE are shown in Fig. 5. The vertical box in the figure represents the distribution range of RE values of test samples. The RE values of qualified samples should be less than that of unqualified samples. If the RE of a qualified sample falls into the distribution range of the RE values of the unqualified samples, it will be deemed as a misjudgment. The average Acc of the 10 times results is taken as the final Acc, as shown in Tab. 2.

![Image](https://i.imgur.com/3Q5yZQG.jpg)

**Figure 5. RE Results**

**Table 2. Acc Results**

| Methods                        | Acc  |
|--------------------------------|------|
| Spectrum Peak Algorithm[1]     | 90.91% |
| OneClass-SVM[9]                | 92.27% |
| OneClass-AutoEncoder[10]       | 98.18% |
| OneClass-SNMF                  | 100%  |

**Discussion**

Compared with the OneClass-AutoEncoder algorithm, the experimental results of the proposed OneClass-SNMF algorithm show that the distribution ranges of RE of qualified samples and unqualified samples not only have no overlap, but also have an obvious difference. Moreover, the RE of OneClass-SNMF algorithm is smaller, which means that it decomposes and reconstructs the original data adequately. The Acc results show that our OneClass-SNMF algorithm achieves the highest accuracy. We also analyze the mistake situations of each algorithm: the samples with damaged tank cover or with largely dented are the main causes of misjudgment, especially the erroneous estimates made by the spectrum peak algorithm are entirely due to these two types.

**Conclusion**

This paper introduce a novel one-class classification method based on SNMF, which only needs to learn the "normality" samples (it is usually easier to get enough training size in practical application) to acquire the practicable classifier. This method is used to inspect the vacuum degree of canned foods. First, the OneClass-SNMF network is trained with the data of qualified products, and then it is used to judge whether the tested products are qualified or not. By comparing the experimental results among different methods, it can be seen that our method obtained the highest detection accuracy, and can correctly judge the unqualified types that are easy to be misjudged by traditional methods. In the following work, we will focus on the practical application of the proposed method.

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