Poster paper

Discriminative imaging for washing powder production by multispectral sensing

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I. INTRODUCTION

Household washing powder consists of more than 20 different chemicals mixture. For commercial industry, it is very important to quantify these chemicals mixture from mixing to packaging phase in order to maintain the quality control. However, it is a daunting task due to the very large scale of the production cycle and chemicals tendency of random flow due to shape and sizes etc. Moreover, it is extremely difficult to quantify the quantity of each constituent by broadband RGB image, as most of them appear in the same shape, size and white colour appearance in the visible spectrum. This imposes a technical challenge in the powder manufacturing industry to seek for an effective quality control technology during powder production and packaging.

Hyperspectral imaging (HSI) is renowned for chemical discrimination through spectral sensing [1]. Yet, it imposes another challenge to quantify subpixel powder chemicals in the mixture due to the limited spatial resolution in the HSI [2], which makes chemical substances mutually fill-up to form a single pixel. This work formulates part of the AMSCI funded CHARIOT project to develop a low-cost system for at-line quantification of powder mixture during production. This paper compares the abilities of powder discrimination using subpixel Adaptive Cosine Estimator (ACE) algorithm [3], Support Vector Machine (SVM) [4] and spectral Unmixing under the Nonnegative Constrained Least Squares (NCLS) [5] within Linear Mixing Model (LMM) [6]. In the last couple of decade, there are a number of different linear and non-linear Unmixing methods have been proposed [2][6]. Among these NCLS is the most common technique utilised by research communities [1]. Moreover, there are quite a number of different solutions of constraining least square problem have been proposed in [10][11].

In this work the performance of the powder discrimination is assessed by 1) ground truth map for colour powder mixture extracted from high-resolution DSLR images, which give real abundance map rather than simulated data as most of the literature describe above used, 2) the pre-mix volume of individual powder constituents for white samples. It is observed that the Unmixing under NCLS method has provided a better means to quantify mixtures of 3, 5 and 7 different chemical powders. Moreover, it is seen that better powder discriminations have been obtained using Band Selection (BS) technique based upon Fuzzy-C on mutual information [9] which performs better than that using all 161 bands at lower computational cost.

II. EXPERIMENTAL TECHNIQUES

Match filter detector is a well-developed technique in HSI, it uses a spectral signature (target probe) to search for the presence of that spectrum in a scene [3]. It attempts to detect and locate pixels containing a target material of known spectral composition. The ACE detector models the target variability by measure the angle between the target pixels to the target spectrum. ACE detector mathematically define as:

$$D_{ACE}(\mathbf{x}) = \left[\frac{\tilde{\mathbf{x}}^T \tilde{\mathbf{P}}_s \tilde{\mathbf{x}}}{\tilde{\mathbf{x}}^T \tilde{\mathbf{x}}} \right] > t, \quad = \left[\cos^2 \alpha \right] > t$$

Where $\tilde{\mathbf{P}}_s$ is the projection and reconstruction operator onto the d target subspace, i.e.

$$\tilde{\mathbf{P}}_s = \tilde{\mathbf{\Phi}}_s \left(\tilde{\mathbf{\Phi}}_s^T \tilde{\mathbf{\Phi}}_s \right)^{-1} \tilde{\mathbf{\Phi}}_s^T$$

and α is the angle between the target subspace and the test vector and the matrix $\tilde{\mathbf{\Phi}}$ contains the available a priori variability information about the target and t is the threshold. Note here, the performance of ACE detector is largely depended on the covariance matrix, in this experiment we have extracted different covariance matrix from the scene and compare the detection performance, this will be discussed in next section in more detail.

The SVM classifier discriminates two classes by fitting an optimal (maximum margin) separating hyperplane to the training samples of two classes in multi-dimensional feature space [8]. Let us consider two-class classification problem with training set $\{x_i, y_i\}_{i=1}^{N}$, where N vector in the d-dimensional feature space $x_i \in R^d (i=1, 2...N)$ a target

$y_i \in \{-1,1\}$ is associated to each vector x_i. The hyperplane for linear surface is defined as:

$$F(x) = w.x + b$$

Where w is normal to the hyperplane and b is the bias.

The SVM algorithm can find the optimal separating hyperplane in a high dimensional space by the use of kernel trick [4]. The radial bias function (RBF) has been the most popular kernel used in HSI applications [7], so in this work we have opted RBF kernel.

Unmixing in HSI is a technique which decomposes the mix spectra into pure constituent, separates different fractions (knows as abundance) of each chemical or material (known as endmembers) present in a mixture. The most commonly use model for HSI Unmixing is the LMM, which assumed the mixture spectrum is a linear combination of pure elements spectra [6] and defined as:

$$x = Ea$$

where, x = mixture, E endmember matrix $E = (e_1, \dots, e_n)$ and $a = (a_1, \dots, a_n)^T$ abundance, where is a>=0. NCLS is a widely use technique to solve HSI subpixel detection problem. NCLS mathematically optimised the fraction of the mixed pixels given the pure spectrum of each endmembers, defined as

$$|x - Ea|^2$$

Several datasets of washing powder in a mixture and a pure form have been collected with Specim spectrograph for Short Wave Infrared (SWIR) HSI system. SWIR camera utilises an infrared thermal detector, (Mercury Cadmium Telluride - MCT) combined with a high performance thermo-electrical cooler (TEC) within the 1100nm to 2100 nm spectral range.

For assessment purpose, the reference has been taken from ground truth map for the mixture of 3 and pre-mix volume for the mixture of 5 and 7, as the ground truth map is not available for these mixtures because most of the samples are white in colour. After processing the HSI data with different methods the error in percentage is computed by the following equation:

$$Error_i = (|ref_i - fraction_i|/ref_i) * 100$$

Where i is the individual sample. For accessing the overall accuracy of individual method average error of a mixture in percentage is subtracted from 100%.

III. RESULT AND DISCUSSION

Methods define in last section have been tested and compared here in this section. Figure 1(a) shows RGB image of 3 chemical mixtures, namely Blown Powder (BP), Blue Carbonate Speckle (BCS) and Sodium Per Carbonate (SPC), the size of the mixture is about 50mm by 50mm. Note here for the purpose of ground truth, colour samples have been chosen

in mix 3. Figure 1(b) and Figure 1(c) show RGB images of 5 and 7 different mixtures respectively.
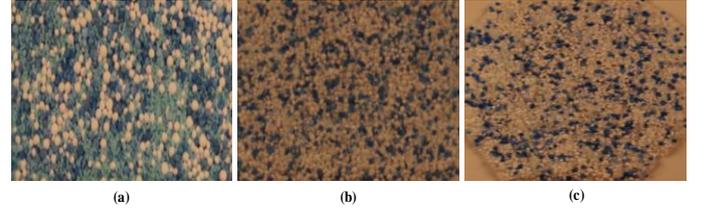

Figure 1: Shows the DSLR RGB images of a) mixture of 3, b) mixture of 5 and c) mixture of 7.

Figure 2(a) shows hand drawn ground truth of 3 chemical mixtures as shown in Figure 1(a) each chemical drawn by using high resolution DSLR RGB image. Table 1 tabulates the fraction of each constituent with respect to different methods utilised in this work along with ground truth abundance fractions and the average error has been listed in the last column. Figure 2(b) and (c) illustrates the detection map of ACE algorithm, where target signature is extracted from pure samples and the mixture sample is treated as the test data. In Figure 2(c) covariance matrix is computed from the background i.e. the whole image except target pixel in a mixture (e.g. for BP detection, the BP pixels are the target pixels). It can be seen that ACE method able to detect each chemical in a mixture when compared with ground truth but the method underestimates each chemical fractions in a mixture, this can also be validated from Table 1. While in Figure 2(c) the covariance matrix is computed from non-target pixels (e.g. for BP detection, BCS and SPC are the non-target pixels). It can be observed in Figure 2(c) ACE algorithm over-estimating the detection and the fraction are much higher than ground truth (see Table 1). Figure 2(b) and (c) highlights the one drawback of ACE detector that it is significantly depend upon the selection of covariance matrix and the detection performance varies if we compute covariance matrix from the different location.

Figure 2(d) shows the results obtained from SVM classifier, where radial bias function kernel is employed. The training data for SVM have been taken from pure samples and again the mixture data is the test set. In this application SVM is used as multi-class problem and one-against-all approach have been utilised. Figure 2(d) shows SVM classifier is unable to classify the mixture faithfully, specially for BP which is the finest particles in all 3 samples, SVM over classify the BCS sample. However, SPC detection rate is much better than other two chemicals. It may be due to the reason that SPC is the large and circular particles of in the mixture that means more pure pixels are present in a SWIR mixture data as compared to BP and BCS. The SVM fundamentally is a binary classifier that makes a decision boundary between two classes and can classify the pure sample more robustly than in a mixture, where two or three chemicals mix together with unknown factors to make an unknown class which is difficult to detect.

Figure 2(e) shows detection map computed by using NCLS method. The pure signature of each constituent and the mixture signature is feed into NCLS algorithm for fraction estimation. For 2D Unmixing map, pixel-wise NCLS have been implemented and their abundance map is shown is Figure 2(e). As it can be seen from results that the abundance map shows quite the same detection of each chemical if it compared with ground truth map. Similarly, Table 1 shows the minimum error (9.95%) as compare to ACE (67&76%) and SVM (~50%) classifiers. Furthermore, the band selection technique fuzzy c-means clustering based on mutual information [9] has been tested here with NCLS method. The 10 selected bands are used in both pure and in mixture data. The abundance map of BS-NCLS Figure 2(f) shows quite the same detection trend if it is compared with ground truth map and NCLS abundance map. Table 1 also gives an evidence that BS-NCLS estimates almost the same abundance as NCLS. The computational cost of BS-NCLS is found to be significantly less 1.38 seconds as compared to NCLS which is 4 seconds for 2D pixel-wise detections.

Table 2 shows the accuracy of mixture 3, 5 and 7 w.r.t different methods used in this work. Clearly NCLS shows much better subpixel fraction estimation in a mixture of 3 and 5. Abundance estimation of mix 7 is not as good as mix 3 and 5, it is mainly due to the particle size, some of the constituent in a mix 7 are in large in size which tends to cover smaller particles and thus generate high error rate as compared to mix 3 and 5.
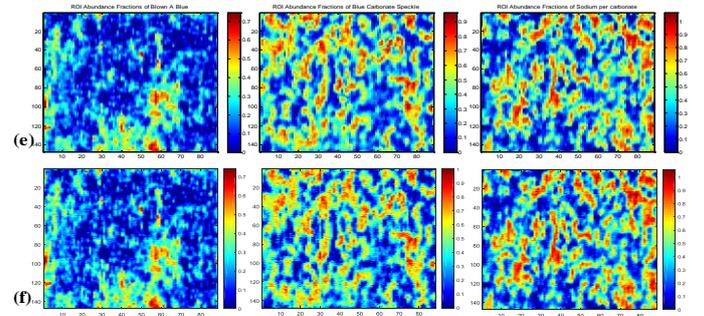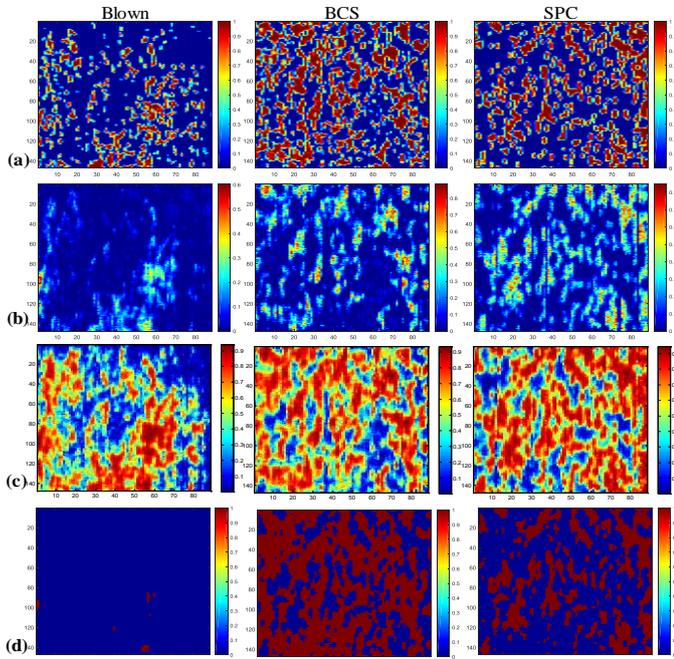

Figure 2: Shows the abundance map of a) ground truth b) ACE (background as CovMatrix) c) ACE (non-target pixel as CovMatrix), d) SVM, e) NCLS and f) band selection NCLS of mixture of 3 BP, BCS and SPC.

Table 1: Tabulates abundance fractions in % of mixture of 3 samples w.r.t. different methods and their average errors

Methods	BP	BCS	SPC	Avg Error
Ground Truth	18.58	41.32	34.01	
ACE (background as CovMatrix)	3.74	12.07	14.89	67.10
ACE (non-target pixel as CovMatrix)	42.22	54.35	58.41	76.83
SVM (RBF Kernel)	0.52	62.07	33.16	49.97
NCLS	18.43	38.94	41.91	**9.95**
BS-NCLS	18.61	38.33	42.15	10.44

Table 2: Tabulates the accuracy in % of mixture 3, 5 and 7 w.r.t different methods.

Methods	Mix 3 Accuracy	Mix 5 Accuracy	Mix 7 Accuracy	Avg. Accuracy
ACE (background as CovMatrix)	32.89	61.64	26.19	40.24
SVM (RBF Kernel)	50.02	27.96	18.37	32.11
NCLS	**90.04**	**93.05**	66.74	**83.27**
BS-NCLS	89.55	91.77	**72.47**	**84.59**

IV. CONCLUSION

This paper shows the performance of the subpixel powder discrimination of HSI data by using 3 different methods, namely ACE, SVM and NCLS. For the assessment of these methods the ground truth map for colour powder mixture and pre-mix volume for the white samples have been utilised. The results showed that ACE method largely depended upon the covariance matrix and detection performance varies noticeably if covariance matrix extracted from the background or from non-target pixels. Likewise, SVM classifier also not able to perform good enough in a mixture data classification or a subpixel classification. However, NCLS method has provided a better estimation of abundance fraction for the mixture of 3, 5 and 7 different chemical powders, with overall accuracy about ~83%. It is also being observed from the experiment that band selection technique based upon Fuzzy-C on mutual information have perform better (overall accuracy about

~84%) or with minimum error difference than HSI (all 161 bands) with lower computational cost (about ~4 times), which is very crucial for near real-time applications.

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