

Detection of Potato and Clod Using an Acoustic Based LVQ Intelligent Algorithm

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Abstract: In this study, an acoustic-based intelligent system was developed for high speed discriminating between potato tubers and soil clods. About 500 kg mixture of potato tubers and clods were loaded on a belt conveyor and were impacted against a steel plate at four different velocities. The resulting acoustic signals were recorded, processed, and potential features were extracted from the analysis of sound signals in both time and frequency domains. These features are used as the input vector to LVQ models, and various LVQ learning algorithms, including LVQ1 and LVQ4 are evaluated. Optimal network was selected based on correct detection rate. Detection accuracy of the presented system was above 96% for potatoes and clods.

Key words: Acoustics, classification, discriminating, LVQ, potato

INTRODUCTION

Having a high rate of production, potato has become one of the most prominent crops in the world. More than 350 million tones of potato tubers are produced every year in the world (FAO, 2008). Fully automated potato harvesters are needed to save harvesting time of this enormous amount. The automate potato harvesting procedures idea has attempted for a long time, in the agro-industries (Main, 1971).

The first step in developing an automated potato harvester is separating potato tubers and clods system (Hosainpour et al., 2010). Clodes may to be mechanically damaged potato tubers. Clods and potato tubers have wide diversity in shape, size and moisture content so developing an automatic system for separating clods and potato tubers was difficult.

Mechanical methods widely used in many research studies for scrubbing partially and completely muddy potatoes (Feller et al., 1985; Gan-Mor et al., 1986; Shyam et al., 1990). However mechanical separating methods are being used in some potato harvesters, cause surface damages and bruising on potato.

Some machine vision based seperating systems have been developed for distinguish between potato tubers and clods but using this system under field conditions have problem and price of camera is another problem (Morrow et al., 1990; Al-Mallahi et al., 2008).

Other non-destructive detecting method is acoustical methods which have been increasingly implemented in detection and classification of agricultural products (Pearson, 2001; Mahmoudi, 2005; Diezma-Iglesias et al., 2004).

Although in the experimental stage, good correlations have been found using the second resonant frequency to determine apple, tomato and melon maturity (Thompson, 2003, Sugiyama et al., 1998). Measurements of acoustic responses of apples were tested and found to correlate well in the first and second resonant frequencies (Chen et al. 1992). Stiffness coefficient in apples is related to their moisture content or some related factor and would not be of use in measuring its maturity or ripeness. In Japan, acoustic impulse responses technique, has been developed and installed in packing systems (Thompson, 2003).

Artificial Neural Networks (ANN) are frequently employed as associative memories for pattern classification. The network typically classifies input patterns into one of the several memory patterns it has stored, representing the various classes. One of the most frequently used unsupervised clustering algorithms is the learning vector quantizer (LVQ) developed by Kohonen, while several versions of LVQ exist (Engelbrecht, 2007).

In very difficult classification problems, the number of stage's increases and the overall training time increases. However, the successive stages use less training time due to the decrease in the number of training patterns. The main goal of this study is to investigate the feasibility of using LVQ algorithm for rapid detection of clods in potato harvesters. Several versions of LVQ were used as a decision making unit for this purpose.

MATERIALS and METHOD

Data for this paper were collected from the entrance of a potato harvester in the 2008 harvesting season and involve 500 kg of a mixture of potato tubers (varieties of potato *Marfona*, *Agria*, *Kosima* and *Granola*), clods and stones. After removal of components smaller than 40 grams, potatoes and other materials including stone and clod was weighed and classified in two groups, potato and material other than potato. Weighing results are listed in Table 1. It should be noted that because vibration of the harvester, flimsy clods before reaching the reservoir will soften and removed.

Table1. Numbers and physical characteristic of used samples

samples	Variety	Number	Mean weight	Std ¹
		N	g	g
Potato	Marfona	378	186	82
	Agria	443	158	73
	Kosima	446	150	88
	Granola	625	115	50
Clod		1483	123	72
Stone		38	108	40

¹ Standard deviation

Test system involve a built to feed samples, drop them onto an impact plate, acquire sound signal upon impact, process the signal data and discriminating

algorithm to classifying two groups potato tubers and material other than potatoes. The system consisted of a feeding platform, an impact plate, an acoustic unit and a PC based data acquisition system. A 5 m long and 0.35 m wide belt conveyor was driven by a one kW hp electric motor. The velocity of the conveyor belt could be changed by using a variable frequency drive (Inverter IG5). Some special cups were mounted on the belt for stimulating and better control of the sample movement. The impact plate was a polished block of stainless steel approximately 22.5 × 30 × 1.5 cm. To study the effect of velocity on detection accuracy, four levels of belt conveyor velocity at 1, 1.5, 2 and 2.5 ms⁻¹ were examined.

A low cost Panasonic Electret capsule microphone (VM-034CY model), sensitive to frequencies up to 100 kHz, was used for capturing impact sound signals. Environmental noise was elimination by isolating microphone chamber. The data acquisition system was triggered by a piezoelectric sensor mounted on the impact plate. By adding this electronic circuit, only impact emission sound signals from samples were recorded and the environmental noises did not interfere with the actual desired signals. Microphone output was send to a PC based data acquisition system, where it was digitized using a sound card (Intel® 82801 BA/BAM AC`97Audio controller) at a sampling frequency of 44.1 kHz, with 16 bit resolution. A personal computer (Pentium IV) was used for acquiring, saving and processing of data as well as controlling the system.

Experiments were conducted in off-line conditions, in each series of experiments 45 samples of potatoes or material other than potato manually loaded on the belt. Separate and individual samples were fall on the impact plate by moving belt conveyor. The released sound signals were acquired by the microphone, digitized by the sound card and saved by using Matlab data acquisition toolbox (MathWorks, 2007).

This procedure were repeated for all belt velocities. The maximum frequency of the sound card was 44.1 kHz. The computer acquired 512 data points from every sample in the time-domain.

For extracting codebook vector (features), recorded sound signals were processed and analyzed in both time and frequency-domains. Although the maximum peak values of clod sound signals were slightly larger than potato ones, the preliminary

attempts to use only time-domain features were not successful. However, in order not to lose any useful transient feature, all 512 data point amplitude (Amp) values were considered as codebook vector. A 1024-point fast Fourier transform (FFT) was computed from each sound signal, using a Mathwork Windows.

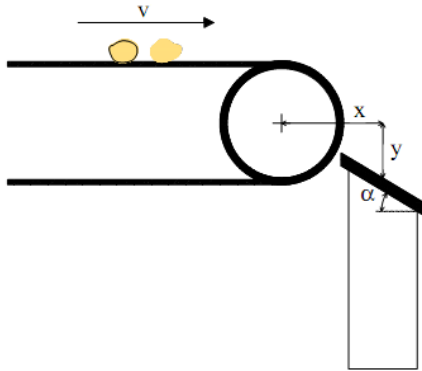


Figure 1. Position of impact plate respect to feeding platform

Table 2. Relation among eliminated components variance and number of selected principle components

Percentage of eliminated components variance	Number of selected features		
	Amp	PSD	NFFT
2%	9	1	1
0.5%	28	4	3
0.1%	98	34	11

Useful codebook signal (input vector) calculated as magnitude, phase and power spectral density (PSD) of FFT components in frequency domain, then by using low pass filter the jagged spikes in the spectrum was removed. A total of 1075 features was obtained for each sample. For real time systems, this dimension of the input vector is large, but the components of the vectors are highly correlated. Principal component analysis (PCA) involves a mathematical procedure that transforms a number of (possibly) correlated variables into a (smaller) number of uncorrelated variables the dimension of the input vectors reduced to a maximum of 30 features. PCA analysis was performed on data using Matlab software. Table 2 shows the relation between number of principle components and percentage of eliminated component variance.

Artificial neural networks classifier: Learning Vector Quantization (LVQ), was adapted by Kohonen for pattern recognition(Kohonen 1986). Its main idea is to divide the input space R^n into a number of distinct regions, called decision regions (Voronoi cells), and for each region one codebook (Voronoi) vector is assigned. Classification is performed based on the vicinity of the input vector x to the codebook vectors; x will be classified as the label of its nearest neighbor among codebook vectors. During the training, the codebook vectors and consequently the borders of decision regions are adjusted through an iterative process (Vakil-Baghmisheh and Pavešić, 2002). Seventeen features(x) selected as input of network. The 3400 data were divided to two sets: 60% of data were used for training, 40% for testing.

Algorithms for LVQ: Let $x(q)$ be an input vector (from training set): $x_t \in R_n$; $t=1; \dots; 2000$ and m_m be the m th codebook vector: $m_m \in R_n$. m_c is the winner codebook vector, so adjust m_c :

$$m_c(t + 1) = m_c(t) + \alpha(t)S(t)[x_q - m_c(t)] \quad (1)$$

in which: $s(t)=+1$ if classification is correct, $s(t)=-1$ if classification is wrong and $\alpha(t)$ is decaying learning rate as a function of time and $0 < \alpha(t) < 1$ (Vakil-Baghmisheh and Pavešić, 2002).

Preliminary LVQ4 algorithm: In this manner updated formula for winner neuron m_c is:

$$m_c(t + 1) = m_c(t) + \alpha(n)S(n)[x_q - m_c(t)] \quad (2)$$

$0 < \alpha(n) < 1$; $s(n) = d_c(n)$ if classification is correct, $s(n) = -1$ if classification is wrong and $\alpha(n)$ is decaying learning rate as a function of time and $d_c(n)$ is the "equalizing factor". In addition, $\alpha(n)$ and $d_c(n)$ must be kept constant during a training epoch. $d_c(n)$ is defined as:

$$d_c(n) = \frac{E_c(n)}{P_c(n)} \quad (3)$$

where $E_c(n)$ and $P_c(n)$, respectively, are the numbers of wrong and correctly classified patterns by codebook vector c in the current epoch. For estimating $d_c(n)$ four methods are offered:

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$$d_c(n) = d_{total}(n-1) \quad (4)$$

$$d_c(n) = d_c(n-1) \quad (5)$$

$$d_c(n) = d_c(n-1) \frac{d_{total}(n-1)}{d_{total}(n-2)} \quad (4')$$

$$d_c(n) = d_c(n-1) \frac{d_c(n-1)}{d_c(n-2)} \quad (5')$$

Considering the irregularities as $n = 1$ and 2 and the cases of zero terms in the denominator, more detailed formulas would be (Vakil-Baghmisheh and Pavešić, 2002):

$$d_c(n) = \begin{cases} \varepsilon & n = 1, \\ d_{total}(n-1) & n \geq 2, \end{cases} \quad (6)$$

$$d_c(n) = \begin{cases} \varepsilon & \text{if } n = 1 \\ d_c(n-1) & \text{if } n \geq 2, P_c(n-1) \neq 0 \\ \lambda & \text{if } n \geq 2, P_c(n-1) = 0 \end{cases}$$

$$d_c(n) = \begin{cases} \varepsilon & \text{if } n = 1, 2 \\ d_c(n-1) \frac{d_{total}(n-1)}{d_{total}(n-2)} & \text{if } n \geq 3, P_c(n-1) \neq 0 \\ \lambda & \text{if } n \geq 3, P_c(n-1) = 0 \end{cases}$$

$$d_c(n) = \begin{cases} \varepsilon & \text{if } n = 1, 2 \\ d_c(n-1) & \text{if } n \geq 3, d_c(n-1) = 0 \\ d_c(n-1) \frac{d_c(n-1)}{d_c(n-2)} & \text{if } n \geq 3, d_c(n-1) \neq 0 \end{cases} \quad (7)$$

in the fourth method, $d_c(n-1)$ is calculated as follows:

$$d_c(n) = \begin{cases} \frac{E_c(n-1)}{P_c(n-1)} & \text{if } P_c(n-1) \neq 0 \\ \lambda & \text{if } P_c(n-1) = 0 \end{cases} \quad (8)$$

After experiments the best learning rate functions were found to be:

$$\text{For LVQ4 } a(n) = k(\exp((-20 - epoch)/100)),$$

We simulate all of above algorithms on training mode and results presented in figure 2 , 3. In table 3 and 4 we summarized results of early LVQ and LVQ4 algorithms on train and test respectively.

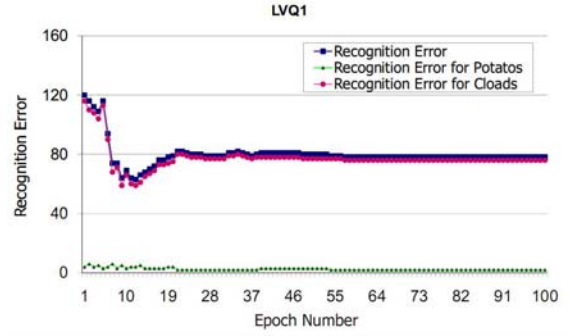


Figure 2. Convergence diagrams of LVQ1 on training database

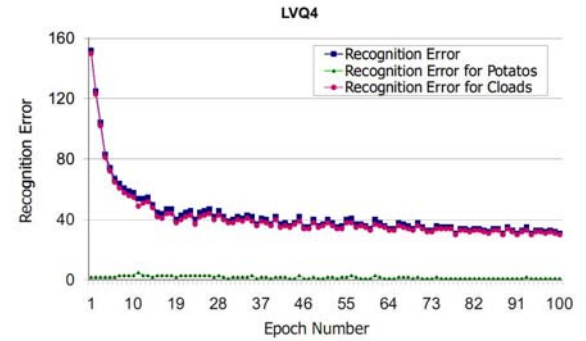


Figure 3. Convergence diagrams of LVQ4a1 on training database

RESULTS and DISCUSSION

The first evident point in Table 3 and 4 is the outstanding performance of new training algorithms and the weak performance of early algorithms i.e. LVQ1 on training and test sets of all databases. In training mode it is obviously found that recognition errors of LVQ4 algorithms had less recognition errors in comparison with early LVQ1 learning algorithm. We test some number of codebook vector for this classification and the best result achieved when 8 codebook vector selected, LVQ4 has best performance and LVQ1 need too have 30 codebook vector for classifying which indicate clods, stones and potatoes for.

CONCLUSIONS

In this paper a separation system, based on combination of acoustic detection and artificial neural networks, was designed for classifying open clods and potato tubers. LVQ network was employed for classification. Features of potatoes varieties were extracted from analysis of sound signals in both time and frequency domains by means of FFT, PSD and PCA methods. Altogether, 17 features were selected for classifications. Selected optimal neural network for classification exhibited LVQ4 structure.

Table 3. Recognition errors of early LVQ algorithms on databases

Training algorithms	Initialazing factor			Recognition error Train Mode			Recognition error Test Mode		
	τ	k	no	E c1	E c2	Overall	E c1	E c2	Overall
LVQ1	6	0.02	30	0.40	0.21	10.85	1.0	7.50	4.25
	8	0.02	30	0.4	14.5	7.5	0.33	5.0	2.67
	16	0.02	30	0.3	12.3	6.3	0.33	4.83	2.6
	20	0.02	30	0.40	11.60	6.0	0.333	4.66	2.5
	30	0.02	30	0.20	7.60	3.9	0.33	3.16	1.75

Table 4. Recognition errors of LVQ4 algorithms on databases

Training algorithms	Number of codebook vector	Recognition error (Train Mode)			Recognition error (Test Mode)		
		E c1	E c2	Overall	E c1	E c2	Overall
LVQ4	5	0	7.10	3.55	0.50	2.66	1.58
	8	0.10	3.0	1.55	0.833	1.167	1.00
	10	0.1	5.7	2.9	0.50	2.50	1.5
	15	0.1	5.10	2.60	0.66	2.50	1.58
	20	0.1	8.2	4.15	0.5	3.0	1.75
	30	0.1	6.3	3.2	0.66	2.5	1.58

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