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AUTOMATION IN COTTON GINNING

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Abstract

This paper discusses a framework for implementation of a machine-vision system for on-line identification of trash objects commonly found in cotton. Soft computing techniques such as neural networks and fuzzy inference systems can classify trash objects into individual categories such as bark, stick, leaf, and pepper trash types with great accuracies. This identification of trash objects to individual categories can be used for the dynamic allocation of trash extraction equipment during the ginning process. Such a system can be implemented in a modern gin, to configure an optimal set of equipment during ginning to produce quality cotton. Classification of cotton in real-time allows for an automated means to assign trash grades to cotton, and could have a significant impact on the entire cotton industry.

Introduction

The cotton industry is a multi-billion dollar enterprise worldwide. The revenues generated by the various sectors of the cotton industry in the United States exceeds 120 billion dollars annually. With liberalization of trade and increasing competition from overseas markets, the U.S. cotton industry is keeping abreast with technological advances to produce quality cotton and stay competitive in the free market system. With increasing demand for quality products in the consumer market the U.S. cotton industry is trying to modernize the ginning process. In order to achieve such a goal, industry is exploring new technologies to further enhance the productivity of modern gins and to produce quality cotton.

Cotton is a natural fiber, which in its raw form contains both lint and non-lint material. The cotton fiber is called lint, and all extraneous matter in cotton is called non-lint material or trash. Seedcotton refers to the harvested cotton that is hauled to the gin plant for processing. The term *ginning* refers to the process of separating the cotton fiber from cottonseeds. Before the fiber can be separated from the seed, extraneous material is separated from the seedcotton. Cleaning equipment is used to extract trash, and used in combination with gin stands, to separate usable fiber from the cottonseeds. In spite of great reduction in the number of gins in the United States over the last century, modern gins are capable of producing large volumes of ginned cotton due to advances in technology and machinery. For example, in the beginning of 1900 there were a total of 29,214 gins with average volume of 320 bales/gin. By the end of 1990, 1533 gins were operational with an average volume of 8,826 bales/gin (Anthony and Mayfield, 1994). Currently 15-20 million bales of cotton are produced in the United Sates each year.

Cotton Quality

Quality of cotton available for commercial use depends on a wide variety of factors (physical attributes). These physical attributes are affected by various factors namely variety, environment, harvesting procedures, and ginning process. In order to maintain uniform cotton quality, the United States Department of Agriculture-Agricultural Marketing Service (USDA-AMS), has established standardized procedures that have worldwide acceptance, for measuring these physical attributes. These attributes are used to assign class grades to cotton as an aid to marketing and final commercial use. Classification of cotton is based on fiber length, length uniformity, fiber strength, micronaire, color, and trash (USDA-AMS, 1999). The presence of trash and its subsequent removal during the ginning process affects some fiber properties, trash grade, and color grade (Rogers, 1984). The presence of trash in ginned lint also impacts the spinning and textile manufacturing industries. As such, trash extraction is a vitally important aspect in the production of quality cotton.

Trash in Cotton

All commercially grown cotton in the United States is harvested mechanically. Two types of harvesting equipment are used to harvest the cotton crop, the spindle picker (machine picked), and the cotton stripper (machine stripped). In spite of advances in harvesting equipment, large quantities of trash are collected along with the cotton. This trash for the most part consists of plant foliage. The amount of trash is significantly higher for stripper-harvested cotton compared to picker-harvested cotton.

The primary objective of a commercial gin is to separate cotton fiber from the cottonseeds and trash. When cotton is harvested even under ideal conditions, pieces of leaf and other trash are picked along with the seedcotton. The cotton is passed through the requisite number of seedcotton cleaning and extraction machinery to extract large trash objects. The gin stand then separates the lint from the seeds. Material left behind in the lint can consist of bark, stick, leaf, pepper trash, grass, hulls, seed coat fragments, and motes. As the name suggests, bark is the outer covering of sticks and is rather stringy in appearance and not easy to separate from the fibrous lint material. Pepper trash refers to small broken or crushed pieces of leaf and other trash objects. Hulls are the outer coverings of the cotton boll. Immature cottonseeds are referred to as motes. The lint is then further cleaned before being baled. In spite of advances in cleaning and ginning equipment, a large number of trash objects remain in the ginned cotton.

Ginning Practices

Current ginning practices do not consider the types of trash, and the amount (by number) of each type present in harvested cotton when evaluating either the sequence or configuration of equipment required to separate trash in cotton. In general, all cotton processed, passes through a predetermined set of equipment. The number, types, and order of equipment needed are based on experimental studies conducted at the USDA ginning laboratories and industry experience (Baker, et al., 1977 and 1982). The exact arrangement of these machines has evolved over the years, largely in response to the functional requirements for handling seedcotton in the dryers and between the various machines (Cocke, 1972, and Read, 1972).

Cotton quality after ginning depends on the quality of harvested cotton as well as the type and the amount of cleaning performed. Efforts based on moisture and trash content measurements at different stages of the ginning process, to optimize the trash extraction and cleaning process to preserve the quality of cotton have been tried successfully. Anthony (1990a) has investigated the performance characteristics of each type of gin cleaning machine and combination of machines in terms of their effects on fiber quality as a function of moisture and trash levels as well as cotton varieties. The first computerized process control system was proposed by Anthony (1989, 1990b) for use in a small-scale research facility at Stoneville, Mississippi. In the proposed system, routing valves were used to select or bypass any combinations of cleaning and/or gin equipment. Three locations in the gin were fitted with sensors to measure moisture, color and trash. These measurements were used to dynamically configure the requisite number of equipment to be included in the processing stream.

Based on these and other research efforts, Zellweger Uster Inc.® has developed *The IntelliGin* system for on-line fiber quality management during ginning. The operational procedure is designed to monitor, control, and optimize, ginning systems for the production of quality lint (Williams, 1997a,b). The *IntelliGin* system gathers real time measurements of fiber color, trash, and moisture content at three strategic locations in the ginning process. Using fiber property measurements as well as the pricing structure of cotton, dryer temperatures are automatically adjusted for optimum fiber moisture. The optimum amount of cleaning equipment is selected to maximize lint quality and yield. Cotton cleaners are fitted with automated bypass valves, to remove certain cleaners from the process stream. Since its inception in 1998, seventeen commercial gins have installed the IntelliGin for processing seedcotton (mostly machine picked). The trash measuring system described in this paper is different from system used by Zellweger Uster® in their *IntelliGin* process control system. The proposed system can differentiate trash as individual types namely bark, stick, leaf, and pepper trash categories.

The selection of the amount of cleaning equipment is based on the amount of trash present in the incoming seedcotton. Trash meters are used to measure the amount of trash present in cotton based on the percentage of the surface area covered by trash particles on the surface of the sample. As such, the types and the distribution (number) of trash objects are not considered during the ginning process. For example, if seedcotton has higher quantities of stick objects, current practice does not allow for the judicious selection of the number of stick cleaning machines to be included in the processing sequence. This might result in seedcotton with higher stick content, entering the gin stand resulting in large quantities of bark in the ginned lint. The amount of lint cleaning performed on the cotton, determines the amount of bark, leaf and pepper trash left behind in the ginned cotton. Although the lint produced may satisfy the color and trash grade requirements, it may contain an excessive number of bark and pepper trash objects that will pose problems for the spinning industry. It is important to recognize that cotton can be over cleaned to achieve the required trash grade, resulting in loss of useful fiber. This consequent loss of lint reduces the bale weight (lint turnout). A Universal Standard Density bale typically weighs about 500 lbs. As a rule of thumb, the first lint cleaner can be expected to extract about 20 lb. of lint per bale, while the second one will extract about 10 lb. (Smith, 1999). If the increase in price for the cleaned cotton does not more than offset the weight loss, then additional cleaning actually reduces the bale value. The additional lint cleaners also affect fiber length, and length uniformity of lint (Baker, et al., 1999).

Knowledge of specific types of trash and the amount of each type can be very useful to configure cleaning equipment. This information can be used in developing a framework for an automated system, to control the sequence/configuration of equipment during ginning. Such a system evaluates the contents of the trash at each stage of the ginning process and passes cotton through the requisite number of cleaning machines. The equipment selection is based on the characteristics of the seedcotton being ginned. This enables the production of lint of superior quality and can provide tremendous benefits to cotton producers, cotton ginners, and the textile industry.

As mentioned earlier, about 15-20 million bales of cotton are grown in the United States each year. 95% of these bales are assigned a trash grade by the USDA-AMS. The approach presented in this paper can be implemented for on-line identification of trash types, and for the computation of the overall trash content during the ginning process. This trash content measurement can be used for the assignment of trash grades for every bale of cotton produced at the cotton gin. Such technology enhancement will greatly reduce the need for large human resources at the various classing offices in the United States. On-line implementation of such a system would be economically attractive to the cotton industry.

Soft Computing

Soft computing is an innovative approach that deals with intelligent systems that combine a wide array of techniques, resources, and knowledge in their design. Most real world applications currently solved use a variety of techniques, which generally are exclusive of each technique. With the approach of soft computing, hybrid systems can be developed which use these techniques synergistically rather than exclusively, where each technique can complement one another in the development of these intelligent systems. This results in a developed system that is adaptive, more responsive to changing environments, and possess human like expertise within a problem domain to make decisions or provide reasoning for the decisions being made. Such systems are referred to as neuro-fuzzy systems. Neural networks that recognize patterns and adapt themselves to ever changing environments; fuzzy inference systems that incorporate human knowledge and make decisions based on some reasoning and inference are some examples of neuro-fuzzy systems.

Several computing paradigms, including neural networks, fuzzy set theory, approximate reasoning, and derivative free optimization methods like genetic algorithms fall in the category of soft computing. Each of these methodologies has their strengths and weaknesses, and the integration of these methodologies for any given problem domain is the basic essence of soft computing.

Three classifiers developed to identify the trash types commonly found in cotton are presented in this paper. The classifiers developed use artificial neural networks, fuzzy-logic based approaches, and hybrid systems to identify trash types in cotton samples. The three classifiers are:

a) Fuzzy clustering technique.
b) Back propagation neural network.
c) Adaptive Network-based Fuzzy Inference System also known as ANFIS.

The classifiers developed are tested for their effectiveness in identifying the trash objects to their respective categories. The classification results serve as a basis for use in the prediction of the trash content and categorization of the individual trash objects in cotton. This enables the ginner to measure the quantity of the individual trash types present in harvested cotton. The technique with the best classification results can be used to identify trash types in real-time (on-line) during the ginning process. Based on the trash types and the amount of each trash type, the ginning process can be optimized by selecting the desired level of drying and cleaning machinery during processing to produce optimal quality lint. This will eventually lead to the development of gin plants that are fully automated.

Trash Identification

The extraction of shape descriptors or features that distinguish the trash objects is an important aspect in the identification of trash types, since features extracted from cotton samples form the feature set (patterns) for various classifier design. When assigning grades to cotton samples, classing specialists can visually inspect the sample and assess the amount of trash. Presence of bark or grass is indicated on classing reports. In the system proposed trash types such as bark, stick, leaf, and pepper trash are identified based on various physical attributes or properties inherent to individual trash types. For example, a bark object can be easily distinguished from other trash types by its stringy appearance. Stick objects are characterized by their oblong appearance (narrow and long in nature). Leaf objects can be distinguished from pepper trash based on the size (area) of the object. However, to categorize the trash types using machine vision systems, unique descriptors need to be identified in order to distinguish trash types. These unique identifiers, extracted for each trash type, would result in higher classification accuracy and improve the overall performance of the classification system.

Numerous methods were evaluated to find these unique identifiers that form the feature space:

a) Features perceived by a classing specialist to be important in distinguishing between the trash types.
b) Relevant default features provided by the imaging system.

c) Computed features suggested in literature, which could provide unique shape descriptors for individual trash objects (Russ, 1994 and Pratt, 1991).

For each object in the image, a set of features was computed. These features form the basis for a component feature vector that defines a point in multi-dimensional feature space. The classifier partitions this multi-dimensional hyperspace into specific regions, where each region corresponds to a type of non-lint material or trash type. Each classification system forms a unique hypersurface separating the feature space into object regions. *Area* and *ferrets X_f and Y_f*, were the default features computed by the image analysis software.

Computed features:

a) *Convex area:* Area of a 32-sided irregular bounding polygon of the object.
b) *Bounding box area:* Product of the ferrets X_f and Y_f. This is the area of a rectangle circumscribing the object with sides of the rectangle parallel to image edges.
c) *Solidity:* Ratio of area to convex area.
d) *Extent:* Ratio of area to bounding box area.

There is no single feature that can identify any of the stated trash types except for pepper trash. All objects with *area* less than 200 pixels can be considered as pepper trash. *Area*, *perimeter*, *shape factor* and *aspect ratio* were previously used as features at the Southwestern Cotton Ginning Research Laboratory (SWCGRL) to identify trash types (Lieberman and Patil, 1992, 1997). In order to obtain better accuracy, various shape descriptors were analyzed for the different trash types. These shape descriptors, along with some of the default features form the feature set or patterns for the various classifiers. These features are used as inputs to the various classifiers to identify the stated trash types.

Figure 1 illustrates the *convex perimeter*, *convex area*, and *bounding box area* measurements for typical bark, stick, and leaf trash objects commonly found in seedcotton. The objects shown are actual blobs extracted from cotton sample images and processed by the image analysis software. Table 1 shows various feature measurements for the trash objects illustrated in Figure 1. Among all the features, extent is the only feature that is rotation variant. Extent measure alone can provide a discriminatory feature to separate bark and stick objects from leaf and pepper objects. This is due to the variation of the *bounding box area* based on the orientation of the trash object in the image plane. This variation is very small for leaf and pepper objects since these two trash types can be approximated as circular objects.

For stick objects oriented either at an angle of 0° or 90°, the *bounding box area* is a minimum. This area is much closer to the actual area of the stick object, resulting in extent values for stick objects closer to unity. The same object oriented at an angle of 45° has the maximum *bounding box area* resulting in low extent measure. The difference between extent measures at 0° and 45° (E^{dif}) provides a distinguishing feature for stick objects.

A bark object's stringy appearance is due to the stripping of the outer covering of the stems of the cotton plant during harvesting and/or ginning. Due to its stringy appearance, the convex perimeter of these objects is different from the actual perimeter of the objects. This results in the *convex area* for bark objects being much larger than the actual area of the object. *Solidity* values for bark objects are typically less than 0.5. In the case of stick, leaf, and pepper objects the convex perimeter is much closer to the actual perimeter of the object. This results in *convex area* of these objects being closer to the actual area of the trash objects. Hence *solidity* measures for stick, leaf, and pepper objects are closer to unity.

Image Acquisition

Most image processing applications involve acquisition of images for processing and extraction of information based on area of interest. Cotton is fluffy and fibrous in nature, a cotton image, when acquired in its free form, contains holes and perforations. For acquisition of cotton images, it is customary to press cotton against a glass plate with the camera mounted across the glass plate. This ensures that the acquired image has a flat or an even (homogenous) surface, with the lint and the trash objects captured as they appear on the surface of the cotton samples. This is generally achieved by increasing the density of the free form cotton with pneumatically driven ram pressing cotton against the glass plate. It is observed in general practice that the images acquired are free of holes or perforations.

For research purposes, images of size 640 x 480 pixels were acquired using a 3-chip CCD Sony® color camera. The imaging hardware consists of a Matrox® IM-1280 imaging board and IM-CLD acquisition board. The acquired images were flat field corrected to remove spatial illumination non-uniformity (Lieberman and Patil, 1997). Trash pixels were separated from the cotton lint background (segmented) using a simple threshold on the intensity plane in HLS (Hue, Luma, Saturation) color space to obtain a binary image where each trash object is identified.

Formulation of Training Data

Training samples for measuring the various features were prepared by placing trash objects on bleached cotton. Each sample contained a single type of trash namely, bark, stick, leaf, or pepper trash. Figures 2 through 5 illustrate the training samples for bark, stick, leaf, and pepper trash types along with the thresholded binary images.

The threshold level was a unique automatic level obtained using the entropy measure on the intensity plane of the RGB color image of the cotton sample (Russ, 1994). The trash objects were chosen from seedcotton to include a wide range with regards to size and shape of the trash types. The distribution of trash types in the training samples was not relative to their distribution in the entire cotton bale. For example, the amount (by number) of pepper trash present in lint is significantly higher compared to the number of bark or stick objects. In addition, depending on the quality of harvested cotton, the trash types may differ in their shape and size. The illustration is a typical set of trash types for a given bale of cotton. The objects were chosen to get a good representation of trash types found in cotton.

Fuzzy Clustering Technique

Clustering techniques essentially deal with the task of splitting a set of patterns into a number of more or less homogenous clusters (or classes). The patterns are separated with respect to a suitable similarity measure so patterns belonging to any one of the clusters are similar and the patterns of different clusters are as dissimilar as possible. In non-fuzzy or "hard" clustering, the boundaries of different clusters are crisp, such that one pattern is assigned exactly to one class. On the contrary, fuzzy clustering provides partitioning results with additional information supplied by the cluster membership values indicating different degrees of membership association or belonging-ness to a particular class (Lin, 1996).

The fuzzy clustering algorithm was used to obtain the fuzzy center for each trash type from the training data set. These fuzzy centers are used to classify the trash objects in five test sample images (Figures 6 and 7 illustrate two of the test samples). The minimum distance criterion is used to classify the trash types. The classification results of trash objects in the five test images are summarized in Table 2.

Back-Propagation Neural Network

Artificial neural networks (ANNs) are systems that are constructed to make use of some organizational principles resembling the human brain. They are good in tasks such as pattern recognition and classification, function approximation, optimization and vector quantization, and data clustering. Traditional computers, due to their architecture, are inefficient at these tasks, especially pattern matching tasks. However, their speed can be utilized in the development of faster algorithm computational tasks and precise arithmetic operations (Medsker, 1994).

The back propagation-learning algorithm is one of the most important historical developments in neural networks. This learning algorithm is applied to multi layer feed-forward networks consisting of processing elements with continuous differentiable activation functions. Such networks associated with the back propagation learning algorithms are also called back propagation networks. Given a training set of input-output pairs $\{(\mathbf{x}^{(k)}, \mathbf{d}^{(k)})\},\ k = 1, 2, \ldots p,$ the algorithm provides a procedure for changing the weights in a back-propagation network to classify the given input patterns correctly. The basis for this weight update algorithm is simply the gradient descent method with differentiable units.

A three-layer back-propagation neural network is trained using inputs *area*, *solidity*, and E^{dif}. The input-output training pairs of data consist of 212 patterns. Based on the weight vectors obtained from the training data, the trash objects in five test images are classified. The classification results of trash objects in the five test images are summarized in Table 2.

Adaptive Network-Based Fuzzy Inference System (ANFIS)

ANFIS is based upon a set of fuzzy rules originally proposed by Takagi, Sugeno, and Kang, commonly referred to as TSK rules. The consequents of these rules are linear combinations of their preconditions (Jang, et al., 1996). The TSK fuzzy rules can be expressed as follows:

$$R^j : \text{IF } x_i \text{ is } A_i^j \text{ AND } x_2 \text{ is } A_2^j \text{ AND} \cdots \text{AND } x_n \text{ is } A_n^j$$
$$\text{THEN } y = f_j = a_0^j + a_1^j x_1 + a_2^j x_2 + \cdots + a_n^j x_n$$

where x_j is the input variable, y the output variable, A_i^j are linguistic terms of the precondition part, and with membership functions of $\mu_{A_i^j}(x_i)$, $a_i^j \in R$ are coefficients of linear equations:

$$f_j(x_1, x_2, \cdots, x_n) \text{ and } j = 1, 2, \cdots, M; i = 1, 2, \cdots, n.$$

Consider the input variables *area*, *solidity*, and E^{dif}. The outputs of the network are fuzzy singletons. For the given input-output training pair, the premise parameters, namely the centers (means), and the widths of the fuzzy membership functions are updated using the hybrid-learning algorithm. The TSK rules for the given input-output data pairs can be expressed as shown in Table 3. The classification results of the trash objects in the five test images are summarized in Table 2 (Siddaiah, et al., 1999a,b).

Trash Content Measurement

Trash Content is defined as the ratio of the total trash area to the image area, i.e.,

$$\text{Trash Content (\%)} = \frac{\text{Trash Area}}{\text{Image Area}} \times 100.$$

The trash area is measured using trash meters. Trash meters count the number of pixels identified as trash based on a certain threshold criteria for a known area of the cotton sample. This measure is currently indicated on cotton classification sheets in addition to classer assigned trash grades during cotton classification. AMS would eventually like to replace the classer assigned trash grade once a reliable system is developed to predict trash grades for cotton. As such, the development of such a system is significant to the industry, since class grades could be assigned to cotton bales at the gin.

The trash content measures for 18 AMS box samples with varying trash levels were computed. These trash boxes are used as standards for calibration of trash meters. Figures 8 and 9 represent two such samples with the lowest and highest trash content.

Table 4 illustrates the AMS and SWCGRL trash content measures for the 18 box samples. It is seen that the SWCGRL measures were higher but consistent with the AMS measures. If an industry standard is developed to tie in the trash content measurements with the classer trash grades, the trash content measurements obtained by the imaging system developed at the SWCGRL can be used in the on-line assignment of trash grades for ginned cotton (Siddaiah, et al., 1999, 2000).

Ginning Process

Figure 10 shows a typical configuration of a modern gin to extract trash and separate fiber from cottonseeds. The entire process is continuous and the flow of cotton through the sequence of machinery is predetermined. The Gin Stand is the heart of the ginning system where the separation of fibers from seeds occurs. The remainder of the equipment used is for drying and the extraction of trash objects. A brief description of each stage is provided, to get a better understanding of the process, for the implementation of the machine vision system for on-line identification of trash types.

The boll trap removes all heavy foreign material (rocks, dirt, etc.) and prevents damage to other equipment during processing. It also removes any unopened green cotton bolls thereby preventing the contamination of mature fiber with bolls containing immature cotton. The automatic feed control provides a uniform flow of cotton so the gin's cleaning and drying systems can operate efficiently. Moisture content in cotton during processing is an important factor that helps determine the quality of ginned fiber. Seedcotton with high moisture content does not clean well and does not lend itself to the rest of the ginning process. Cotton is passed through tower or other types of dryers to maintain the fiber moisture levels at desired levels. The inclined cleaners remove small trash particles. Their cleaning efficiency is generally low. However, one of their most important functions is to break up large clumps of raw cotton and to remove any fine dust and small leaf and stick particles in seedcotton. Results have shown that the total trash removal efficiency of a six-cylinder inclined cleaner with grid rods generally range from 50-55 percent (for fine trash) (Baker, et al., 1977, 1982).

In the next stage of processing, seedcotton is passed through a stick cleaning machine or a similar machine for the extraction of larger trash objects. Cleaning efficiencies of stick machines vary widely, depending on the condition of seedcotton, and on machine design variables. A modern stick machine can be expected to remove about 65 percent of burs, 50 percent of sticks, and 10-35 percent of fine trash (dust and some pepper trash). It is customary to pass cotton through an additional stage of tower drying, inclined cleaner and maybe a second stick machine. Some ginners use a combined bur and stick machine (CBS machine) in the place of stick machine and impact cleaners instead of the second inclined cleaner (Anthony and Mayfield, 1994).

The function of the extractor feeder is to feed seedcotton to the gin stand uniformly and at controllable rates. In addition, the extractor feeder also removes a portion of trash objects left from prior seedcotton cleaning equipment. They can have overall cleaning efficiencies as high as 40 percent for machine picked cotton. Cotton flows from the extractor feeder into the gin stand for the separation of fiber from cottonseeds.

The final cleaning stage involves the use of lint cleaners. Lint cleaners remove the bulk of bark and leaf objects present in the ginned lint. Typically, two stages of lint cleaners are used as a default number during processing. Occasionally, three stages of lint cleaning machines are used for some types of cotton (machine stripped).

Implementation in a Modern Gin

In order to configure an optimal sequence of cleaning equipment during processing, the prime locations to categorize the trash types need to be identified. Based on the nature of the trash types, and the amount of each type of trash present at these locations, the number and types of machines required for processing can be automatically configured during the ginning process.

The first location is before the inclined cleaners where there is physical extraction of trash objects from seedcotton. An imaging system, at this location could be used to evaluate the types of trash, and the amount (by number) of each type present in seedcotton (location **A** in Figure 10). This enables us to estimate the amount of bark, stick, and leaf trash objects present before the seedcotton is passed through the other trash extraction equipment. Determining the amount and the type of trash objects enables the appropriate allocation of resources (i.e. inclined cleaners, stick machines) to clean the cotton. For example, if 60% of the total trash objects are stick objects, and since stick machines operate at 50 percent efficiencies, the cotton stream will be passed through additional stages of stick cleaning if available. Similarly, based on the amount of leaf in the seedcotton additional stages of inclined cleaners can be included in the process stream. The majority of stick, bur, and leaf trash objects could be effectively removed from seedcotton before it enters the gin stand.

It is extremely important that most of the large trash objects be removed from seedcotton before it enters the gin stand to prevent the contamination of ginned lint with other types of trash. Typically, large stick and leaf objects in seedcotton are the source for bark and pepper trash in ginned lint. The amount of bark, leaf, and pepper trash in ginned lint could be reduced significantly if the imaging system at location **A** can allocate the appropriate equipment for the removal of stick and leaf objects.

An imaging system after the gin stand could categorize trash present in lint cotton (location **B** in Figure 10). Based on the estimates of the amount of the trash objects, the number of lint cleaners could be determined. Since lint cleaning affects fiber properties and bale turnout, additional imaging systems could be installed to evaluate the fiber properties and grades of cotton after each stage of lint cleaning. Once cotton is passed through the requisite number of lint cleaners, the cleaned cotton would be compressed into bales and covered to protect from contamination during transportation and storage.

The proposed approach could be effective in optimizing gin machinery for the extraction of trash objects commonly found in cotton. The approach is significantly different from existing techniques. The optimization is based on characterization of trash objects to individual types at various stages of the ginning process. Two critical locations are identified for the implementation of machine vision systems, for on-line identification of trash objects. The imaging system at location **C** can be used to assign a final trash grade at the gin for classification purposes before the bales are shipped to the warehouse.

Conclusion

The paper presents a general framework for implementing a machine-vision based imaging system to automate the ginning process to produce quality cotton. Soft computing techniques discussed indicate that trash objects commonly found in cotton can be categorized as bark, stick, leaf and pepper trash with great accuracies. The on-line identification of trash objects to individual categories could be used to configure an optimal set of cotton cleaning and extraction equipment. The implementation in a modern gin could result in the production of higher quality lint and subsequent finished consumer products. The system could be expected to provide significant energy savings to ginners, due to the judicious selection of equipment based on the characteristics of the cotton being processed. The impact of such an automated system is wide ranging and could have significant benefits to the entire cotton industry.

Disclaimer

Mention of a trade name, proprietary product, or specific equipment does not constitute a guarantee or warranty by the U.S. Department of Agriculture and does not imply its approval to the exclusion of other products that may be suitable.

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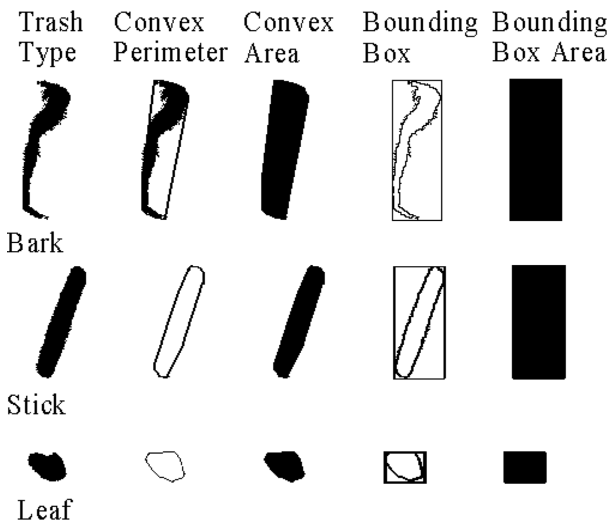


Figure 1. Trash types with feature measurements.

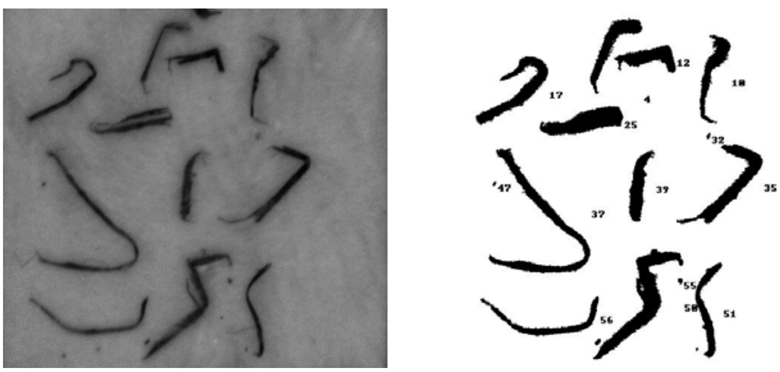


Figure 2. Bark trash type.

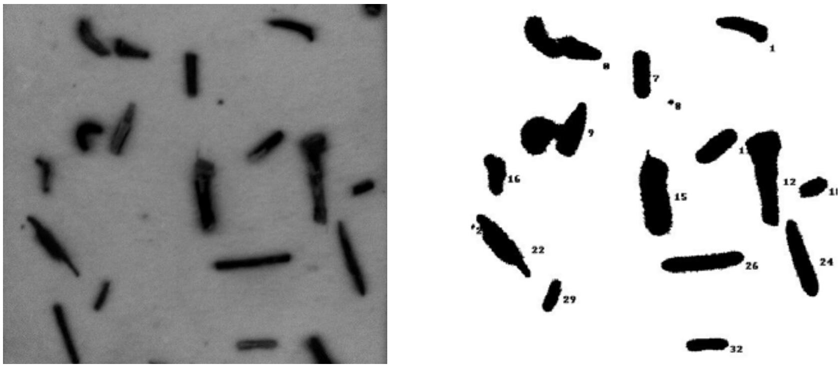


Figure 3. Stick trash type.

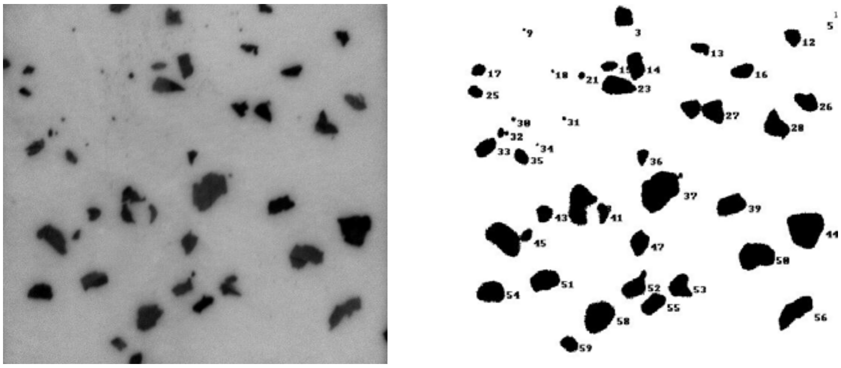


Figure 4. Leaf trash type.

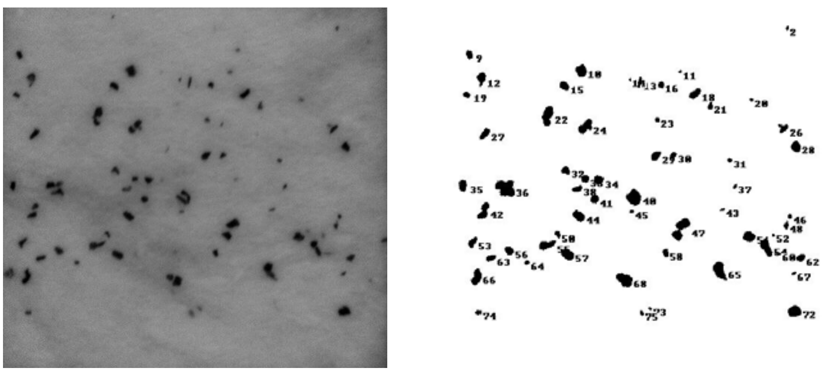


Figure 5. Pepper trash types.

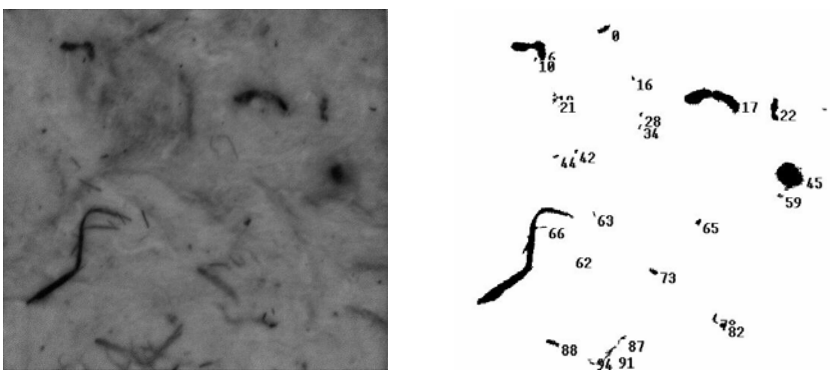


Figure 6. Cotton test sample #1.

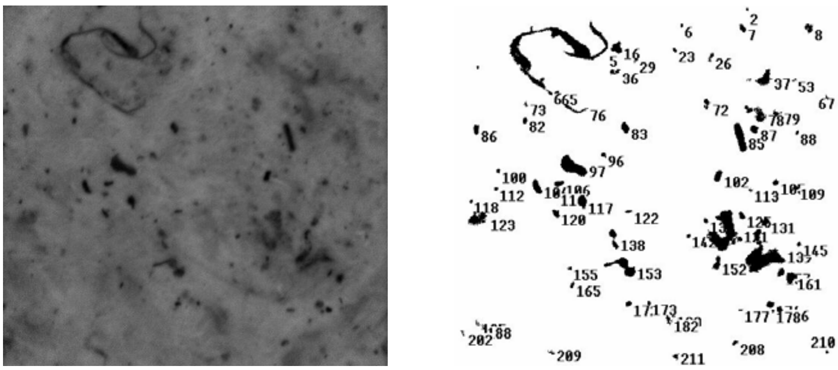


Figure 7. Cotton test sample #2.

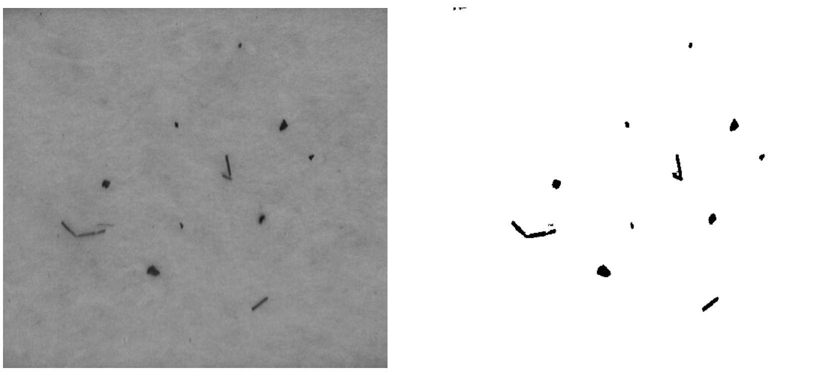


Figure 8. AMS cotton box sample #1 (Trash Content = 0.27).

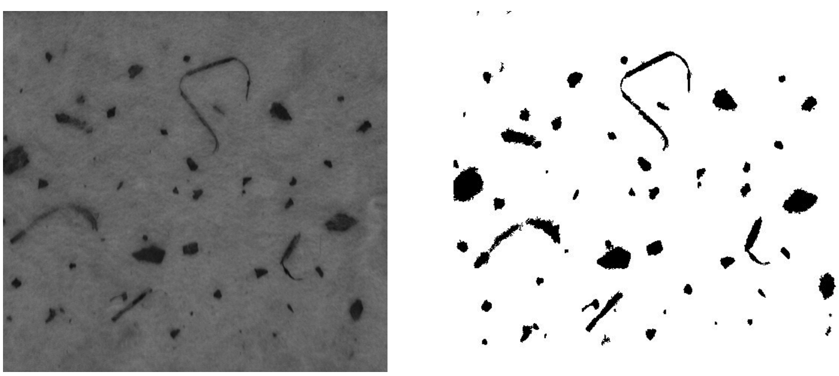
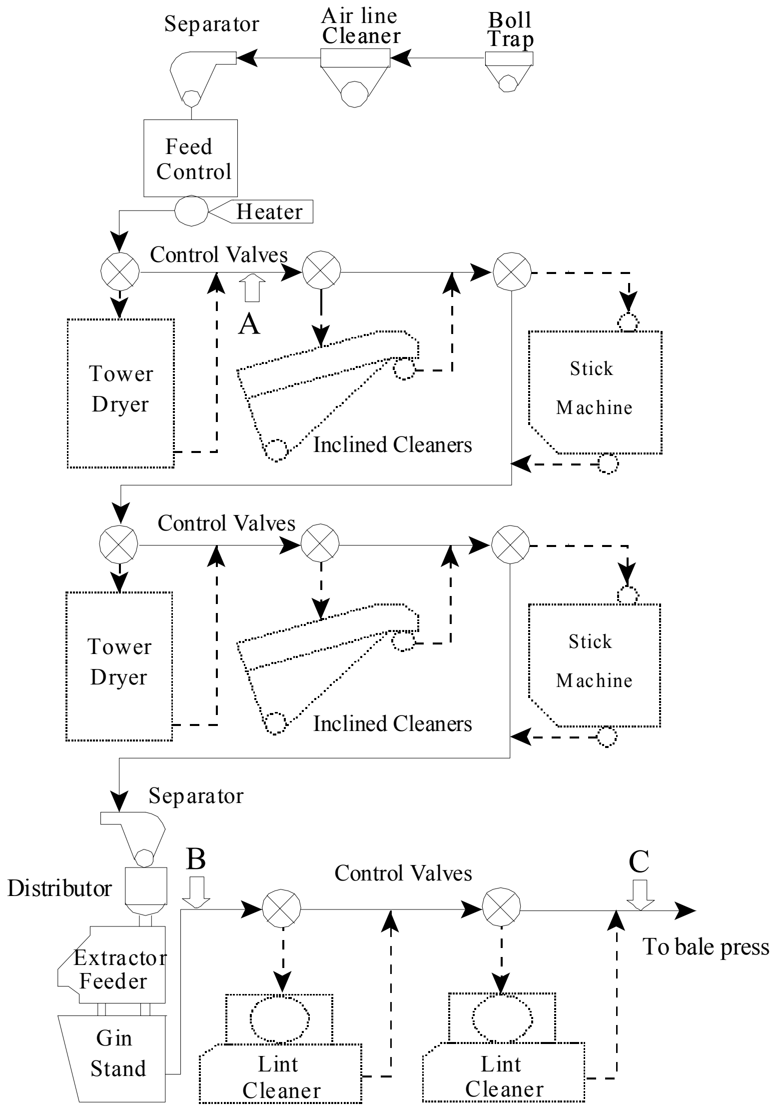


Figure 9. AMS cotton box sample #6 (Trash Content = 2.87).



A Imaging system for trash identification in seed cotton

B-C Imaging system for trash identification in lint cotton

Figure 10. Schematic for trash identification.

Table 1. Feature measurements.

Trash type	**Bark**	**Stick**	**Leaf**
Area	1526	1578	581
Convex area	3123	1638	624
Bounding box area at 0°	4640	2079	900
Bounding box area at 45°	8692	5700	840
Perimeter	392.9700	238.5920	97.8000
Convex perimeter	274.7300	222.4640	95.1100
Solidity	0.4886	0.9634	0.9311
Extent at 0°	0.3289	0.7590	0.6456
Extent at 45°	0.1756	0.2768	0.6917
E^{dif}	0.1533	0.4822	0.0461

Table 2. Classification results.

Classifier	Total Number of Objects	Actual Trash Type	Classified: Bark	Stick	Leaf	Pepper	Classification Rate (%)
Fuzzy Clustering	10	Bark	0	4	6	0	88.57
	4	Stick	0	0	0	4	
	16	Leaf	0	0	2	14	
	215	Pepper	0	0	0	215	
Neural Network	10	Bark	6	4	0	0	90.20
	4	Stick	1	2	1	0	
	16	Leaf	0	3	6	7	
	215	Pepper	1	2	5	207	
ANFIS	10	Bark	6	4	0	0	95.10
	4	Stick	0	2	0	2	
	16	Leaf	0	2	14	0	
	215	Pepper	0	0	0	215	

Table 3. TSK fuzzy rules for trash identification.

Rule	**IF *Area* is**	**AND *Solidity* Is**	**AND E^{dif} is**	**THEN *Trash Type* is**
R^1	Small	Small	Small	Pepper
R^2	Small	Small	Large	Pepper
R^3	Small	Large	Small	Pepper
R^4	Small	Large	Large	Pepper
R^5	Large	Small	Small	Bark
R^6	Large	Small	Large	Bark
R^7	Large	Large	Small	Leaf
R^8	Large	Large	Large	Stick

Table 4. AMS and SWCGRL trash content measurements for the cotton trash boxes.

Sample No.	AMS Values	SWCGRL Values (avg. of 10 reps)	Ratio AMS to SWCGRL Values
# 1	0.2716	0.6258	0.4340
# 2	0.4209	1.0284	0.4093
# 3	0.9006	2.1106	0.4267
# 4	1.4160	2.9832	0.4747
# 5	1.7370	3.4957	0.4969
# 6	2.8687	5.5055	0.5211
# 7	0.1010	0.2191	0.4609
# 8	0.2903	0.6316	0.4596
# 9	0.4428	1.0374	0.4268
# 10	0.6791	1.4967	0.4537
# 11	1.1573	2.3822	0.4858
# 12	1.9060	3.9445	0.4832
# 13	0.1066	0.2312	0.4611
# 14	0.2727	0.5953	0.4581
# 15	0.4344	0.9574	0.4537
# 16	0.7009	1.4068	0.4982
# 17	1.1077	2.1989	0.5038
# 18	0.4422	0.9677	0.4570