Global Optimized Multiscale Tobacco Leaves Inspection through Graph Cut

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Abstract

We present a novel multiscale methodology for automatic machine vision application aiming at detecting the size ratio of tobacco leave, and the inspection data will be feedback to adjust running parameters of packaging systems. Firstly, the image is represented by a multiscale Markov Random Field(MRF) model, namely, hidden Markov tree(HMT), which models inter and intra scale dependices of wavelet coefficients. Secondly, according to convex optimization theorem, the energy on hidden Markov tree model is reformulated as a convex version in terms of pseudo marginals. Finally we give the tobacco target segmentation results of the inspection system, which appears to be of better segmentation quality compared to that of the conventional nonconvex energy function.

Introduction

Machine vision systems have been developed to perform industrial inspection tasks in manufacturing line, which can replace human visual separation and at the same time allow real-time signal feedback for on-line manufacturing process adjustment. For example, machine vision systems are in existence that can recognize apple defects [1], printing quality perception based on RBF neural network [2], fault segmentation in fabric images using Gabor wavelet transform [3]. In this paper, we investigate machine vision application for size ratio inspection of tobacco leave in a packaging line.

The size ratio of tobacco leave is one of the most important parameters in the tobacco manufacture and packaging line which is used to evaluate the tobacco quality and adjust running parameters. Nowadays, this parameter is obtained manually by the operator. In particular, the operator firstly performs stochastic sampling of tobacco leave from manufacturing line and put them onto vibration grading sifter from which the tobacco leaves are separated into different sizes. A typical vibration grading sifter is illustrated in Figure 1. Secondly, the weight of tobacco leaves with various areas is weighted by the operator. Finally, the data is registered and feedback to the other operator who would adjust the manufacturing parameters according to it. The drawback of this inspection method is obvious. On the one hand, this measuring method is off-line which will take a relative long time, that is, the measuring could not synchronize with the parameter adjustment. On the other hand, the measuring process wastes redundant manpower costs.

In this paper, we present a novel multiscale inspection methodology which is used to detect the size ratio of tobacco leave automatically with the help of machine vision devices. The segmentation accuracy of the acquired tobacco leave image is the key step for size ratio computation which is used to estimate tobacco quality and feedback control of manufacture system. We first represent the image using a multiscale Markov Random Field(MRF) model, namely, hidden Markov tree(HMT), which models inter and intra scale dependices of wavelet coefficients. According to convex optimization theorem, the energy on hidden Markov tree model is then reformulated as a convex version in terms of pseudo marginals. Finally we give the tobacco target segmentation results of the inspection system, which is compared to that of the conventional nonconvex energy function.

Figure 1. *A typical vibration grading sifter. The grading sifter has four layers, in which the holes have different sizes. In precise, the higher the layer, the larger the holes. After vibrating a specific time, the tobacco leave are grouped into four classes, each of which has a specific range of sizes.*

Hidden Markov Tree

Descrete wavelet transform is employed to decompose each frame I in a multiscale representation structure. The key idea of wavelet decomposition is to model different aspects of a dataset using basis expansion, with larger-scale components modeling overall trends and smaller-scale components modeling finer details. Since Haar wavelet is orthogonal and linear in phase, it has formed the basis of many previous works on multiscale decomposition for the purpose of image segmentation.

The standard way to obtain 2D wavelet decomposition is to use the tensor product of 1D Haar filters(low-pass: $g = 1/\sqrt{2}\begin{bmatrix}1 & 1\end{bmatrix}$ and high-pass: $h = 1/\sqrt{2}\begin{bmatrix}-1 & 1\end{bmatrix}$) repeatedly along vertical and horizontal directions of the frame I_t. The outputs are subsampled by a factor of two and consist of three high-pass subbands HL, LH, HH and one low-pass subband LL, corresponding to the four filters $h^T * h$, $g^T * h$, $h^T * g$, $g^T * g$, respectively.

Then we define the hidden Markov tree to model the distribution of wavelet coefficients $\mathbf{w}$ obtained from wavelet decomposition. Let $G = (V, E)$ be a directed graph with the set of vertices V and the set of edges E. For each node $s \in V$, let x_s be a variable taking values in some discrete space X_s. In the binary segmentation case, $X_s \in \{0,1\}^{3\times L}$. Let (s,t) denote the directed edge in E that linking the nodes from s to t. Let j and k denote values taking by X_s and X_t, respectively. It is important to note that each node s in the graph G corresponds to a wavelet coefficient w. An extreme case of increasing the number of decomposition scale by Haar wavelet happens in the situation of full scale decomposition, i.e., decompose image I up to $L = \min\{\log_2 M, \log_2 N\}$ scales. In this case, the graph G is a tree.

Having formed the hidden Markov tree, it is necessary to represent the global distribution in terms of local constraints. A typical representation is the Gibbs form, in which a distribution is specified as the exponential of a sum of functions on the cliques. In particular, the distribution on the WHMT G is given by

$$p(\mathbf{x} \mid \boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta})} \exp(\sum_{s\in V} \theta_s(x_s) + \sum_{(s,t)\in E} \theta_{st}(x_s, x_t))$$

where $Z(\boldsymbol{\theta})$ is the partition function, $\theta_s(x_s)$ and $\theta_{st}(x_s, x_t)$ are unary penalty function and pairwise interaction potential, respectively. Note that here we employed pairwise cliques instead of high-order ones to form the joint distribution, because the latter case will inevitably lead to a high computational cost. Similar to [4], we denote the sum of unary and pairwise terms by energy $E(\mathbf{x} \mid \boldsymbol{\theta})$, i.e.,

$$E(\mathbf{x} \mid \boldsymbol{\theta}) = \sum_{s\in V} \theta_s(x_s) + \sum_{(s,t)\in E} \theta_{st}(x_s, x_t) \tag{1}$$

The main difference between our energy function and [4] is that our energy can be used to model classification cues computed at multiple scales. Since the minimum of E corresponds to the maximum a posteriori labeling of $\mathbf{x}$, we will focus on global minimization of the multiscale energy function.

Energy Reformulation

To achieve global optimization of the multiscale energy function, we aim to seek a reformulation $\tilde{E}$ of E that is convex in marginal distribution. In this sense, the local minimum computed by any efficient approximate optimization algorithm is guaranteed to be global minimum of the new multiscale energy function $\tilde{E}$. The key idea is motivated by the intuition that the larger the entropy, the less a priori information one has on the value of the random variables. In particular, we define the negative entropy of marginal distribution on the hidden Markov tree as

$$H(\boldsymbol{\mu} \mid T) = \sum_{s\in T} H(\mu_s) + \sum_{(s,t)\in T} H(\mu_s \mid \mu_t)$$

where $\boldsymbol{\mu}$ is the collection of node and edge pseudo marginals of the subtree T embedded in graph G, denoted as μ_s and μ_{st} respectively. By concatenating the negative entropy of all subtrees, the energy function of the hidden Markov tree thus can be reformulated as

$$\tilde{E}(\boldsymbol{\mu} \mid \boldsymbol{\rho}, \boldsymbol{\theta}) = \sum_{s\in V} \rho_s H(\mu_s) + \sum_{(s,t)\in E} \rho_{s|t} H(\mu_s \mid \mu_t) \tag{2}$$

where ρ_s and $\rho_{s|t}$ are the appearance probabilities of node s and edge (s,t) in graph G, respectively. In this paper, we assume that the pseudo marginals take values in the interval (0,1]. According to the definition of negative entropy, i.e., $H(\mu) = \mu \cdot \log \mu$, the unary energy function $H(\mu_s)$ thus can be calculated, the result of which is illustrated in Figure 2. From Figure 2 we can find that the unary energy function is convex in terms of pseudo marginals. The advantage of reformulating the original energy function (1) as a convex function (2) is that the local minimum computed by any approximate optimization algorithm, such as graph cut [4], tree-reweighted message passing [5], is guaranteed to be global minimum of the new energy function.

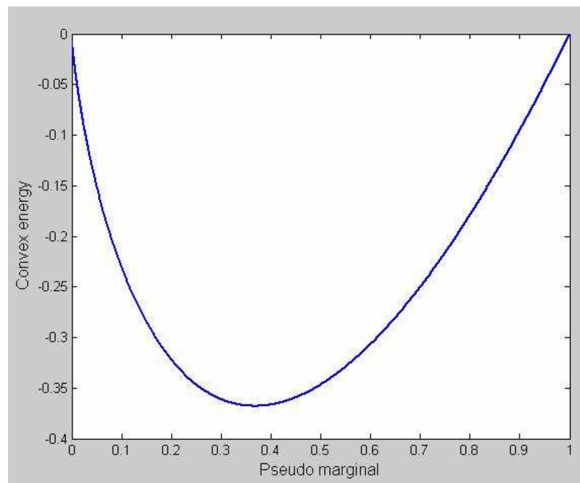

Figure 2. *The unary energy function. This energy is convex in terms of pseudo marginals.*

Experiments

To demonstrate and evaluate our method, we chose to use two frame of real images as inputs, which are acquired by a tobacco packaging machine equipped with a line scan CCD camera. Figure 3 shows the original experimental setup of image acquisition system in a tobacco packaging line. The task is to extract the tobacco objects from backgrounds accuartely regardless of the dynamic conditions. We use a personal computer with CPU 1.86GHz and 1G memory to perform the testing. The programs are written in Matlab7.0.1.

In this paper, we compared the segmentation results of two frames which are captured by image acquisition system shown in Figure 3 by using convex energy function (in Equation (2)) and nonconvex energy function (in Equation (1)) construction. The efficient graph cut algorithm is selected to perform energy minimization of the multiscale convex energy function. the energy minimization is an iterative process, each of which contains three stages.

The first stage is the growth stage. The active nodes search adjacent nonsaturated edges, i.e., the edges such that $tree\_cap(s \to t) > 0$ and capture new children from free nodes.

Figure 3. *The original experimental setup of image acquisition system in a tobacco packaging line.*

Here $tree\_cap(s \to t)$ denotes the residual capacity of $edge(s,t)$. In this way, the search trees expand until they encounter a neighboring node that belongs to the opposite tree, thus a path P from source s to sink t is detected.

The second stage is the augmentation stage. At this phase, the residual graph is augmented by pushing the flow, the amount of which is the bottleneck capacity on P, through the path. Once $edge(s,t)$ on the path becomes saturated, the son of $edge(s,t)$ becomes an orphan. In this way, the search trees break into forests after augmenting.

The third stage is called adoption stage in which each orphan tries to find a new valid parent within the same search tree. A valid parent s of t should satisfy $tree\_cap(t \to s)$. If there does not exist a valid parent of s, it becomes a free node.

To obtain a quantitive measure about the segmentation results, in the following, we select the criteria of segmentation accuracy. The segmentation accuracy is represented by Pa which is defined as the percentage of pixels classified correctly by the algorithm. From Table 1 we can see that the segmentation accuracy of the two frames using convex energy function construction is 98.22% and 96.06%, respectively. In addition, the segmentation accuracy by convex energy improved 2.81% and 1.29%, respectively.

Table 1: Segmentation results of two frames using convex and nonconvex energy function.

Energy	Pa of frame 1(%)	Pa of frame 2(%)
Convex	98.22	96.06
Nonconvex	95.41	94.77

Conclusion

In this paper, we present a multiscale methodology for automatic machine vision application for the purpose of detecting the size ratio of tobacco leave, which can be feedback to adjust running parameters of packaging systems. The images are represented by a hidden Markov tree model. According to convex optimization theorem, the energy on hidden Markov tree model is reformulated as a convex version in terms of pseudo marginals. The advantage of reformulating the original energy function as a convex function is that the local minimum computed by any approximate optimization algorithm is guarangeed to be global minimum of the new energy function. Finally we give the tobacco target segmentation results of the inspection system, which appears to be of better segmentation quality compared to that of the conventional nonconvex energy function.

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Author Biography

Yinhui Zhang received his BS and MS in mechinical engineer and Printing Engineering from Xi'an University of Science and Technology(2000 and 2005), respectively. Since then he has worked in the Department Packaging Engineering in Kunming University of Science and Technology, Kunming. His work has focused on the automatic machine vision identification and machine learning. He is a member of IEEE and IEEE Computer Society.