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Unhealthy Detection in Livestock Texture Images using Subsampled Contourlet Transform and SVM

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ABSTRACT

In this paper a new split and merge algorithm based on Contourlet transform and Support Vector Machine (SVM) is presented for automatic segmentation and classification of unhealthy in Livestock Texture Images. We focused on the liver textural images of livestock to verify if there is any unhealthy on its textural image. The Contourlet transform is used because it allows analysis of images with various resolution levels and directions. It effectively captures smooth contours that are dominant features in textural images. In addition, we have used SVM classifier to classify the texture features. The proposed method provides a fast algorithm with enough accuracy that can be implemented in a parallel structure for real-time processing. The simulation results show the effectiveness of the new proposed algorithm.

Keywords: *Livestock, Texture, Image, Unhealthy, liver, Contourlet, SVM*

1. INTRODUCTION

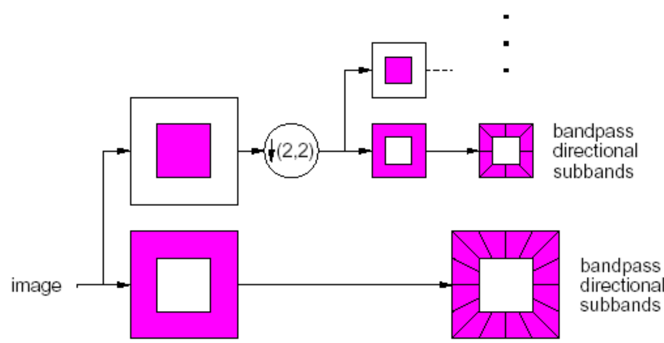
There are many kinds of popular diseases in poultries and livestock's which carried on slaughter houses. For the safety and health reasons, these kinds of infected livestock's should be recognized and omitted from the slaughter line. In a traditional method, an inspector, usually a veterinarian or his/her assistant, inspects visually the line of slaughter, and omits the poultries which look to be unhealthy due to their thin body or unusual skin color. Even this method may look to be enough safe, but increasing demand on daily and fresh meat in the market, direct us to enhance the inspection method by using an automated machine vision system. Substitution of human inspection with a machine has many benefits including: decreasing the overall payment cost, increasing safety and quality of the meat production process and finally, applying a fast and consistent inspection rule over all the slaughter houses of the country. The inspection system should be designed to be an efficient composition of human intelligence and experience along with the fastness of a machine.

In this paper, the problem of automatic segmentation and classification of the livestock textural images using Contourlet transform and SVM is discussed. Here we used the liver images of each livestock to verify the healthy. It means that we focus on the liver texture and determine if there is any unhealthy on it. We would like the classification task to be computationally inexpensive and enough fast to be applied in a real-time environment.

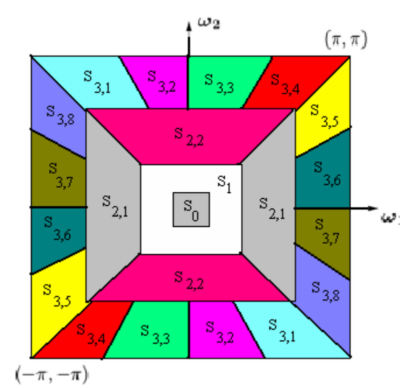
The organization of the paper is as follows: In Section 2 Cotourlet transform briefly explained. In Section 3 SVM algorithm is discussed. The proposed approach for automatic unhealthy detection based on Contourlet transform and SVM is discussed in Section 4. In Section 5 the experimental results are outlined. Finally the conclusion is the subject of Section 6.

2. CONTOURLET TRANSFORM

The Contourlet transform is a new two-dimensional extension of the wavelet transform proposed by Do and Vetterli [1]. Figure 1 shows the fundamental structure of this transform. The contourlet expansion is composed of basis



(a)



(b)

Fig 1: Contourlet Transform

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images oriented at various directions in multiple scales, with flexible aspect ratio that could effectively capture smooth contours of seabed images. This transform employs multiscale and directional filter banks with critical down-sampling operation, shearing operation, and coefficient re-arrangement. Contourlets can represent a smooth contour with fewer coefficients than that of the wavelets. The Contourlet transform, as illustrated in Figure 1(a), employs an efficient tree structured implementation, which is an iterated combination of the Laplacian Pyramid (LP) [2], to capture the point discontinuities, and the Directional Filter Bank (DFB) [3], to gather the nearby basis functions and to link point discontinuities into linear structures.

Since the DFB was designed to capture the high frequency directionality of the input image and it is poor in handling low frequency content, the DFB is combined with the LP, where the low frequencies of the input image is removed before applying DFB. Figure 1(b) shows the resulting frequency division, where the whole spectrum is divided both angularly and radially and the number of directions is increased with frequency. It was shown that the discrete contourlet transform achieves perfect reconstruction and has a redundancy ratio that is less than 4/3. It has been shown that the discrete Contourlet transform is shift variant, and achieves perfect reconstruction [4].

The nonsubsampled contourlet transform [5] is a redundant expansion of the contourlet transform to allow practical processing on square-size directional sub-bands. The redundancy is achieved by discarding any down-sampling operation in the Laplacian pyramid scheme. We modified this transform by doing down-sampling at each scale to have the chance of multiresolution analysis on square-size directional sub-bands. We can imagine that the subsampled contourlet transform is similar to the standard contourlet transform without using shearing operator and coefficient re-arrangement. Figure 2 displays an overview of the proposed subsampled contourlet transform [6].

3. THE SUPPORT VECTORE MACHINE

Support vector machine (SVM) [7] has been developed initially for the supervised classification. Because of its excellent performance in nonlinear and high dimensional pattern recognition with small samples, SVM is regarded a powerful machine learning tool that has been widely applied in texture segmentation and other applications of machine learning including function approximation and probability estimation. Suppose the training set is:

$(x_1,y_1),\ldots,(x_m,y_m)$, $x_i \in R^n$, $y_i \in \{-1,1\}$ where n is the dimension of the input vector, m is the number of samples, and y_i indicates which class x_i belongs to. The SVM attempts to obtain a good separating hyper plane between the two classes. If the data are linear separable, the desired optimal hyper plane can be defined by

$$w.x + b = 0 \qquad (1)$$

where w is the normal vector of the hyper plane, b is the distance from the origin to the hyper plane. If we suppose the training data satisfy

$$\begin{aligned} w.x_i + b &\geq 1 \ \text{ if } \ y_i = 1 \\ w.x_i + b &\leq -1 \ \text{ if } \ y_i = -1 \end{aligned} \qquad (2)$$

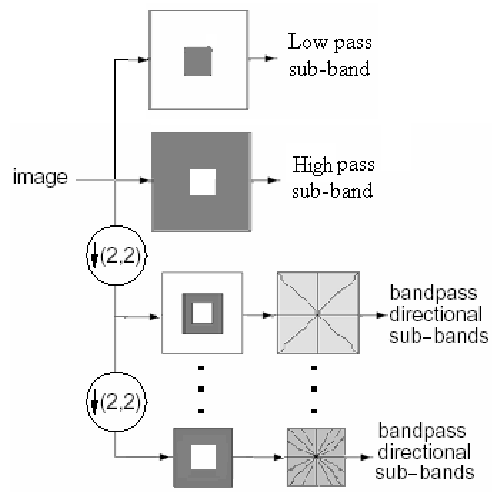

Fig 2: The Subsampled Contourlet Transform [6]

the minimum distance from the training vector to the hyper plane is

$$\min \frac{|w.x+b|}{\|w\|} = \frac{1}{\|w\|} \qquad (3)$$

Thus, the support vectors can be approached via solving the following quadratic convex programming

$$\min \frac{1}{2}\|w\|^2 = \frac{1}{2} w.w^T \qquad (4)$$

$$s.t. \, y_i(w.x_i + b) \geq 1 \quad i=1,\ldots,m \qquad (5)$$

Practically, the training set may not be linear separable. Therefore, we should introduce the slack variable $\xi_i \geq 0, i = 1,.., m$ to relax the separable constrains (5) as follows

$$y_i(w.x_i + b) \geq 1 - \xi_i \qquad (6)$$

The objective function (4) should be changed accordingly to

$$\min \frac{1}{2}\|w\|^2 = \frac{1}{2} w.w^T + C\sum_{i=1}^{m} \xi_i \qquad (7)$$

where C is a penalty parameter to control the relaxation. Usually, the quadratic convex programming (7) is reformulated with Lagrange multiplier method and solved numerically by quadratic programming. The general schema of SVM is illustrated in Figure 3.

4. THE PROPOSED APPROACH

4.1 The Methodology

In this section a new split and merge algorithm based on subsampled Contourlet transform and Support Vector Machine (SVM) is presented for automatic segmentation and classification of unhealthy in the liver Texture Image of

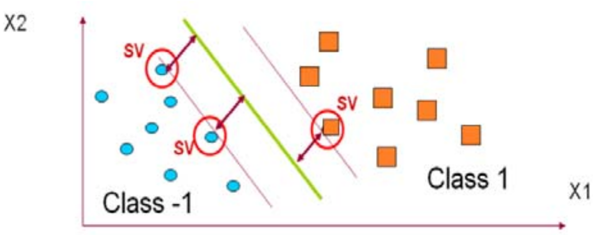

Fig 3: General schema of SVM

Livestock. The architecture of our approach is illustrated in Figure 4. A digital camera takes a picture from the liver of livestock. After preprocessing including contrast stretching, the image should be segmented into the object and background. Segmentation is a challenging problem in the field of computer vision. However, since the background of our camera is black, we used a simple threshold to discriminate the object from the background.

The resulted texture images are is decomposed using three levels of subsampled contourlet transform. Then features obtained from 12 directional band pass sub-band coefficients (8 at level 3, 2 at level 2, 1 at level 1, and 1 at level 0). Let $s_{0,0}$ be the low pass sub-band and $S_{1,1}$, $s_{2,1}$ - $s_{2,2}$, and $s_{3,1} \ldots s_{3,8}$ be band pass directional sub-bands at the first, second, and third decomposition levels, respectively. Since $s_{0,0}$ and $s_{1,1}$ have the same resolution size, we use them together to construct the highest resolution segmented image. On the other hand, $s_{2,1} \ldots s_{2,2}$ and $s_{3,1} \ldots s_{3,8}$ are used to construct the segmented image with medium and lowest resolution, respectively.

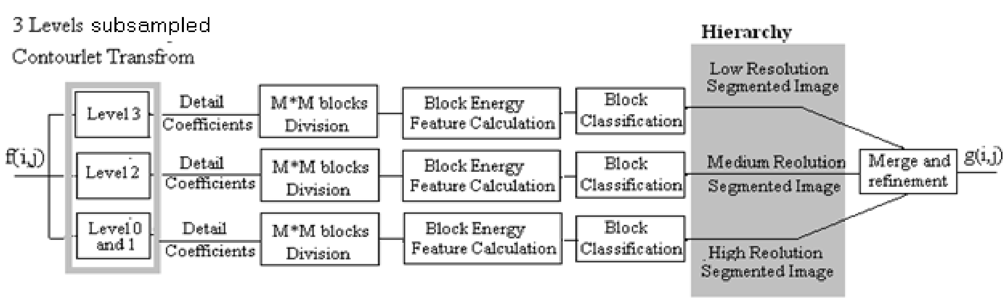

Fig 4: Block diagram of the proposed method

Following the block diagram of Figure 4, each decomposed level image split into $M \times M$ blocks. In this work M is chosen to be 4 based on the resolution of the acquired images. The energy of each block is calculated and each block is classified using trained SVM classifier. Finally, the classified blocks on the boundaries of the segmented image are refined and merged to produce the final segmented image.

Squared root of average energy of the subsampled contourlet coefficients of the block on each sub-band is calculated as:

$$E_{u,v}(x,y) = \sqrt{\frac{\sum_{i=x}^{x+M} \sum_{j=y}^{y+M} S_{u,v}{}^{2}(i,j)}{M^{2}}} \qquad (8)$$

4.2 SVM Block Classification

Support Vector Machine classifier that is used in this stage is pre-trained using $M \times M$ parts of predictable textures. The calculated features from each block are imported to a polynomial SVM as an input vector, and this classifier is determined class of each block. In this paper many different kernels are tested and finally 3rd degree polynomial kernel showed that produces better results.

4.3 Merge and Refinement

Since different textures are revealed at different scales the hierarchy composed of three coarse segmented images obtained from three-level subsampled contourlet decomposition should be merged and the boundaries between classified regions must be refined. To do this, the following algorithm, originally presented by Javidan in [6],

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with some minor modifications is used. This modified algorithm is another contribution of this paper since it gives good results for the subsampled contourlet decomposition as well.

a. Block refinement

The main purpose of this part is to compare the class label of a block with the labels of its neighbors and modify it if necessary. At this point, block refinement is performed on each of three segmented images of the hierarchy, separately. Consider each non-overlapping block in any of the segmented images. Again M is chosen to be 4 as the same value as considered previously. Like a major vote system, if the block's class label is identical to that of the all four-connected block neighbors, do nothing. Otherwise, if all four-connected neighborhood blocks or at least three of them have the same class label, replace the class label of centered block with the class label of its major neighbors. This process should be done block-wise in a raster scan fashion, from top left corner of the image.

b. Image size expansion

Because of the decimated (down sampling) property of the subsampled contourlet decomposition, the size (dimension) of the segmented image of level three of the decomposition is one quarter of the size of the segmented image at level one and the level two is one half of the size of the level one as well. As a result, the level three and level two must be expanded to the size of level one before merging. Remember that the size of the segmented image obtained from level one of the decomposition is equal to the size of the original image.

c. Merging of three segmented images

Following dimension expansion, scan all pixels (points) of the three segmented images simultaneously from top left corner to the bottom right corner in a raster scan form. For each point of the new constructed image assign a class label that exists in the corresponding points of at least two images of the three segmented images. Otherwise, select the class label of the corresponding point of the lowest resolution segmented image obtained from level two of the subsampled contourlet decomposition. In other words, in cases of no agreement between finer segmentation results obtained from level one and level two (i.e. there are differences between details of regions of the image under segmentation), the coarser segmentation obtained from level 3 which contains less details, gives the most discriminate.

d. Boundary pixel refinement

Scan all points of the resulted image obtained in previous part from top left corner in raster scan form. Consider the pixels of boundaries of adjacent texture regions and test to see if they are similar with all 4-connected neighbors. If any point on the boundary (edge) is evaluated to be of different class label from at least one of its 4-connected neighbors, the class label of that point in the new constructed image should be changed. This change should be based on the equivalent class label of the corresponding point in the original fine segmented image obtained from level one of the subsampled contourlet transform (because it contains detail information of the regions). Otherwise, leave the class label of the new constructed image to be the same as the class label of that point of the merged image.

e. Deleting disconnected islands

The isolated regions with small area should be deleted from the merged image obtained in previous part. Discard any disconnected region which has area less than a known threshold by replacing it with its neighbors. This threshold relates to the sonar image resolution.

5. EXPERIMENTAL RESULTS

For testing the proposed approach, 22 images covering both healthy and unhealthy livestock acquired from a modern slaughter house. The images are from the liver including 11 healthy and 11 unhealthy livestock. Figure 5 shows two samples of these images. Figure 5 (a) shows a healthy liver while Figure 5 (b) shows an unhealthy liver. For getting better results, the background at the imaging point covered with a black screen. After preprocessing of the acquired images, including contrast stretching and color level adjustment, the images were segmented using a simple threshold. Just as an example, Figure 6 shows a real sample image and the segmented results. For better understanding of the proposed method, the intermediate results are outlined.

As another example Figure 7 shows another liver texture image and the final segmented results as an unhealthy tissue

6. CONCLUSION

In this paper a new split and merge algorithm based on the concept of subsampled Contourlet transform and SVM classifier for automatic classification of the livestock images in slaughter houses is introduced. In a traditional method, an inspector, usually a veterinarian or his/her assistant, inspects

Fig 5: (a) a healthy liver (b) an unhealthy liver

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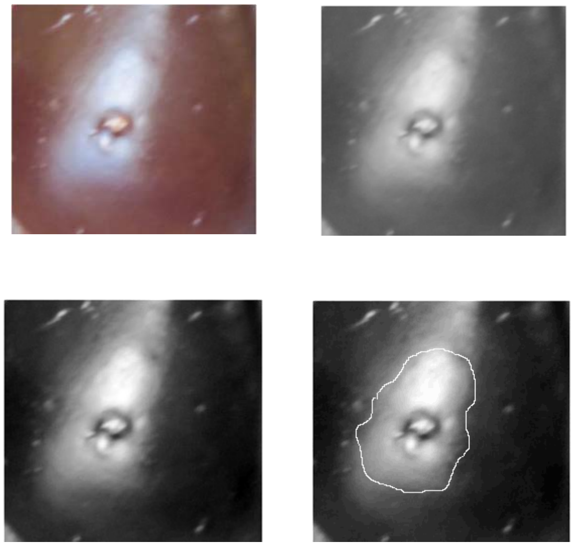

Fig 6: (a) Original images. (b), (c) after preprocessing (d) Final unhealthy detection

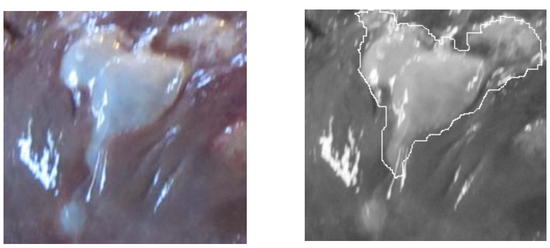

Fig 7: (a) Original image of an unhealthy liver (b) Final Detection

visually the line of slaughter, and omits the carcass which look to be unhealthy. Substitution of human inspection with a machine has many benefits including: decreasing the overall payment cost, increasing safety and quality of the meat production process and finally, applying a fast and consistent inspection rule over all the slaughter houses of the country.

The subsampled contourlet transform appears to be a suitable tool for this task and best parameters for this transform are obtained. The energy of each contourlet sub band coefficient is used to construct the texture feature vector. SVM is selected as an excellent nonlinear classifier, and best parameters for this classifier are obtained. The post processing performance relies on refinement approach has been demonstrated to be able to enhance contourlet crisp segmentation and gave better results than other well known techniques. The main advantage of the proposed method is a relatively small vector of features, which is sufficient for texture classification. In addition, it was fast enough to be applied for real time analysis in a new automatic texture segmentation system.

Experimental results on 22 real sample images from both healthy and unhealthy images, showed the fidelity of the proposed approach with accuracy rate of %91.

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Alireza Mollaei received Professional Doctoral in the veterinarian field from Kazeroun Branch, Islamic Azad University. He is now the vice chancellor of Beyza Branch, Islamic Azad University.