Cattle Face Recognition Using Local Binary Pattern Descriptor

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Abstract— In response to the current need for positive identification of cattle traceability, this paper presents a novel facial representation model of cattle based on local binary pattern (LBP) texture features and some extended LBP descriptors are also introduced. Algorithm training was performed independently on several normalized gray face images of 30 cattle (with each having a set of six, seven, eight, and nine images respectively). Robust alignment by sparse and low-rank decomposition was also used to align the images because of variations in illumination, image misalignment and occlusion in the test image. The performance of this technique was assessed on a separate set of images using the weighted Chi square distance [1]. The LBP descriptor shows its excellence in efficiency and accuracy with regard to the encouraging results on cattle face recognition. More training sets and modified algorithms will be considered to improve recognition rates. Future work should aim at improving the automation of the system and combining the LBP histogram with other effective histograms.

I. INTRODUCTION

Recent outbreaks of major diseases such as bovine spongiform encephalopathy, foot and mouth disease, and swine fever, have prompted the implementation of animal identification and verification programs internationally. The major components of a secure animal identification and source verification system include: rapid, inexpensive, and accurate acquisition of information security against fraud, human administration and easy and rapid transmission, storage and retrieval of data [2]. Animal ear tags have been proved to be not very successful as a means of identification for such reasons as the loss of tags, tempering, and animal welfare. The insertion of ear tags normally results in an inflammatory response (extreme discomfort and pain) and the ear tags could cause both short-term and long-term complications of the integrity of the ears [3].

While an animal can be allocated an identification number and the system of identification can be made as tamperproof as far as possible, it would be beneficial to verify an animal's identity against an invariant parameter, particularly in case of suspected fraud. A physical, anatomical, or bimolecular invariant trait that uniquely identifies an animal is under consideration. Means of identifying livestock through biometric markers include DNA "fingerprinting", autoimmune antibody matching, iris scanning, retinal imaging, muzzle print matching [4], and facial recognition [5].

Facial images are the most common biometric characteristic used by humans to gain personal recognition, hence the interest in using this biometric feature. As one of the best performing texture descriptors, the LBP operator [6] has been widely used in various applications. It has proven to be highly discriminative and its key advantages, namely, its invariance to monotonic gray level changes and computational efficiency, make it suitable for many demanding image analysis tasks [1]. Owing to all those superiorities and its efficiency and accuracy, cattle face recognition using LBP descriptor is taken into consideration.

II. RELATED WORKS

For cattle identification, some research groups use muzzle pattern as a biometric approach. Muzzle pattern is a dermatoglyphic trait of cattle similar to fingerprints for human beings [7]. The oval, rounded, or irregular structures spread over the muzzle have been identified as "beads", and the elongated structures, straight or curved, as "ridges" [8][9]. A system of coding has been developed for cattle identification by analyzing muzzle pattern characteristics. They used muzzle pattern as a biometric-based identifier for cattle by acquiring muzzle patterns through lifted ink prints and digital images. A three-stage matching algorithm was evaluated for scanned muzzle ink prints and performed successfully in all cases. For digital images, the techniques of principal component analysis and Euclidean distance classifier were used [10]. The result using this pattern is quite impressive. But its main disadvantages [11] are the length of time required to take a print and the difficulty in obtaining a good-quality print. Compared with the Muzzle pattern, the LBP descriptor is easier to implement. The time required to take pictures does not play a very important role in this pattern. The necessity to obtain a good-quality print in Muzzle pattern will also limit its application. But to LBP, the images of cattle taken by a digital camera can reach an excellent recognition rate. If aligned, the result can be better. So for good performance, we used an algorithm named "robust alignment" by sparse and low-rank decomposition [15] to align the cattle images. This method seeks an optimal set of image domain transformations such that the matrix of transformed images can be decomposed as the sum of a sparse matrix of errors and a low-rank matrix of recovered aligned images and reduce the challenging optimization problem to a sequence of convex programs that minimize the sum of ℓ1-norm and unclear norm of the tow component matrices.

Another method is ear tags matching. One of our teams uses this method in cattle recognition. But some people think any method of identification should not only be effective but also safeguard the welfare of the animals. In this case ear tag matching is not a good approach, for ear tags often bring pain to animals and may lead to many communicable diseases. In addition, the numbers and letters on the tags may be washed out by rain or the rapid water when the animals have a bath in summer. And these tags can also be blurry, and thus affect the recognition. What we need is facial images when using LBP descriptor and we all know that the face can not be changed much in many years. Face recognition has been investigated as a biometric-based identifier for sheep using a holistic analysis of face images by means of the independent component technique. A group conducted a research using ICA [12] and got an exciting result [5]. According to their research, facial recognition, being non-invasive and inexpensive, is a potential biometric marker of sheep and can be used as a means of sheep identification. This research encourages us to apply our method to cattle face recognition. So far there have been no researchers or groups using LBP descriptor for cattle face recognition. Therefore, in this paper, our investigation will focus on the recognition of cattle face using LBP.

III. LBP-BASED FACE DESCRIPTION

The LBP descriptor was originally designed for texture description. The operator assigns a label to every pixel of an image by thresholding the 3×3 neighborhood of each pixel with the center pixel value and considering the result as a binary number. As shown in Fig. 1, if the intensity of center pixel is bigger than (or equal to) that of its neighbors, a bit 1 is set at the corresponding location. Otherwise, a bit 0 is set. Then the eight bits generated from intensity comparisons are put in a circular order (we collected bits in the clockwise direction) and considered as a binary number, which can be converted to a base-10 number in [0 255]. This is the LBP value for the center pixel, which acts as an index to the LBP histogram. Then the histogram of the labels can be used as a texture descriptor. The facial image is divided into several regions and texture descriptors are extracted from each region independently. The descriptors are then concatenated to form a global description of the cattle face.

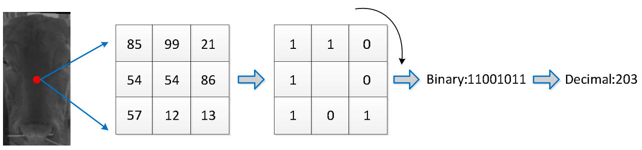


Fig. 1 The basic LBP operator.

An extension to the original operator is the definition of the so-called uniform patterns [13]. A local binary pattern is seen as uniform if the binary pattern contains at most two bit transitions from 0 to 1 or from 1 to 0 when the bit pattern is considered circular. For example, the patterns 00000000 (0 transitions) and 01110000 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 10101010 (8 transitions) are not. In the computation of LBP histogram, the number of histogram bins is smaller, because the histogram has a separate bin for every uniform pattern and all nonuniform patterns are assigned to a single bin.

There are many measures when defining the distance between two images, like histogram intersection and log-likelihood statistic. But psychophysical findings, indicate that some special facial features play a more important role in face recognition [14]. It can be anticipated that some of the facial regions contribute more than others do, so the regions can be weighted in the computation of the distance .We use the weighted Chi square distance which can be defined as

$$X_w^2(x,m) = \sum_{i,j} w_j \frac{(x_{i,j} - m_{i,j})^2}{x_{i,j} + m_{i,j}} \tag{1}$$

in which x and m are the histograms to be compared, indices i and j refer to i^{th} bin in the histogram corresponding to the j^{th} local region and w_j is the weight for region j.

IV. EXPERIMENT ANALYSIS

Our approach is assessed on the face recognition using 30 cattle (100 images per cattle). From Fig. 2, we can get the general idea of the cattle classification based on the LBP descriptor.

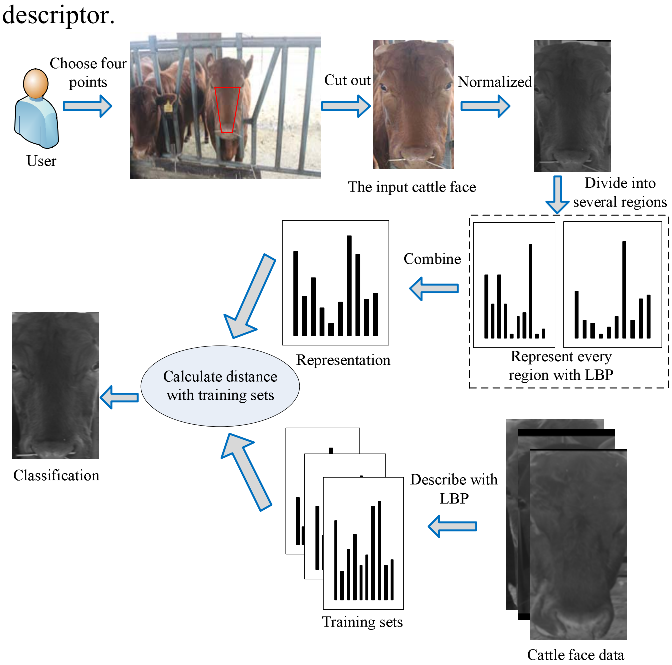
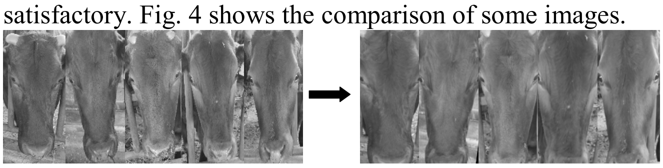


Fig. 2 Overview of our approach.

We took all these images with a Canon digital camera at a cattle farm of Northwest A&F University once every three to five days. Each image has 1200×2400 pixel. And then we cut out the images to get the front cattle facial images and normalize them with the same scale when put into use. Fig. 3 shows the frontal cattle facial images of all species under investigation.

Fig. 3 Frontal cattle facial images of all species.

As we can see, all of the cattle facial images are of various poses with different backgrounds, thus bringing about an unsatisfactory result when using LBP. So for good performance, we used an algorithm named RASL to align our images. What we did was choosing two points from each cattle face just at its inside corner of eyes and then saving as some files that extend the name called ".mat". Next we used Matlab tools and run RASL codes to align our images of cattle and got 100×200 pixels images. Because of different pose and different resolution, some images did not make a good aligned result. As a whole, though, the result was satisfactory. Fig. 4 shows the comparison of some images.



original aligned

Fig. 4 The comparison of some images

The selection process is entirely based on human observation. 60 percent to 90 percent of images per cattle were used as training sets at the stage of the facial description algorithm, and the rest images were used as test images at the recognition stage.

Some parameters can be chosen to optimize the performance of the LBP-based algorithm. The division of the images into different regions helps to find the weights w_j for the weighted Chi square distance and the optimal window size. Each image is a rectangle, so we divided the image into 10×20 windows and the block size was 10×10 pixels based on our experience for the sake of our experiments on cattle face recognition. TABLE □ shows the result of the experiment in which 90 percent images are used as training sets while the rest as test images.

TABLE I
THE RECOGNITION RATES OF DIFFERENT BLOCK SIZE

Block size	5×10	10×10	10×20	20×20
Recognition rates	59%	70.5%	61.5%	54.7%

To find the weights w_j for the weighted Chi square distance, we use only one of the 10×20 windows at a time in the training set which includes 2700 images (90 images per cattle) and the windows were assigned a weight with regard to the recognition rate. But according to the results, the recognition rates are not significantly different after image alignment. The obtained weights are illustrated in Fig. 5.

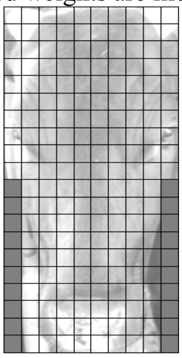


Fig. 5 A cattle face divided into 10×20 windows. The weights set for weighted Chi square distance. Gray indicates weight 0, and others indicate 1.

For good performance, we also used some extended LBP descriptors named NI-LBP which can be defined as

$$NI-LBP=\sum_{n=0}^{7}s(x_n-u)2^n, s(x)=\begin{cases}1, x\geq 0\\ 0, x<0\end{cases} \tag{2}$$

where $u=\frac{1}{8}\sum_{n=0}^{7}x_n$. x_n represents the pixel in a 3×3 neighborhood except the center pixel. The threshold u is selected in order to preserve LBP characteristics and to increase robustness. And the other one named MBP (Median Binary Pattern) [16] seeks to derive the localized binary pattern by thresholding the pixels against their median value over a 3×3 neighborhood. In MBP, the central pixel is also included in this filtering process, resulting in 29 binary patterns.

In comparison with those of different methods, the recognition rates of the weighted methods were not significantly higher after alignment. But compared with that without alignment, this result is obviously higher. LBP means using non-weighted methods; RASL means using RASL to align images; WLBP means using weighted methods. The results are shown in TABLE □ and Fig. 6 respectively.

TABLE II
THE RECOGNITION RATES OF DIFFERENT METHODS

	60% as training sets	70% as training sets	80% as training sets	90% as training sets
LBP	67.7%	71.4%	71.8%	70.5%
WLBP	75.9%	79.9%	81.8%	80.2%
RASL+LBP	89.5%	91.0%	90.1%	95.2%
RASL+WLBP	90.1%	91.2%	90.8%	95.3%
RASL+NI-LBP	88.8%	89.8%	89.0%	93.3%
RASL+MBP	87.0%	88.4%	87.8%	92.8%

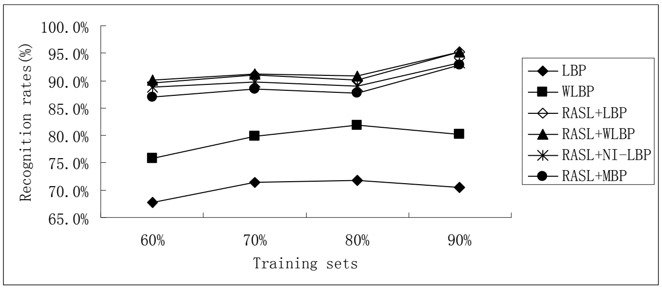


Fig. 6 The recognition rates of different methods

V. CONCLUSIONS & DISCUSSION

LBP is a novel and efficient facial representation algorithm. It divides an image into many regions, provides a description of each region using local binary patterns, and then combines these descriptors into a histogram of the facial image. Our program was written in C sharp. When running this application, our computer used Windows 7 operating system with an Inter Core I3 M380, 2.53GHz dual core processor and 4G RAM, and the running time of classifying an image was 40.339s when the windows are 10×20 and the training sets are 2700 (90 images per cattle).

The LBP operator has been widely used in many applications. Many results show that it is a manoeuvrable algorithm indeed. But as there are no cattle facial images database, what we can do is to use our digital camera to get images by ourselves. We spent a lot of time and energy accomplishing this task and then made these images normalized. We also know that the LBP will produce excellent results on registered images. Therefore, we use a Matlab tool to align the images. And the final result is heart-stirring just as expected.

VI. FUTURE WORK

We have a strong faith in the improvement of our recognition rates. Future work includes creating a face database of cattle so as to ensure image availability. Then we will try to divide these images into different regions. Different window sizes will also be considered to find a suitable size according to recognition rates. The most important thing is to find a suitable weight of the weighted Chi square distance. We think a good selection of weights will improve recognition rates significantly and an effective and robust alignment algorithm will also contribute a lot. By the way, improving the automation of the system will strengthen its practicability and help us save a lot of time. Besides the progress of current research only focus on the frontal cattle facial images and image transformation will be put into research in next steps. So we will have a long way to go in cattle face recognition using LBP descriptor.

When more and more researchers focus their energy on LBP descriptor, more robust and novel extended LBP descriptor and different histograms will be developed to improve the persuasion of this effective descriptor. In this case we need to conduct more research with different methods. Besides, we will also try our best to explore new modified methods in this region.

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