Age Classification Combining Contour and Texture Feature

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Abstract. Age classification based on computer vision has widespread applications. Most of previous works only utilize texture feature or use contour and texture feature separately. In this paper, we proposed an age classification system that integrate contour and texture information. Besides, we improve the traditional Local Binary Pattern(LBP) feature extraction method and get pure texture feature. Support Vector Machines with probabilistic output (SVM-PO) is used as individual classifiers. Then we use combination mechanism based on fuzzy integral to merge the output of different classifiers. The experiment results show pure texture feature outperforms other features and it can be well combined with contour feature.

Key words: Age Classification, Contour Feature, Texture Feature, Located Local Binary Patterns, Fuzzy Integral

1 Introduction

Age classification has a lot of applications, such as supervision of minors, demographics, commercial advertisement and so on. Most of previous researches only use texture feature [1, 2] or use contour features and texture features separately [3, 4]. We find both the shape of faces and skin roughness can help determine a person's age. Fig. 1(a) shows faces which can be discriminated by contour feature. All 8 images have soft skins, but the upper four faces are close to circles while the lower four faces are close to ovals. Fig. 1(b) are example of faces that can be distinguished by texture feature. We can see wrinkles on the forehead and at the corner of eyes clearly.

Seeing the above example, it is natural to expect better performance by combining contour feature and texture feature. Although [3] also use these two features, they didn't use them at the same time. First, contour feature is adopted to determine whether the facial image is a child or not, then it's classified as young people or elderly people according to texture feature. In this paper, we propose an age classification system that combing features together and achieve a performance which is comparable to humans.

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Fig. 1. Classify the facial image by different features: (a)Classify by contour feature; (b)Classify by texture feature

The remaining part of the paper is organized as follows: in section 2, the age classification system we proposed is introduced in details. In section 3, we describe the features extraction method we use in our system. Experiments and analysis are conducted in section 4, followed by conclusion and discussion in section 5.

2 Age Classification System

Fig. 2 shows the whole process of our system. Before feature extraction, we need preprocess the images. The initial image is cropped into two sizes to accommodate two feature extraction methods. To extract contour feature, the image should include the whole face, because the position of chin is very important. To extract texture feature, including the organs is enough, and the advantage is that we can avoid the impact of backgrounds.

Feature extraction methods are very important in pattern recognition. Contour feature is easy to modeling comparatively speaking, while there are many methods to describe texture feature, like Local Binary Patterns, Gabor Feature, Local Gabor Binary Mapping Pattern(LGBP) [5]. We tried several methods of them and find LBP is the most stable and efficient. Then several classifiers depend on different features are trained with SVM-POs, for the preparation of classifier combination.

At last, we combine the output of SVM-POs and get the final result. Almost all of the combination mechanisms belong to two categories of information integration techniques. One is to combine the features before classification, the other is to combine

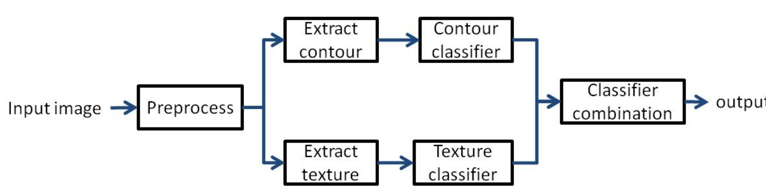


Fig. 2. The proposed age classification system by combining contour and texture classifiers.

the results of classifiers. All the combination methods we use in our experiment belong to the latter categories, for example, choquet fuzzy integral. The probabilistic outputs are combined into a single composite score with trained fuzzy measure or hierarchical classifiers, and the class with highest probability will be output.

3 Feature Extraction

In this section, we will briefly introduce the feature extraction methods we use and discuss their characteristic.

3.1 Contour Feature

Kwon and Lobo did researches on age classification first. They consulted studies in cranio-facial research, art and theatrical makeup, plastic surgery and found with the growth of a people, the shape of head turns from circle to oval. So they put forward utilizing the proportion of distance between organs to decide whether a facial image belongs to child or adult [3]. We also use this information in our experiment, but we do not calculate the proportion, instead, we more accurately use 58 points to describe the contour of a face.

To detect the contour, we adopt Active Appearance Model (AAM) [6], a statistical model which derives from Active Shape Model (ASM) [7]. Before using AAM, we should normalize the face, otherwise the detection result will be imprecise. We first detect the position of two eyes [8], then rotate and scale the face to locate the eyes at the same position. After normalization, AAM can easily find the contour with 58 points $P_1, P_2, \ldots, P_{58}$, as show in Fig. 3. We don't use AAM to find the position of calvaria because it will be affected by hair seriously.

Then we just stretch the x and y coordinates and get a 116 dimension contour feature vector $\{P_{1x}, P_{1y}, \ldots, P_{58y}\}$, which is also the base for texture feature extraction.

3.2 Texture Feature

Texture feature has better performance than contour feature under many circumstances. Many researches have been done on this and LBP has been proved powerful on texture description. The LBP operator value can be calculated as Fig. 4.

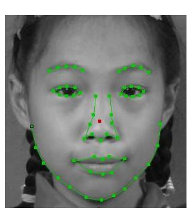


Fig. 3. AAM detection result.

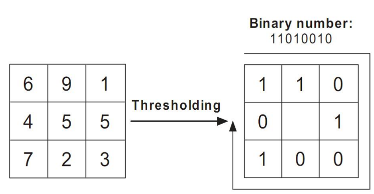


Fig. 4. Illustration of the LBP value computation.

We apply LBP operator on every pixel and divide the image into m non-overlapping rectangular regions $\{R_0, R_1, \ldots, R_m\}$, the histogram of j-th region is:

$$H_j = \{h_{0,j}, h_{1,j}, \ldots, h_{59,j}\} \quad (1)$$

where 59 is the number of bins for uniform LBP operator. At last, we concatenate all H_j together and get the final LBP feature:

$$V = \{H_0, H_1, \ldots, H_{m-1}\} \quad (2)$$

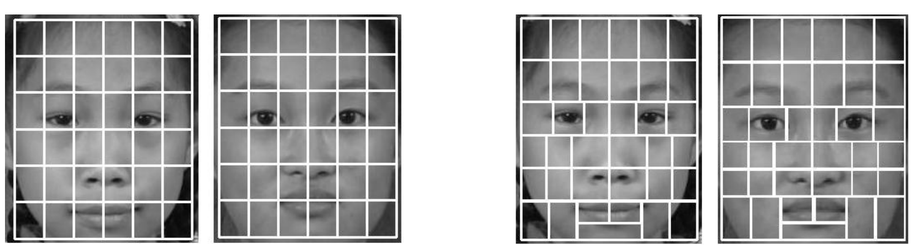
There are two ways of dividing the image into regions. The traditional way is to cut the image into $n \times n$ regions equally (and get the LBP$_n$ feature), as shown in Fig. 5(a). This way of dividing is easy, because we do not need to know the position of organ and it performs good too. However, it is not pure texture feature. As we can see the mouth of right image is upper than that of the left one. So the same region doesn't correspond to the same part of face, and the final LBP$_n$ vector will also contains contour information. We can extract texture feature more explicitly with the contour information, and we call it Located Local Binary Patterns(LLBP).

Fig. 5(b) shows how we decompose the image in our experiment. Skin around eyes is the most important part of face in age classification [2], so we first locate the regions of eyes by points of canthi. Here we set a fixed height of eye regions to prevent from getting too narrow region caused by squinting. The process of mouse and nose regions is similar to that of eyes, and the remaining regions are divided averagely according to the number of regions. We can certainly divide the image in a better way, but our method has already surpassed all others in the experiment. Before classification, we should zoom the regions to have same sizes, otherwise, the obtained feature will still contain contour information.

Bin Xia proposed LGBP feature in [5]. They use gabor filters on image first [9], then extract LBP feature on transformed images. Before classification, feature dimension will be decreased on every region. We also implemented this method as a comparison.

4 Classifier Combination

Originally SVM only predict class labels, we can use strategies like Majority Voting Rules or Borda Count to integrate the outputs, but it's a rough estimation. In our exper-



(a) (b)

Fig. 5. Two divide method

iment, the SVM output probability for every class instead of single class label, and the combination results are better. To get probabilistic output, our goal is to estimate

$$p_i = p(y = i|\mathrm{x}), i = 1, \ldots, k \tag{3}$$

where k is number of classes.

Since we use one-against-one strategy, we can get the probability of multi-class problem from pairwise class probabilities $r_{ij} \approx p(y = i|y = i \text{ or } j, \mathrm{x})$, which is estimated as Eq. 4 proposed in [10].

$$r_{ij} \approx \frac{1}{1 + e^{A\hat{f}+B}} \tag{4}$$

where A and B are estimated by minimizing the negative log-likelihood function using training data and decision values $\hat{f}$.

Then p_i can be obtained from all the r_{ij}'s solving the following optimization problem [11]:

$$\min_{\mathbf{P}} \frac{1}{2} \sum_{i=1}^{k} \sum_{j:j \neq i} (r_{ji}p_i - r_{ij}p_j)^2 \quad \text{subject to} \sum_{i=1}^{k} p_i = 1, p_i \geq 0, \forall i. \tag{5}$$

Noticing the equality

$$p(y = j|y = i \text{ or } j, \mathrm{x}) \cdot p(y = i|\mathrm{x}) \;=\; p(y = i|y = i \text{ or } j, \mathrm{x}) \cdot p(y = j|\mathrm{x}), \tag{6}$$

then the objective function can be reformulated as

$$\min_{\mathbf{P}} \frac{1}{2} \mathbf{P}^T Q \mathbf{P} \tag{7}$$

where

$$Q_{ij} = \begin{cases} \sum_{s,s \neq i} r_{si}^2 & if\ i = j, \\ -r_{ji}r_{ij} & if\ i \neq j. \end{cases} \tag{8}$$

Simple combination rules like sum or product rule were proved efficient in [12]. There are a bit more complicated methods that need training, such as weighted sum, hierarchical classifiers. Here we use another widely used combination strategy: fuzzy integral.

Fuzzy integrals are integrals relies on the concept of fuzzy measures. Let $X = \{x_1, x_2, \ldots, x_n\}$ be a finite set and let $P(X)$ indicates the power set of X. Then a fuzzy measure g over set X is defined as:

Definition 1. $g : P(x) \rightarrow [0, 1]$ *such that:*
(1) $g(\emptyset) = 0, g(X) = 1;$
(2) $A \subseteq B \Rightarrow g(A) \leq g(B)$

The choquet fuzzy integral we use can be based on any fuzzy measure[13]. Given an unknown sample T, the confidence of T belongs to class c_j can be calculated by $C_g(h_j(x_1), \ldots, h_j(x_n))$, denoted as $C_g^j(T)$, where $h_j(x_i)$ is the confidence of T belongs to class c_j given by classifier x_i. The calculation of $g(h_i)$ can be solved by quadratic programming [14].

Table 1. Experimental data

Training data		Test data	
Age Group	Number	Age Group	Number
≤18	215	≤18	71
19∼23	221	19∼23	73
24∼50	219	24∼50	74
≥50	149	≥50	50
Total	804	Total	268

5 Experiments

Our experimental data come from frontal faces of BCMI-Omron age database. We set 18 years old as the boundary of adults and children, because laws in most countries do like this. So this kind of set has practical value. The other two boundaries are set as 23 and 50 years old to make the database has a good distribution. (See Tab. 1). One-fifth of the data are chosen randomly as testing data.

To have a comparison, we also asked three participants to classify the data. The participants did the test twice. At the first time, they directly classify the image according to their life experience. We find the two younger participants (22 years old both) didn't do well (with precision 67.16% and 70.52%), while the elder(50 years old) reached 76.12%, as expected [15]. So they were asked to do the test again. This time, they saw the training data before classification and reached 81.72% on average.

Tab. 2 shows the accuracy of different feature extraction methods. The classifiers are all SVM with RBF kernel and probability output. For Kwon's system, we set 18 years old as the boundary between children and adults. From the results, we can see the LLBP we proposed outperforms all other methods. LBP_6 and LBP_7 also performs good, because they contain both texture and contour information, as mentioned before. In addition, although contour feature get a low accuracy relatively speaking, it's still good than the easiest gray feature, so it's still useful for combination.

Then, we take a look at the combination results. Besides fuzzy integral, weighted sum, product rule and hierarchical classifiers are also chosen in our experiment. Tab. 3 shows 6 combinations of different classifiers. We first compare different combination methods, we can see from the results that fuzzy integral is the best among them, slightly better than weighted sum.

At last, we compare the combination results of different sets. From Tab. 2 and Tab. 3 we can see the integration of LBP_6 and LBP_7 doesn't make much progress, the reason is that these two features contain similar information, so they don't complement each others. To prove LLBP we propose is really better, we combine LLBP and LBP_6 with contour feature separately. As we expected, the raise of LLBP is greater than LBP_6 on fuzzy integral and weighted sum, but they both get decreased on hierarchical classifiers and product rule. This is because the performance of contour classifier is not very good, so it becomes a drag. We then combine LLBP with LBP_n. This time, the precision get increased a lot, because traditional LBP feature is nearly as strong as LLBP and it contains contour information at the same time. Although it seems that the performance of combination just get improved slightly, the best result which combines contour feature,

Table 2. Accuracy of different feature extraction method

Methods	Accuracy	Methods	Accuracy
Gray	60.82%	Kown's	74.63%
Contour	69.03%	LGBP	76.12%
LBP_6	77.24%	LLBP	**77.99%**
LBP_7	77.24%	Human	81.72%

Table 3. Classifier combination results

	Hierarchical	Product	Weighted Sum	Fuzzy Integral
LBP_6+LBP_7	77.61%	77.61%	77.99%	77.99%
Contour+LBP_6	76.49%	77.24%	77.61%	77.61%
Contour+LLBP	77.24%	77.61%	78.73%	78.73%
LBP_6+LLBP	78.73%	79.10%	79.48%	79.48%
LBP_7+LLBP	78.30%	79.10%	79.10%	**79.48%**
Contour+LBP_6+LLBP	79.10%	79.48%	79.48%	**80.23%**

LBP and LLBP together through fuzzy integral achieves 80.23%, only a bit lower than human's decision, so we think it's an encouraging result.

6 Conclusions and Future Work

We improve the traditional LBP feature extraction method in this paper, pure texture feature is extracted by dividing the image more reasonably and it outperforms all the baselines. Moreover,we integrate contour feature with texture feature by fuzzy integral and the accuracy of age classification is increased. Here, we still divide the image into rectangles. In fact, the regions can be irregular shape and will fit the shape of face better. A further extension of our work is to utilize hair information, we plan to extract the color and hairstyle information to get better performance.

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