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Face Sequence Matching with Certainty Factor Evaluation

Hiroshi Mo and Shin'ichi Satoh
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The utilization of face information enables many multimedia applications, especially for news programs, dramas, and movies. In order to utilize face information, face matching methods play important role. But, face matching is difficult, because face information has variation according to facial expression, pose, lighting condition, etc. In order to cope with this problem, we introduce a rejection mechanism in face sequence matching. It is expected that faces with not enough information for matching are excepted by the rejection mechanism taking advantage of certainty factor evaluation. This paper describes a method of robust face sequence matching with rejection mechanism.

1 Introduction

Recently, the technique of content-based access to videos is becoming more important with developing of multimedia systems. In order to access based on video contents, face information is quite important. Because human information has very important role for situation of video scene. The utilization of face information enables many multimedia applications such as face annotation, video content retrieval and so on. In order to utilize face information, face matching methods play important role.

The face matching is difficult, because face information has variation according to facial expression, pose, lighting condition, etc. Many methods have been proposed for face matching. For example, there are face feature-based methods [1], image-based methods [2, 3, 4], and a combination of feature- and image-based methods [5]. However, most of them have concentrated only on still images rather than faces in videos. And, they have been developed for high-quality experimental images taken under strictly controlled lighting conditions with fixed pose and facial expression.

In order to cope with this problem, we propose a method of robust face sequence matching with rejection mechanism. In matching process, faces with

not enough information for matching are excepted by the rejection mechanism taking advantage of certainty factor evaluation. Thus, it is possible to increase accuracy of matching by rejecting, for example, the small size face and the small number of faces in a sequence, because it doesn't have enough information for face sequence matching.

In this paper, we propose an approach to effective face sequence matching for content-based video indexing. From experimental results, we denote to achieve good performance by using the proposed approach.

2 Face Sequence Matching**2.1 Framework**

The framework of face sequence matching is shown in Fig.1. In order to realize face sequence matching, face sequence extraction is required. We use the face detector system based on neural network [6]. The system detects face regions of various sizes and at various locations. The face sequence is extracted by tracking the detected face regions using skin color information [7]. The system outputs face sequence from video relating detected faces included in each face sequence. Each detected faces is normalized into a 64 pixels \times 64 pixels image using the eye positions, which are equivalently 4096-dimensional vectors having intensity value, then converted to a point in the 16-dimensional eigenface space.

Each face may have very large variation even among face images of the same person, due to variation in lighting condition, pose, face expression, etc. In order to realize face sequence matching, it is necessary to choose an appropriate face from a face sequence. To cope with this problem, we can use a closest pair of faces selected from face sequence.

Therefore, we propose face sequence matching method based on face matching of closest pair of faces. This method is based on expectation that the closest faces have similar pose, facial expression, etc. Here, to calculate the face similarity, the eigenface-based method [2] is used in our experimentation.

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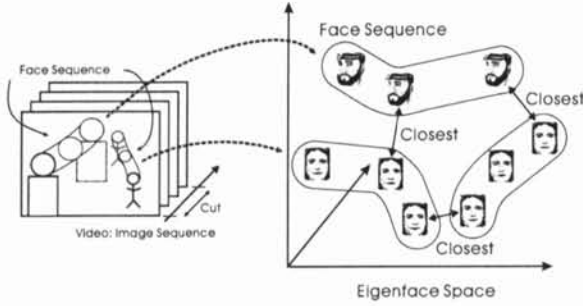


Figure 1: Framework of face sequence matching

2.2 Face Sequence Distance

To calculate face sequence distance, we use a similarity between the closest pair of faces selected by comparing two face sequences. This method depends on the presumption that when two face sequences correspond to the same person, the closest pair of them corresponds to faces having a similar pose, facial expression, etc.

The face sequence distance d_{closest} is defined as follows:

$$d_{\text{closest}}(S_i, S_j) \stackrel{\text{def}}{=} \min_{k,l} (|f_{i,k} - f_{j,l}|) \quad (1)$$

where $f_{i,k}$ and $f_{j,l}$ are vectors in the eigenface space corresponding to faces belong to the face sequence S_i and S_j , respectively.

3 Certainty Factor Evaluation

3.1 Certainty Factor

The face sequence matching is realized by evaluation of distance of closest pair in eigenface space. The closest pair method achieved good matching performance. However, there are some applications which require much higher accuracy in face sequence matching. Therefore, in order to have higher accuracy, we introduce a rejection mechanism for face sequence matching.

The small size face and the small number of faces in a sequence don't have enough information for face sequence matching. In order to except face with not enough information for matching, we proposed the matching method that uses the certainty of face sequence for matching. Here, we will then define certainty of face sequence matching for the closest pair method.

We assume that the size of faces has largest effect on the certainty. A larger face image has richer information in general. Thus, we define the certainty based on the size of faces m_f as follows:

$$m_f(F) = \min\left(\frac{w(F)^2}{w_{max}^2}, 1\right) \quad (2)$$

where $w(F)$ is the width of the face region of the face F , and w_{max} is the width of a normalized face. Fig.2(a) shows the certainty of the face size.

The certainty of face matching m_{ff} between face F_i and F_j is then defined:

$$m_{ff}(F_i, F_j) = \min(m_f(F_i), m_f(F_j)). \quad (3)$$

And, since the closest pair method assumes that face sequences have sufficient variation, the certainty depends on distributions of faces in face sequences. For simplicity, we assume that faces in a sequence have independent contribution to the certainty. Then the certainty of sufficient variation m_s of the face sequence S is defined as follows:

$$m_s(S) = 1 - (1 - \xi)^{n(s)} \quad (4)$$

where $n(s)$ is the number of face images in the face sequence S .

Fig.2(b) shows the certainty of the face number in a face sequence. We define the certainty of face sequence matching between face sequences S_i and S_j :

$$m_{ss}(S_i, S_j) = \min(m_s(S_i), m_s(S_j)). \quad (5)$$

For comparison, we define three variations of the certainty of face sequence matching between face sequences S_i and S_j as follows:

$$m_1(S_i, S_j) = m_{ff}(F_{i,k}, F_{j,l}) \quad (6)$$

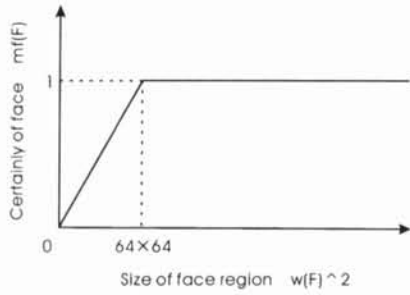
$$m_2(S_i, S_j) = m_{ss}(S_i, S_j) \quad (7)$$

$$m_3(S_i, S_j) = m_{ff}(F_{i,k}, F_{j,l}) \cdot m_{ss}(S_i, S_j) \quad (8)$$

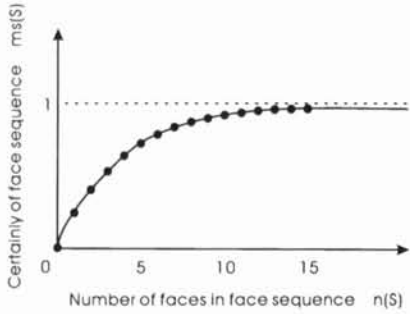
where $F_{i,k}$ and $F_{j,l}$ are the closest pair between S_i and S_j ; m_1 evaluates the certainty of face matching between the closest pair; m_2 uses the certainty of sufficient variation of faces in face sequences; and m_3 combines these two by multiplication.

3.2 Rejection Mechanism

We mechanize rejection for face sequence matching by taking advantage of the evaluation of certainty of face sequence matching. Rejection process is simple. A face sequence pair S_i and S_j is rejected if certainty $m_n(S_i, S_j)$ is small than a threshold θ ($n = 1, 2, 3$).



(a) Certainty for face size



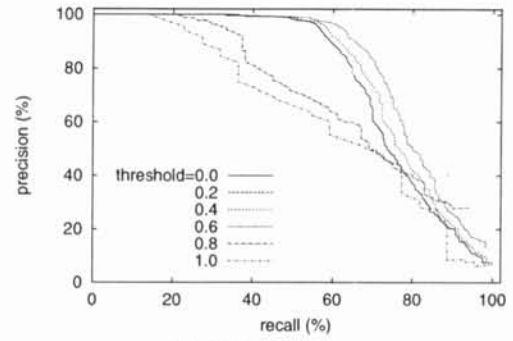
(b) Certainty for face number

Figure 2: Certainty function

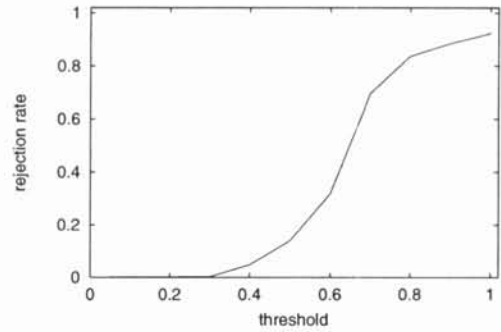
4 Experimental Results

We used a segment of five hours of CNN Headline News for the experiments. The system extracted 556 face sequences comprising 8,134 detected faces (15 face images per a sequence on average). For a training set for Eigenface calculation, we used the best frontal view face images [7]. To evaluate precision and recall, we manually named extracted face sequences, 288 face sequences in all.

The results of face sequence matching with rejection mechanism are shown in Fig.3, 4 and 5. In each figure, (a) shows ROC curves varying threshold θ , and (b) plots rejection rate versus θ . Fig.3, 4 and 5 show the results for m_1 , m_2 and m_3 , respectively. In each figure, ROC curves for threshold $\theta = 0.0$ are the same for face sequence matching without rejection mechanism. Fig.3 shows that there is some improvement by rejection using m_1 for face sequence matching when $\theta = 0.6$. From Fig.4, rejection using m_2 achieves a good performance comparing with m_1 , especially when $\theta = 0.8$. In this case, the recall is 83% and the precision is 85%, however, a rejection rate is more than 70%, which is too high. Fig.5 represents that there is improvement using m_3 from using m_1 and m_2 . Especially, in the case of $\theta = 0.2$, the result is improved with low rejection rate. Even with a much smaller rejection rate of 34%, the method using m_3 realizes a steady performance improvement with $\theta = 0.2$.

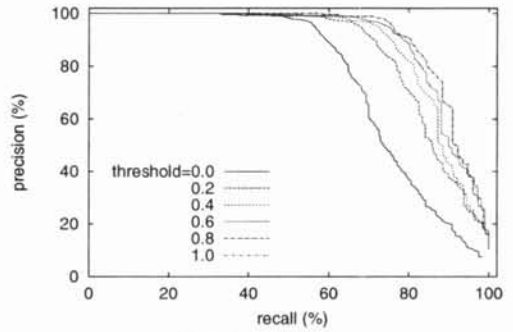


(a) ROC curves

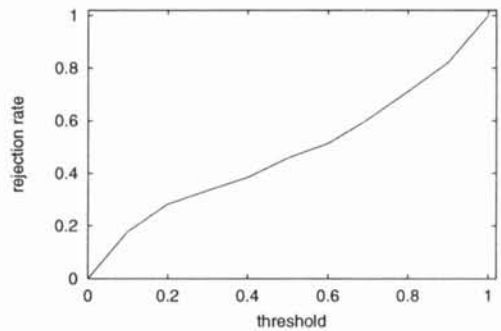


(b) Rejection rate

Figure 3: Matching results with rejection m_1

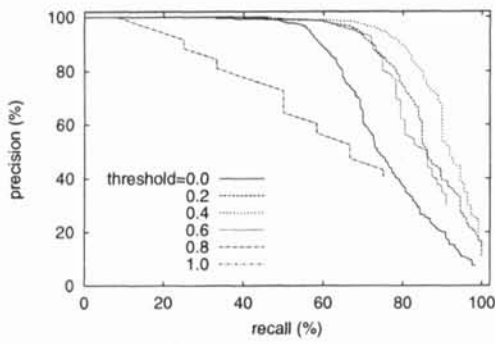


(a) ROC curves

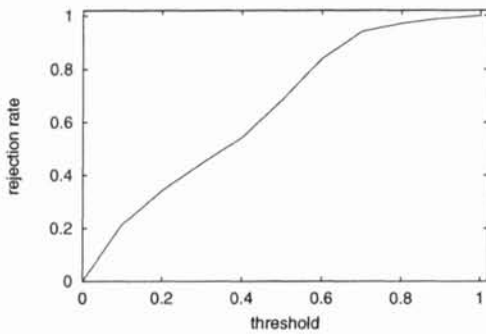


(b) Rejection rate

Figure 4: Matching results with rejection m_2



(a) ROC curves



(b) Rejection rate

Figure 5: Matching results with rejection m_3

To clearly compare the matching performance of the three methods, we plot precision/recall versus rejection rate as shown in Fig.6. From each ROC curve, the value when precision is the same as recall is selected and used as the representative value. When m_1 is used, the maximum performance improvement is small. m_2 achieves much higher improvement, but at the expense of a high rejection rate. m_3 is superior to the others when the rejection rate is between 10% and 25%, which could be an acceptable rejection rate for most applications.

From these results, the proposed method are effective for face sequence matching.

5 Conclusion

In this paper, we proposed an efficient method of face sequence matching for content-based video indexing. In this method, the face sequence matching is realized by using eigenface-based method with rejection mechanism using certainty factor of extracted face sequences form videos. The proposed method can match the face sequence pair robustly for variation of face condition in the face sequence.

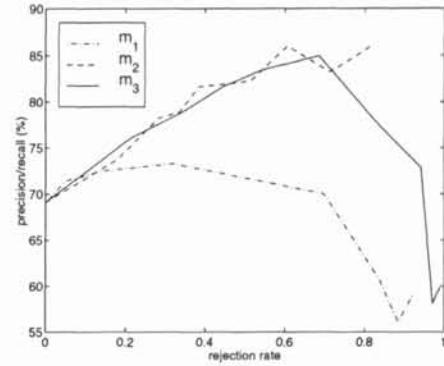


Figure 6: Performance comparison of matching

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