Fast and Robust Smile Intensity Estimation by Cascaded Support Vector Machines

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***Abstract*—Facial expression recognition is one of the most challenging research areas in the image recognition field and has been studied actively for a long time. But it has not achieved enough performance under the practical environment yet. Especially, smile is the most important facial expression used to communicate well between human beings and also between human and machines. Therefore, if we can detect smile and also estimate it's intensity at low calculation cost and high accuracy, it will raise the possibility of inviting many new applications in the future. In this paper, we focus on smile in facial expressions and study feature extraction methods to detect a smile and estimate its intensity only by facial appearance information (Facial parts detection, not required). We use Local Intensity Histogram (LIH), Center-Symmetric Local Binary Pattern (CS-LBP) or features concatenated LIH and CS-LBP to train Support Vector Machine (SVM) for smile detection. Moreover, we construct SVM smile detector as a cascaded structure both to keep the performance and reduce the calculation cost, and estimate the smile intensity by posterior probability. As a consequence, we confirmed that our proposed method provided the comparable performance with the existing method, and it also achieved both low calculation cost and high performance even with the practical database.**

***Index Terms*—Face, facial expression, smile intensity, SVM.**

I. Introduction

The visual information plays a very important role in our everyday life. Especially, in regard to communication between human beings, we can come to understand deeply and smoothly each other to pay attention to behaviors and facial expressions as well as languages. Facial expression analysis has been approached by several research fields, for example in psychology [1], brain science, etc. In engineering [2] too, many researchers have tried to analyze, estimate and understand facial expressions and human emotions by face images, by voice signals, by bio-signals, etc. for a long time. But, it is still difficult to recognize facial expressions only by face images automatically, because there are many problems such as inconsistencies in individuals, lack of criterion to judge facial expressions, disparities between simulation data and practical data and a mismatch between the expressions and the emotions. Therefore, there is no critical solution to recognize those by computer automatically under the practical environment and active research is still very much in progress.

In particular, smile (In a wide sense, facial expressions, which are observed when human beings derive pleasure) is one of the most important facial expression used to communicate well between human beings and also between human and machines. If we can automatically detect smile with real-time and at high accuracy, it will serve a useful function to existing applications like digital still camera and Human Machine Interface (HMI) and also raise the possibility of inviting new applications like rehabilitation and welfare in the near future.

In general, there are two major approaches to detect smile. One is feature-based method [3] and the other is appearance-based method [4]. Feature-based method has the robustness for the variation of face positions and angles, because it can normalize those and analyze more detailed information around facial parts. But it generally requires finding some facial parts such as eyes, mouth, etc. So, if it does not find those facial parts, it can't provide the result. On the other hand, appearance-based method does not need to find facial parts and can provides the result of smile detection without facial parts detection. As a result, although it is susceptible to the position of facial parts and the variation of face angle, it has low calculation cost.

In this paper, we study the method to detect smile and estimate its intensity using only facial appearance information with real-time and high performance, which is robust to the position gap of facial parts and face angle within approximately ±30 degrees of frontal, and we construct the practical smile intensity estimation system. Fig. 1 shows the process flow of our proposed system.

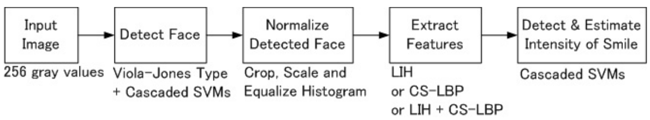

Fig. 1. Process flow of our proposed system

First of all, we detect faces from the input image by face detector, which is a combination of two different types of classifiers and then crop, scale and normalize the influence of illumination changes by the histogram equalization. After that, we extract features, using either Local Intensity Histogram (LIH), Center-Symmetric Local Binary Pattern (CS-LBP) [5] or LIH+CS-LBP, which is constructed by concatenating the above two features as facial appearance information. At last, smile is detected and it's intensity is estimated by Cascaded SVMs.

II. Face Detection

Fig. 2. shows face detection flow in our proposed system.

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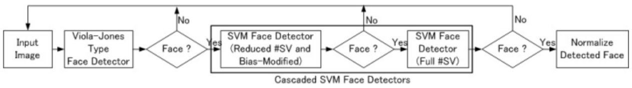

Fig. 2. Face detection flow of our proposed system

Our face detector consists of two different detectors [6]. One is Viola-Jones type face detector [7], which uses Haar-Like features and based on AdaBoost learning algorithm. The other is SVM based face detector such as [8]. Viola-Jones type has the advantage of detecting faces rapidly. But, it's false positive rate depends on the number of cascades and it often include many false positives. On the other hand, SVM is known as very robust classifier. But, it's calculation cost increases with the number of search points, support vectors and dimensions of feature vector, generally. To combine these two different types of classifiers, we can rapidly detect face candidates from whole input image by Viola-Jones type face detector, and then find the true faces only from a small number of face candidates by SVM based face detector, accurately. Moreover, we create SVM based face detector as cascaded structure [9]. It consists of sub detector, which has a small number of support vectors by applying Reduced Set Method (RSM) [10] and main detector, which consists of all support vectors. This cascaded structure has the ability to keep high performance, while reducing the calculation cost.

After the face detection, we crop the face region from the input image and scale it into 40 × 40 pixels and normalize by the histogram equalization to suppress the influence of illuminations and then process feature extractions for smile detection as described in the next section.

III. Smile Detection and Intensity Estimation

We try to detect smile and estimate smile intensity using 256 gray values, where the size of face is 40 × 40 pixels. That means it is not necessary to identify facial parts in our method. Fig. 3 shows the process flow of our smile detection and smile intensity estimation.

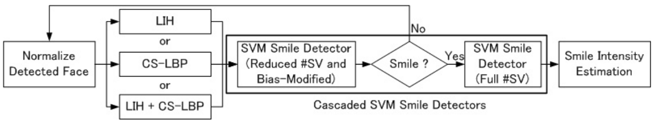

Fig. 3. Smile detection and intensity estimation flow of our proposed system

In this paper, we study three feature extractions, namely such as Local Intensity Histogram (LIH), Center-Symmetric Local Binary Pattern (CS-LBP) and LIH+CS-LBP, which combines the above two features as facial appearance information. In addition, we construct the cascaded SVM smile detector similar to SVM face detector, to maintain the performance while reducing the calculation cost. At the end, we estimate smile intensity based on the posterior probability estimated by the output from SVM smile detector.

A. Feature Extraction

Generally, face detector does not insure the accuracy of the detected face positions, means that positions of facial parts such as eyes, mouth and etc., are not always corresponding for each detected face. Therefore, the robust features for facial parts positions and face angles are necessary to detect smile only by appearance information, accurately. In this paper, we divide the face image into some grid cells and extract local features for each cell, after that we build the final feature by concatenating all local features. We use Local Intensity Histogram (LIH) and Center-Symmetric Local Binary Pattern (CS-LBP) as local feature and describe how to extract those features in the following subsections.

1) *Local Intensity Histogram (LIH)*

LIH is built by concatenating the intensity histograms in local regions and the extraction steps are as follows:

1) Divide face image into $M \times N$ cells.
2) Build an intensity histogram with L bins for each cell.
3) Normalize the histogram for each cell.
4) Build the final feature by concatenating the normalized intensity histograms of all cells to form a $(M \times N \times L)$ dimensional vector.

Fig. 4. shows the processing example, where face image is divided into 8 × 8 cells and 8 bins.

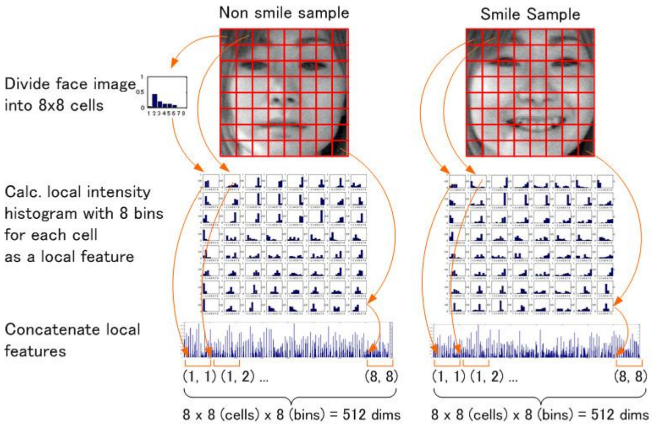

Fig. 4. Feature extraction by LIH (8 × 8 cells, 8 bins)

2) *Center-Symmetric Local Binary Pattern (CS-LBP)*

CS-LBP is a simple method and it is also has the ability to extract features, which has robustness for illumination changes. Additionally, it can also represent texture information as more compact binary patterns. CS-LBP is calculated by,

$$CS-LBP_{R,N,T}(x,y)=\sum_{i=0}^{(N/2)-1} s(n_i-n_{i+(N/2)})2^i,\; s(x)=\begin{cases}1 & x>T\\ 0 & otherwise\end{cases} \quad (1)$$

where T is an encoding threshold, n_i and $n_{i+(N/2)}$ correspond to the gray values of center symmetric pairs of pixels of N equally spaced pixels on a circle of radius R. In this paper, N is fixed to 8 and R is fixed to 1, so CS-LBP is calculated as shown in Fig. 5.

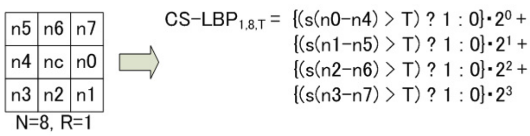

Fig. 5. Calculation of CS-LBP in this paper (N=8, R=1)

The following steps show the process to extract CS-LBP feature:

1) Divide face image into $P \times Q$ cells.
2) Calculate a CS-LBP for each cell and build a CS-LBP histogram.

Build the final feature by concatenating the CS-LBP histograms of all cells to form a ($P \times Q \times 16$) dimensional vector.

Fig. 6. shows the processing example, where face image is divided into 5 × 5 cells.

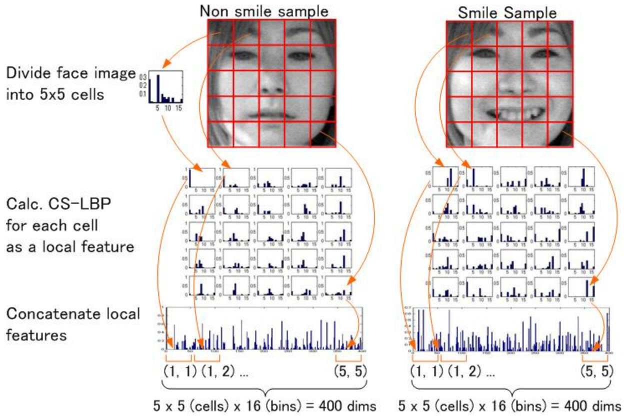

Fig. 6. Feature extraction by CS-LBP (5 × 5 cells)

B. Detection and Intensity Estimation

In this paper, we use SVM with RBF kernel function. RBF kernel function is defined as,

$$K(\mathbf{x}_i, \mathbf{y}_j) = \exp(-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|}{2\sigma^2} \qquad (2)$$

Here σ is a kernel parameter. Then the decision function with kernel is given as,

$$y = \sum_{i \in S} \alpha_i K(\mathbf{x}_i, \mathbf{x}) - h \qquad (3)$$

where S and $\mathbf{x}_i$ means a set of support vectors and support vector, K is a kernel function, $\mathbf{x}$ is the input vector. Here, α_i shows weight for support vector and h represent the bias term. In smile detection case, if $y >= 0$ implies smile and non-smile, otherwise. In addition, we estimate smile intensity to evaluate the posterior probability of SVM outputs. Using sigmoid function, smile intensity is defined as,

$$s_i = \frac{1}{1 + \exp(-\lambda y)} . \qquad (4)$$

where s_i is smile intensity that ranges from 0 to 1 and λ is the gain. In this paper, we fix λ to 5.

Furthermore, we construct cascaded smile detectors as same as SVM face detector. It consists of sub smile detector, which is reduced the number of support vectors constructed by RSM and main smile detector, which has all the set of support vectors.

IV. Data Preparation

We constructed the original image database, which consisted of sports games TV programs to train and test our smile detector. In such TV programs, the spectators are often shooted and their expressions and emotions vary with the outcome of games. It is good for us, because the most spectators show same facial expressions with the outcome of their supporting athletes or teams. Therefore, we can collect smile and non-smile images with a high degree of efficiency. Construction steps are shown as follows:

1) Extract the spectator's scenes from recorded sports games TV programs manually.
2) Automatically Detect face from the spectator's scenes by face detector.
3) Remove the miss-detections manually.
4) Select only the faces, which include both eyes completely (it correspond to the variation of face angles within ±30 degrees in Yaw).
5) Judge smile or non-smile manually.

As a result, our original smile/non-smile database contained 6,460 faces, which consisted of 2,730 smile samples and 3,730 non-smile samples. In addition, we also used the following two pubic databases to evaluate the generalization performance of our smile detection and smile intensity estimation method: The MPLab GENKI-4K Database [11]

This database contains 4,000 face images spanning a wide range of subjects, facial appearance, illumination, geographical locations, imaging conditions, and camera models. All images are labeled for smile or non-smile by human coders. And the face angles are almost within ±20 degree in Yaw, Roll and Pitch. It is good to evaluate the robustness of our smile detector. Facial Expression and Emotion Database (FEED) [12]

This database contains frontal face images showing a number of subjects performing the six different basic emotions defined by Eckman & Friesen. It provides image sequences from neutral to expressional face. Therefore, it is good for testing transition of facial expression.

V. Experiments

In this paper, we tested our system by 5-fold cross validation, which was one of several approaches commonly used for evaluation purpose. We compared each performance by Area Under the Curve (AUC), which was obtained by Receiver Operating Characteristics (ROC) Analysis.

A. Performance Evaluation by LIH

With respect to LIH, we investigated the optimal number of cells and bins. We first compared the performance according to the number of cells with the fixed number of bins, which is 8 (See Fig. 7.) Here, we used our original database and smile detector, which was consisted of all support vectors (not cascaded).

When increasing the number of cells until 8, AUC was gradually improved, but decreased again thereafter. So, 8 × 8 cells show the best performance.

Next, we compared AUC by varying the number of bins, while keeping the number of cells constant as 8 × 8 (See Fig. 8.) 4 and 8 bins showed almost the same better performance, but 4 bins provided the best. It means that we need just 4 gray values to detect smile.

As a result of these experiments, with respect to LIH, the optimal parameters were 8 × 8 cells and 4 bins (That is a 256 dimensional vector) and that performance provided 0.979522 for AUC.

B. Performance Evaluation by CS-LBP

With respect to CS-LBP, we investigated the optimal number of cells and the encoding threshold. We first compared the performance according to the number of cells with constant encoding threshold equal to 0.00 (See Fig. 9.) Here, we used our original database and smile detector, which was consisted of all support vectors (not cascaded).

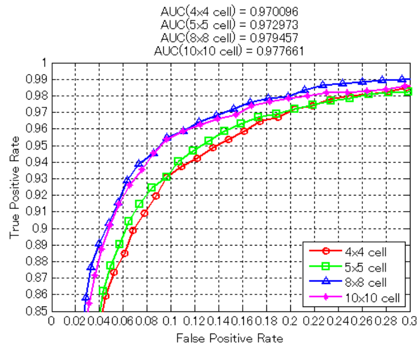

Fig. 7. Comparison of ROC curves by LIH when changing the number of cells

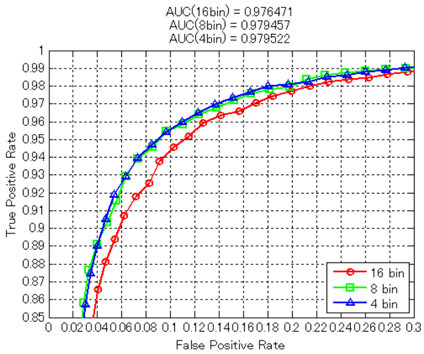

Fig. 8. Comparison of ROC curves by LIH when changing the number of bins

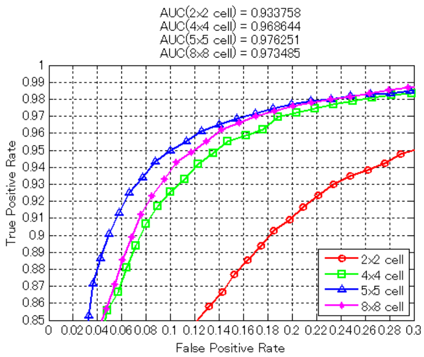

Fig. 9. Comparison of ROC curves by CS-LBP when changing the number of cells

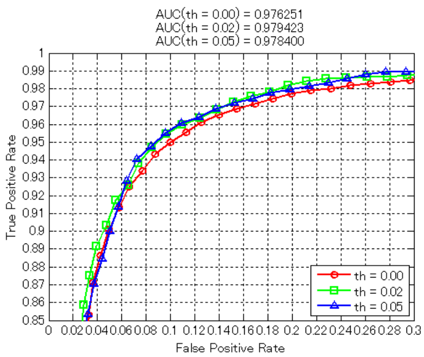

Fig. 10. Comparison of ROC curves by CS-LBP when changing the encoding threshold

As increasing the number of cells, AUC was higher, but too match cause to degrade the performance. In this experiment, 5 × 5 cells gave the best.

Next, we compared AUC according to the encoding threshold with constant 5 × 5 cells (See Fig. 10.) Almost the same performances were shown, but in this experiment, the encoding threshold of 0.02 provided the best AUC.

As a result of these experiments, with respect to CS-LBP, the optimal parameters were 5 × 5 cells and encoding threshold of 0.02 (That is a 400 dimensional vector) and It provided 0.979423 for AUC.

C. Performance Evaluation by LIH+CS-LBP

In this section, we describe the experiments with LIH+CS-LBP feature, which is combined LIH and CS-LBP. Here, the parameters of each feature extraction methods are followings:

1) Parameters of LIH
   - The number of cells :8 × 8
   - The number of bins :4
2) Parameters of CS-LBP
   - The number of cells :5 × 5
   - Encoding threshold :0.02

LIH+CS-LBP, which was a 656 (= 256 (LIH) + 400 (CS-LBP)) dimensional vector, improved the performance. Here, it provided 0.982269 for AUC and it was better than using only LIH or CS-LBP (See Fig. 11.)

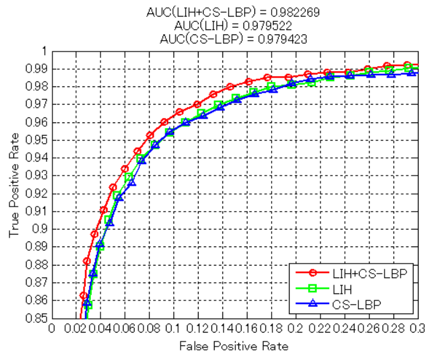

Fig. 11. Comparison of ROC curves of all the three features with our original database

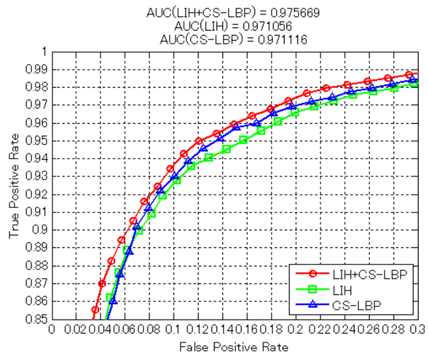

Fig. 12. Comparison of ROC curves of all the three features with combined database

Next, we evaluated the generalization performance of our smile detector using both our original database and the GENKI-4K database. Because our original database contained mostly Asian people with various face angles. On the other hand, the GENKI-4K contains multiracial, multi illuminations and multi cameras. So, to combined the above two database, we evaluated by more images, which had rich variations. In this experiment, the total number of images became 10,460 combining the both database and it consisted of 4,892 smiles and 5,568 non-smiles. Fig. 12 shows the results. In this case too, LIH+CS-LBP feature provided the best performance (AUC = 0.975669). Moreover, AUC of all three features provided the value greater than 0.97.

The result of these experiments showed that our smile detector worked robust under the practical environment.

D. Performance Comparison with the Existing Method

In this section, we compare the performance between our proposed method and the existing method, which proposed in [3]. At first, we changed the size of face image from 40 × 40 pixels into 24 × 24 pixels to correspond to the existing method. Here, we extracted features by LIH, CS-LBP and LIH+CS-LBP with following parameters:

1) Parameters of LIH
   - The number of cells :8 × 8
   - The number of bins :4
2) Parameters of CS-LBP
   - The number of cells :6 × 6
   - Encoding threshold :0.02

And we only used GENKI-4K dataset, which was subset of the dataset used in [3] to evaluate AUC. Under these conditions, our proposed method provided 0.968314 for AUC (See Fig. 13.)

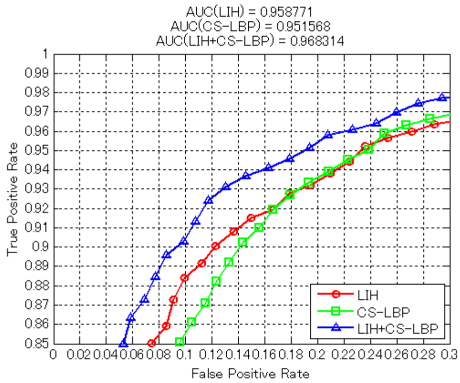

Fig. 13. ROC curves of 24 × 24 face image

On the other hand, the existing method reported 0.979 as the best AUC with Box Filter as feature extraction and Gentle Boost as classifier. But, the existing method applied precise face image registration using the information of human labeled eyes, before detecting the smile. And the existing method in [3] also reported the result of using eye labels by eye detection system and the performance was degraded to 0.963 with Gabor Energy Filters as feature extraction and linear SVM as classifier in this case. As described in this paper, our proposed method never uses the information of labeled eyes and face image registration to detect smile without face parts detection. Moreover, the dimensionality of the existing method was very large, Box Filter was 322,945 and Gabor Filter was 23,040. On the other hand, our proposed method was just using 832 dimensional vectors.

As a result of this experiment, our proposed method showed the comparable performance with the existing method under the condition of no precise face image registration, and the dimension of feature vector was much less.

E. Performance of Cascaded SVM Smile Detector

In this section, we describe the comparison of the performance and calculation cost, with our cascaded SVM smile detectors. Here, we used the combined database, which was composed of our original database and the GENKI-4K database, and selected LIH+CS-LBP as feature extraction method. The parameters of LIH were set to 8 × 8 cells and 4 bins and the parameters of CS-LBP were set to 5 × 5 cells and the encoding threshold of 0.02. The numbers of support vectors were reduced either to 32, 64, 128, 256, 512 or 1024 by RSM.

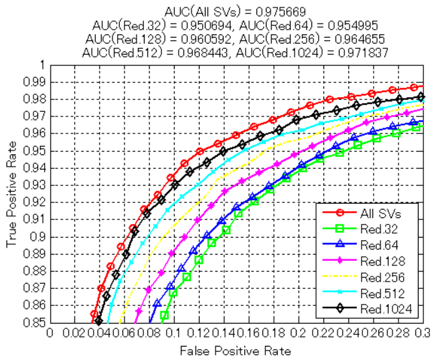

Fig. 14. ROC curves of reduced SVMs

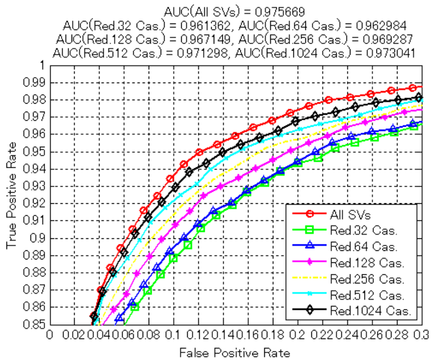

Fig. 15. ROC curves of cascaded SVMs

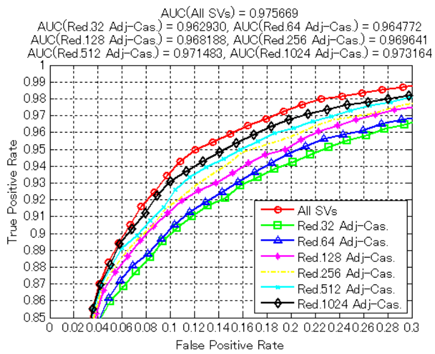

Fig. 16. ROC curves of bias-adjusted cascaded SVMs

Fig. 14 showed the detection performances according to the number of support vectors. The performance degraded as the number of support vectors decreased.

Next, we investigated the effects of cascaded structure. Fig. 15 shows the performance according to the several cascaded SVMs, which consist of sub smile detector and main smile detector. Similar to the previous case, when the number of support vectors decreased, the performance degraded. But when we compared Fig. 14 and Fig. 15, AUC in Fig. 15 was better than in Fig. 14. It showed that the cascaded detectors worked better rather than just the reduced detectors.

Next, we adjusted a bias term (h in (3)) of sub smile detector lower to suppress the miss rejection cases at the sub smile detector. In this paper, we adjusted a bias to achieve True Positive Rate as well as main smile detector's one in advance. The results of these bias-adjusted cascaded detectors showed a little better performance than just cascaded detectors (See Fig. 16).

At the end of this section, we showed a comparison of the number of support vectors, AUC and calculation speed of smile detector structures (See Table I).

TABLE I: COMPARISON OF THE NUMBER OF SVS, AUC AND CALCULATION SPEED (ON MATLAB@3.0GHZ CORE2 QUAD)

Classifier	#SVs	AUC (LIH+CS-LBP)	CPU Time [msec]
Normal SVM (with all SVs)	3567	0.975669	17.3698
Cascaded SVMs	32 (& 3567)	0.961362	7.5823
	64 (& 3567)	0.962984	7.7662
	128 (& 3567)	0.967149	8.0570
	256 (& 3567)	0.969287	8.4609
	512 (& 3567)	0.971298	9.7745
	1024 (& 3567)	0.973041	12.3801
Cascaded SVMs (Bias-adjusted)	32 (& 3567)	0.962930	8.6267
	64 (& 3567)	0.964772	8.5697
	128 (& 3567)	0.968188	8.5719
	256 (& 3567)	0.969641	8.8934
	512 (& 3567)	0.971483	10.1280
	1024 (& 3567)	0.973164	12.7219

Both cascaded SVMs and bias-adjusted cascaded SVMs with over 512 support vectors in sub smile detector achieved comparable in performance (AUC > 0.97) to original non-cascaded SVM, while reducing 30-40 % in the calculation cost. As a result of these experiments, our proposed cascaded SVM smile detectors could reduce calculation cost significantly with a little performance degradation and it can work on real-time (i.e. 30 fps and more).

F. Intensity Estimation

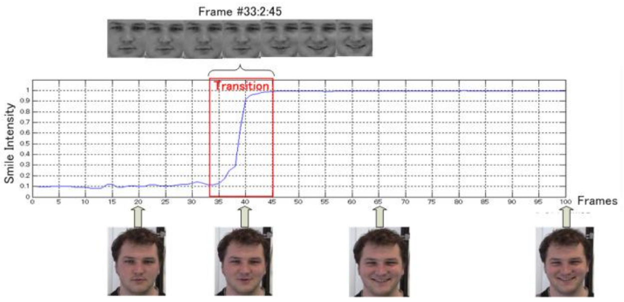

Fig. 17. Smile intensity estimation result of subject #0001, sequence #1

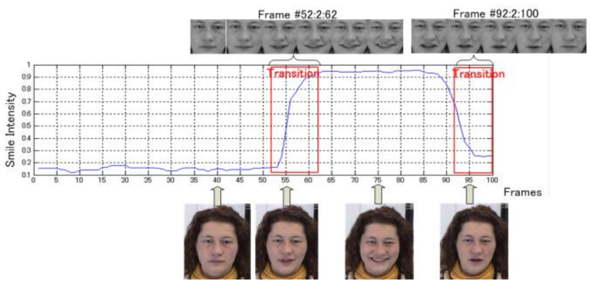

Fig. 18. Smile intensity estimation result of subject #0005, sequence #1

The FEED database is suitable to evaluate a change of a certain facial expression, because it has 100-150 image sequences, which contain the variation from neutral face to a certain facial expression for each subject. Fig. 17 and Fig. 18 showed the result of our smile intensity estimator to 2 subjects. These results proved that our smile intensity estimator could track the transition from neutral to smile well. Especially, it could represent the subtle facial expression changes as shown in red rectangle area in each figure.

VI. CONCLUSION

In this paper, we studied how to detect smile and estimate smile intensity only by facial appearance information, and proved the validity of our proposed system through several experiments. We constructed original smile/non-smile database. We investigated the optimal parameters for LIH and CS-LBP to detect smile with the above database. We compared the performance of smile detection using LIH, CS-LBP and LIH+CS-LBP. In our result, with respect to LIH, we achieved 0.979522 for AUC with 8 × 8 cells and 4 bins and for CS-LBP, achieved 0.979423 with 5 × 5 cells and the encoding threshold of 0.02. Combined feature, LIH+CS-LBP worked better among all the three features. That produced a AUC value of 0.982269 as the best performance.

In addition, we combined our original database and the GENKI-4K database, which contained several races, cameras and illumination conditions to evaluate the generalization. It provided 0.975669 for AUC with LIH+CS-LBP feature. This result indicates that our proposed system is robust and works well even under the practical environment. We constructed cascaded SVMs for smile detector, which was composed of sub smile detector, consisted of small number of support vectors and main smile detector consisted of all support vectors. As a result, we could keep AUC higher than 0.97, while delivering a 30-40 % reduction in the calculation cost.

With respect to smile intensity estimation, we showed that our estimator could track the subtle expression changes from neutral to smile using the FEED database. In the future, we plan to detect the other facial expressions and estimate those intensities based on the proposed methods described in this paper.

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