A fast online cascaded regression algorithm for face alignment

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Abstract—Traditional face alignment based on machine learning usually tracks the localizations of facial landmarks employing a static model trained offline where all of the training data is available in advance. When new training samples arrive, the static model must be retrained from scratch, which is excessively time-consuming and memory-consuming. In many real-time applications, the training data is obtained one by one or batch by batch. It results in that the static model limits its performance on sequential images with extensive variations. Therefore, the most critical and challenging aspect in this field is dynamically updating the tracker’s models to enhance predictive and generalization capabilities continuously. In order to address this question, we develop a fast and accurate online learning algorithm for face alignment. Particularly, we incorporate on-line sequential extreme learning machine into a parallel cascaded regression framework, coined incremental cascade regression (ICR). To the best of our knowledge, this is the first incremental cascaded framework with the non-linear regressor. One main advantage of ICR is that the tracker model can be fast updated in an incremental way without the entire retraining process when a new input is incoming. Experimental results demonstrate in an incremental way without the entire retraining process that the proposed ICR is more accurate and efficient on still or sequential images compared with the recent state-of-the-art cascade approaches. Furthermore, the incremental learning proposed in this paper can update the trained model in real time.

Index Terms—face alignment, cascaded regression, ELM, incremental learning

I. INTRODUCTION

Face alignment aims to locate a sparse set of facial landmarks for a given facial image or video. It is a topic of interest in the domain of Computer Vision because many subsequent face analysis tasks, such as face recognition [1], facial animation, and authentication on the Internet of Things [2], heavily depend on the accurate localizations of facial landmarks. Over the decades, various face alignment procedures have been proposed, which can be broadly classified into generative models and discriminative models. The generative approaches adopt an analysis-by-synthesis loop where the optimization strategy attempt to find the optimal shape parameters by maximizing the joint posterior probability between the pre-built deformable model and feature of the input image. The representative examples of this category are Active Appearance Model (AAM) [3] and Gauss-Newton Deformable Part Model (GN-DPM) [4].

The discriminative models seek to learn discriminative information (i.e. discriminative function [5], [6]) which directly maps representation of facial appearance to facial landmarks. Many discriminative methods utilize popular Cascaded Regression (CR) framework, in which a series of regressors are learned in a cascaded manner to gradually refine the initialization to ground-truths. Numerous cascaded regression methodologies have shown to produce excellent results on face alignment tasks and validate the CR framework’s superior efficiency and accuracy [7]–[11]. The most efficient of these methods is LBF [12] using a set of local binary features to learn a cascade linear regressors and its running speed can be achieved over 3000fps on a standard desktop for locating a few dozens of landmarks. The authors of [6] attempt to provide a theoretical explanation of cascade linear regression from the perspective of least squares optimization and solve it as a supervised descent methodology. While these cascaded linear regression methods are very efficient, they are suffering in poor fitting capability to exploit the non-linear and complex relationship between feature space and shape variations in unconstrained scenarios.

Considering the limitations of linear regression, some non-linear regressors based on decision-making tree, such as boosting [13] and random forest [14] were introduced into cascaded regression. However, these ensemble learning models are prone to over-fitting and suffered from very high computational burden [15]. With the research wave of deep learning [16] has been carved out in the image domain, many deep-based methods [7], [17]–[19] have been proposed and
achieved breakthrough successes in some big scale datasets. Because of their complicated structure and a great number of hyperparameters, these deep frameworks tend to consume massive time to train the models. Moreover, deep structure encounters a complete retraining process if the training data is supplemented.

Although these discriminative methods have accomplished superior performance for face alignment under unconstrained faces or some more challenging situations, they are limited by a static generic model that is built completely on offline training data. Nevertheless, such a static model can not be updated in real time to handle some certain specific tasks (e.g. person-specific landmarks tracking for video). Since the entire training procedure is very time-consuming and very expensive, how to best exploit discriminative cascade regression for incremental learning is an intractable issue. A few studies [9], [20] have started to work on this vital issue from the viewpoint of the incremental linear regression function. However, linear regressor tends to be limited to a linear relationship between dependent and independent variables.

In order to overcome the aforementioned limitations, in this paper, we study incremental training of cascaded regression with non-linear regressor. As the foundation of our algorithm, CR framework is one of the most practical and effective framework for localizing facial landmarks. Nevertheless, traditional CR framework still has two limitations to achieve incremental training. (1) It successively trains a series of regressors stage by stage. The entire procedure (4 or more cascaded stages) is too slow to satisfy the requirements of online learning in real time. (2) In the cascade executions, the input of each stage intensely depends on the outputting shapes of the previous stage. In that case, if the certainly stage-regressor is incrementally updated, the whole input set of the subsequent stage will be recomputed by new regressor and all samples formerly trained must be reloaded. Obviously, these limitations can lead to a vast resource-consuming and time-consuming when the scale of data is so large.

For these, we propose incremental cascade regression (ICR), which aims to train and update the series of non-linear regressors in a parallel manner instead of a sequential one. In special, we adopt Monte Carlo sampling methodology [6], [9] to approximate the shape space, in which the facial shape is no longer depend on the outputting of the previous stage. Meanwhile, ICR is equipped extreme learning machine (ELM) as the discriminative regressor to learn the mapping between facial feature representations and the shape variations. ELM has powerful capability to approximate any linear or non-linear mapping (e.g. the least square constraints in face alignment). Moreover, ELM has very fast training speed and low computational cost without the hassle of parameters tuning when compared to the gradient descent-based regressors or decision-tree based regressors. As shown in Figure 1, ICR divides into two parts: offline and online training procedures. In the offline training procedure, a generic model can be learned by a parallel cascade regression of ELM. Then the online training procedure can update the trained model by using the Monte Carlo sampling methodology [6], [9]. In this way, incrementally updating the trained regressor of each stage does not depend on the outputting of the previous stage, so we can update all the regressors in parallel. Meanwhile, we adopt an online sequential extreme learning machine (OS-ELM) [21] method to update the trained ELM regressors. The OS-ELM [21] is an incremental learning strategy of extreme learning machine (ELM) [22]. In summary, our main contributions are as follows:

- To the best of our knowledge, ICR is the first parallel cascaded regression framework equipped the non-linear regressors.
- ICR is capable of replenishing new training data and very fast updating the model without retraining from scratch, which can constantly increase the generalization and robustness of model.
- We evaluate ICR on three datasets and demonstrate the importance of incremental learning in achieving state-of-the-art performance on sequential training data.

II. RELATED WORK

As described above, the existing methods can be split into generative and discriminative categories. Both categories have proposed diverse models for offline face alignment with varying degrees of success. The main problem that our method can address is incremental learning for face alignment. In this section, we will focus on closely related works on this task.

On the generative side, very limited research has been introduced to AAM [23], in which the incremental principal component analysis (iPCA) [24] is used to update the generic AAM’s linear appearance model with current face image. However, this method heavily relies on prebuilding a robust parametric model as well as AAM and need images of the same person for training, which is less generalization and unpractical.

On the discriminative side, Asthana et al. [9] proposed a incremental version of SDM called iPar. In this work, a parallel strategy is used to implement the incremental update of the modified linear regressors. For each cascade stage, they utilize a set of perturbations from a pre-populated Gaussian distribution instead of the outputting shape variations of the previous stage. In this way, computing each regressor is
independent of the other stages, which can facilitate the whole training procedure in a parallel manner. As experimentally shown by [9], such approximate training strategy achieves similar accuracy as the model of SDM trained in a sequential manner. This study offers a new idea and premise for fast training incrementally discriminative regressors. However, linear regressors used in iPar are too weak to exploit the complex relationship between shape variables and appearance features.

Inspired by [9], we propose a incremental cascade regression, coined ICR, that pay more attention to non-linear discriminative regression in a parallel cascaded regression framework.

III. METHOD

In this section, we present a cascade regression of extreme learning machine and its online training version. As a preliminary, we first take a brief review the ELM algorithm in detail.

A. Extreme Learning Machine

ELM is an efficient way of building the single layer feed forward neural networks(SLFNs) [25]. Given N input-output training samples, arbitrary distinct samples \((x_i, y_i) \in \mathbb{R}^n \times \mathbb{R}^m\). Here, \(x_i\) is a \(n \times 1\) input vector and \(y_i\) is a \(m \times 1\) target vector. ELM with \(K\) hidden nodes and activation \(G(\cdot)\) can be mathematically modeled as

\[
\sum_{k=1}^{K} \beta_k G(a_k, b_k, x) = y, \quad i = 1, 2, \ldots, N,
\]  

(1)

where \(a_k \in \mathbb{R}^n\) and \(b_k \in \mathbb{R}\) are the randomly chosen learning parameters of hidden nodes, \(G(a_k, b_k, x)\) is the output of \(i\)-th hidden nodes w.r.t the input \(x\) for additive units with the activation function \(g(\cdot)\)(e.g., sigmoid), \(G(\cdot)\) is defined as

\[
G(a_k, b_k, x) = g(a_k \cdot x + b_k),
\]  

(2)

where the \(a_k \cdot x\) denotes the inner product of vectors \(a_k\) and \(x\) in \(\mathbb{R}^n\). The compact form of \(K\) equations in Equation(1) is:

\[
\mathbf{H}\beta = \mathbf{Y},
\]  

(3)

where

\[
\mathbf{H}(\mathbf{a}_1, \ldots, \mathbf{a}_K, \mathbf{b}_1, \ldots, \mathbf{b}_K, \mathbf{x}_1, \ldots, \mathbf{x}_N)
\]  

\[
= \begin{bmatrix}
G(\mathbf{a}_1, \mathbf{b}_1, \mathbf{x}_1) & \ldots & G(\mathbf{a}_K, \mathbf{b}_K, \mathbf{x}_1) \\
\vdots & \ddots & \vdots \\
G(\mathbf{a}_1, \mathbf{b}_1, \mathbf{x}_N) & \ldots & G(\mathbf{a}_K, \mathbf{b}_K, \mathbf{x}_N)
\end{bmatrix}_{N \times K}
\]

\[
\beta = \begin{bmatrix}
\beta_1^T \\
\vdots \\
\beta_K^T
\end{bmatrix}_{K \times m}, \quad \mathbf{Y} = \begin{bmatrix}
y_1^T \\
\vdots \\
y_N^T
\end{bmatrix}_{N \times m}.
\]  

(4)

\(\mathbf{H}\) is the output matrix of hidden layer, where the \(k\)-th column of \(\mathbf{H}\) is the output vector of \(k\)-th hidden node with respect to inputs \(x_1, x_2, \ldots, x_N\). In the Equation(3), the learning parameters of hidden layer nodes can be randomly generated, So the output weights \(\beta\) can be estimated by finding the least square solution of the linear system, according to the expression:

\[
\tilde{\beta} = \arg \min_{\beta} ||\mathbf{H}\beta - \mathbf{Y}||_2^2 = \mathbf{H}^\dagger \mathbf{Y},
\]  

(5)

where \(\mathbf{H}^\dagger\) is the Moore-Penrose generalized inverse of \(\mathbf{H}\). In practical, it is usually comes that \(N > K\). The Equation(5) can be rewritten as

\[
\tilde{\beta} = \mathbf{K}^{-1}\mathbf{H}^T \mathbf{Y},
\]  

(6)

where, \(\mathbf{K} = (\mathbf{H}^T \mathbf{H})^{-1}\).

B. Cascade Regression of Extreme Learning Machine

A facial shape can be formed by a vector \(s = [r_1, c_1, \ldots, r_L, c_L]^T\) consisting of \(L\) facial landmarks, where the \([r_l, c_l], l = 1, 2, \ldots, L\) are the 2D coordinates of the \(l\)-th landmark. Cascade regression frameworks usually begin with an initial shape \(s^0\), and progressively refine the shape to the ground-truth \(s^*\) via adding a shape increment \(\Delta s\) stage by stage. The \(\Delta s\) is estimated by regressing the shape-indexed feature around current shape estimate. The shape-indexed feature can be represented as \(f(I, s) \in \mathbb{R}^{f \times 1}\), where, \(I\) is the input image, \(f\) is the dimensionality of the feature. The function \(f\) can be a learning-based mapping [12], [17] or a hand-crafted feature(e.g. SIFT [6], Hog [26]). Linear regression has been most favoured in various works based on cascade regression because its superior efficiency. However, it is not suitable for incremental learning framework because the shape variations are more and more complicated with increasing incremental training data. Therefore, we propose a cascade regression of extreme learning machine(CRELM).

Given a set of \(N\) facial images \(I = \{I_i\}_{i=1 \ldots N}\) and their corresponding ground-truth shapes \(S = \{s_i^*\}_{i=1 \ldots N}\). The set of shape increments can be calculated by \(\delta s_i = s_i^* - s_i^{t-1}\), where, \(s_i^{t-1}\) is a \(2l \times 1\) shape vector from \(t-1\) stage. For achieving a robust representation against illumination, we use SIFT features extracted from patches around the current shape of each stage. To decrease the training error for stage \(t\), we can learn the stage-regressor \(G^t\) via minimizing the least-squares error function:

\[
\arg \min_{\beta^t} \sum_{i=1}^{N} ||\delta s_i - G^t(f(I, s_i^{t-1}))||_2^2.
\]  

(7)

Let \(x = f(I, s) \in \mathbb{R}^{f \times 1}\), \(G(x) = \sum_{k=1}^{K} \beta_k G(a_k, b_k, x)\) and \(\Delta S = [\delta s_1, \ldots, \delta s_N]^T\), we can rewrite the Equation(8) as the format of ELM:

\[
\tilde{\beta} = \arg \min_{\beta^t} ||\Delta S - \mathbf{H}\beta^t||_2^2,
\]  

(8)

where, \(\mathbf{H}^t = \mathbf{H}(\mathbf{a}_1^t, \ldots, \mathbf{a}_K^t, \mathbf{b}_1^t, \ldots, \mathbf{b}_K^t, \mathbf{x}_1, \ldots, \mathbf{x}_N)\) is computed by Equation(4) and we choose sigmoid function as the activation mapping \(G(a, b, x) = \frac{1}{1 + \exp(-a \cdot x + b)}\). The Equation (8) can be resolved by (6). We represent the learned regressor for stage \(t\) as \(G^t = [a_1^t, b_1^t, \tilde{\beta}^t, \mathbf{K}^t]\), where
\[ \tilde{\beta} = \mathbf{K}^{-1} \mathbf{H}^T \Delta \mathbf{S} \] (for clearing, here, we omit it). After learning the regressor, the training shapes for \( t \) stage can be updated by:

\[ s_i^t = s_i^{t-1} - G^t \left( \mathbf{I}_i, s_i^{t-1} \right). \]  

The training procedure is sequentially iterated until the average of the shape differences \( \delta s_i^t \) no longer decrease.

### C. Parallel Cascade Regression of Extreme learning machine

In order to better approximate the non-linear relationship between the image features and shape variations, in Section III-B we introduce an efficient non-linear mapping in cascade regression framework. However, this way will inevitably increase the time-consuming of training process. Besides, it is observed that the sequential procedure involved in training CRELM is not suitable for the task of incremental learning. In CRELM, as shown in Figure 2(a), since the shape variations \( \delta s^t \) is totally depend on the outputting of previous stage, if new training data inputs, the entire cascade of regressors have to be retrained from the beginning. For example, if a set of new samples \( s_{\text{new}} = \{s^i\}_{i=1}^{N'} \) have to be added, the first regressor \( G^1 \) can be easily updated to \( G_{\text{new}}^1 \) by utilizing the new shape variations \( \delta s_{\text{new}}^1 = s^0 - s_{\text{new}} \). However, the first regressor \( G_{\text{new}}^1 \) has changed on once, the subsequent set of inputs \( s_{\text{new}}^2 = \{s^2, s_{\text{new}}^2\} \) must be re-computed by propagating the entire augmented set \( s_{\text{new}}^1 = \{s^1, s_{\text{new}}^1\} \) through \( G_{\text{new}}^1 \). In this case, all the regressors will be retrained in sequence and all previously trained samples must be reloaded, which is time consuming and extremely expensive.

The authors of [9] pointed out that the shape variations \( \delta s_i^t \) at each stage can be approximated by a set of random perturbations drawn from a Gaussian distribution \( \mathcal{N}(\mu^{(t)}, \Sigma^{(t)}) \), the mean \( \mu^{(t)} \) and covariance \( \Sigma^{(t)} \) can be calculated by training the sequential cascade of regression. In addition, it has been verified in work [9] that the training procedure based on the sampling strategy can deliver a similar testing accuracy as the sequential manner. Inspired by [9], we adopt Monte Carlo sampling methodology to train a parallel cascade regression of extreme learning machine(Par-CRELM). In Par-CRELM, the shape variations \( \delta s \) required for learning the cascade of regressors do not rely on previous stages and the training can be performed in parallel. In particular, Firstly, we compute the the statistics \( \sigma^{(t)} = (\mu^{(t)}, \Sigma^{(t)}) \) for shape variations \( \{\Delta s_i^{(t)}\}_{i=1}^{N} \) at each stage while training the cascade of regressors using the proposed CRELM on the offline train set. Then, we train the Par-CRELM procedure, the shape variations for training the cascade of ELM regressors are drawn from the corresponding stage-distribution rather than the calculated from previous stage. We have shown the parallel process in Figure 2(b).

One advantage of this modification of CRELM is that the regressors of all stages can be learned in parallel with similar alignment accuracy as sequential training. Another advantage is that it provides a premise for fast incremental learning that will be showed in the Section III-D.

#### D. Incremental Cascade Regression of Extreme learning machine

After training Par-CRELM, the offline regressors \( \{G^t\}_{t=1}^{T} \) and the distribution \( \mathcal{D}\{\sigma^{(1)}, \ldots, \sigma^{(T)}\} \) of shape variations are preserved. Here, we present the proposed incremental cascade regression of extreme learning machine(ICRELM) in detail.

Given a set of new training data \( I_{\text{new}} = \{I_i\}_{i=1}^{N'} \) and \( S_{\text{new}} = \{s^i\}_{i=1}^{N'}, \) where \( N' \) is the number of new samples. We record trained regressors and distributions as \( \{G^t\}_{t=1}^{T} \) and \( \{D_i^{T}\}_{t=1}^{T} \). For arbitrary stage, \( G^t \) contains learned parameters \( \{a^t, b^t, \tilde{\beta}^t, \mathbf{K}^t\} \). ICRELM aims to update the cascade of regressors \( \{G^t\}_{t=1}^{T} \), in which \( a^t, b^t \) do not need to be update in parallel using the new training data. For stage \( t \), let us randomly sample \( N' \) shape variations \( \{\delta s_i^{(t)}\}_{i=1}^{N'} \) drawn from \( \mathcal{N}(\mu^{(t)}, \Sigma^{(t)}) \) for the new training images and extract the shape-index features \( \{x_i^{(t)}\}_{i=1}^{N'} \). The least-squares error function for all training data becomes:

\[
\tilde{\beta}^{t}_{\text{new}} = \arg \min_{\tilde{\beta}^{t}_{\text{new}}} \left\| \left[ \Delta s_{\text{new}}^0 \right] - \left[ H_{\text{new}}^t \right] \tilde{\beta}^{t}_{\text{new}} \right\|^2_2, 
\]

where

\[
\Delta s_{\text{new}}^0 = \begin{bmatrix} \delta s_1, \ldots, \delta s_{N'} \end{bmatrix}^T, \quad H_{\text{new}}^t = H(a^t_1, \ldots, a^t_K, b^t_1, \ldots, b^t_K, x_1, \ldots, x_{N'}) \]

is computed by Equation 4 using the trained parameters \( \{a^t, b^t\} \) of regressor \( G^t \). Then, the output weight \( \beta \) can be calculated by Equation 7:

\[
\tilde{\beta}^{t}_{\text{new}} = \mathbf{K}^{t-1}_{\text{new}} \left[ H_{\text{new}}^t \right]^T \left[ \Delta s_{\text{new}}^0 \right].
\]

where

\[
\mathbf{K}^{t}_{\text{new}} = \mathbf{K}^t_0 + H_{\text{new}}^t H_{\text{new}}^t.
\]

Referring to [21], we can update the \( \tilde{\beta}^{t}_{\text{new}} \) via:

\[
\tilde{\beta}^{t}_{\text{new}} = \tilde{\beta}^{t}_0 + \mathbf{K}^{-1}_{\text{new}} H_{\text{new}}^T (\Delta s_{\text{new}} - H_{\text{new}} \tilde{\beta}^{t}_0) \]

This way, a cascade of regressors can be updated in parallel. The complete training procedure of ICRELM is described in Algorithm 1.

**Algorithm 1 ICRELM Update Procedure**

**Require:** \( I_{\text{new}}, S_{\text{new}}, \{G^t_0 = [a^t, b^t, \tilde{\beta}^t, \mathbf{K}^t_0]\}_{t=1}^{T}, \{D^t_0\}_{t=1}^{T} \), \( T \) stages, \( N' \) number of new samples.

**Ensure:** updated regressors \( \{G^t_{\text{new}} = [a^t, b^t, \tilde{\beta}^t_{\text{new}}, \mathbf{K}^t_{\text{new}}]\}_{t=1}^{T} \), \( t = 1, \ldots, T \).

1. **Parallel for** \( t = 1 \rightarrow T \):
   2. Get \( N' \) samples \( \{\delta s_i^{(t)}\}_{i=1}^{N'} \) from distribution \( \sigma^{(t)} \)
   3. Extract index-shape features \( \{x_i^{(t)} = f(I_i, s_i^{(t)})\}_{i=1}^{N'} \)
   4. Generate \( \Delta s \in \mathbb{R}^{N' \times 2d} \) and \( \mathbf{X} \in \mathbb{R}^{N' \times 2d} \)
   5. Compute \( H_{\text{new}}^t \) using Equation 4
   6. Update \( \mathbf{K}^t_{\text{new}} \) using Equation 13 and \( \tilde{\beta}^t_{\text{new}} \) using Equation 14

7. **End for**
IV. EXPERIMENTS

The experiments for face alignment will be presented in two parts. The first part is to evaluate the accuracy of the model which constantly updated by ICRELM with continuous batches of new training data. The second part investigates the static models trained by proposed Par-CRELM and other state-of-the-art methods on public datasets. First of all, We briefly introduce the three datasets used in the experiments of face alignment and evaluation criteria for them.

A. Implementation Details

1) Datasets:
   • LFPW (29 landmarks) [27] is collected from the web including 1000 training and 300 test images. However some URLs are invalid, we only use 798 training and 221 test images. The images exhibit large variations in pose, occlusion, facial expression, and illumination.
   • HELEN (68 landmarks) [28] contains 2,330 high-resolution web images which are divided into training and test sets. Two sets have 2000 and 300 images respectively.
   • 300-W (68 landmarks) [29] is collected from existing datasets including LFPW, HELLEN, AFW and a challenging dataset called IBUG. We follow the same division in [7], [12], specifically, the training set is made up by the training samples of HELEN, the training samples of LFPW, and AFW, with 3148 images in total. According to the difficulty of alignment, the test set is grouped into Common (the test samples from LFPW and HELEN, total 554 images) and Challenging (IBUG, total 135 images) sets.

Since these datasets provide prescribed face bounding boxes, we do not use any face detectors and thus no face are missed during testing.

2) Standard Evaluation Protocols: We adopt two types of comparisons with the value of average error and curve of cumulative error for evaluation. They are prescribed as following:

   - **Average error:** following almost works, we leverage the standard landmarks mean error normalized by inter-pupil distance. It can be computed by \( \frac{1}{N} \sum_{l=1}^{N} \frac{1}{2} \sum_{p=1}^{L} |p_l - p_l^*|^2 \), where, \( p_l \) and \( p_l^* \) denote the \( l \)-th landmark coordinates of estimated and ground-truth facial landmark positions respectively, the \( p_{l_{eyeb}} \) and \( p_{r_{eyeb}} \) denote the inter-pupil distance. We report the error averaged over all annotated landmarks from each testing database. For clarity, we omit the notation \( \% \) in the report result.
   - **CED curve:** we also draw the cumulative error distribution curve of errors can be computed by the equation: \( CED = \frac{1}{N} \sum_{l=1}^{N} \frac{1}{2} \sum_{p=1}^{L} |p_l - p_l^*|^2 \), where the numerator denotes the number of samples on which the error less than the error \( e \).

3) Settings: In the feature learning, we extracted a SIFT descriptor on 32 \( \times \) 32 local patches for each landmark. We set the number of hidden nodes as 500, 1000, and 1800 for LFPW, HELEN, 300-W datasets respectively. Following almost face alignment models, we fixed the number of cascade stages to \( T = 4 \).

B. Validity of Online Learning

This experiment aims to validate the utility of the ICRELM(Section III-D) when the new data batches continuously arrive. For this purpose, we have designed the following experiments for LFPW, HELEN, and 300-W datasets. Each dataset was partitioned equally into 6 batches. We used Par-CRELM(Section III-C) to train a offline model on the first batch as the baseline. Then, we employed ICRELM to continuously update the generic model batch-by-batch. From Figure 3, we can observe that a consistent increase in the face alignment accuracy as the online model is incrementally updated with new batch of training data. The worst curve is produced by offline model. It is inevitable that the model trained with small samples tend to have poor generalization and robustness. The other curves are generated after adding 16\%, 33\%, 50\%, 66\%, and 83\% samples in batches from corresponding dataset.
curves illustrate that ICRELM method can update the model effectively when necessary and achieve higher and higher accuracy as training data increases. It is also observed in these curves that the accuracy of the updated model is no longer significantly raised after the data increases by 66%. It is because the difference between training sets is getting smaller and smaller, and the generalization capability of the model tends to be stable. It is notable that the ICRELM has a very fast speed to update the generic model. ICRELM is implemented in Matlab and ran on an Intel Single Core i5-4570@3.2GHz CPU at over 110fps, 33, and 24fps on LFPW, HELEN, and 300-W dataset respectively.

C. Comparison with static models

Offline model is the foundation of online learning. In order to validate the capability of the model trained by Par-CRELM on different datasets, we compare its results with existing state-of-the-art methods including CNN-based frameworks [7], [17], [31]–[35], 3D-based model [35] and various cascade regressions (CRs). These results have been reported in the Table I. On the LFPW dataset (Table I(a)), as we can see, Par-CRELM outperforms all the listed CR-based methods. Meanwhile, Par-CRELM can also generate a competitive result compared with CNN-based architectures. For each dataset, the Par-CRELM is lower than DR. Except for structural difference, one possible reason is that DR uses more cascaded iterations than Par-CRELM. Correspondingly, more time was consumed than ours both in training or testing. On the HELEN dataset (Table I(b)), our approach has a more accurate result than CFAN, MTCNN. Specifically, CFAN maps the local features to the shape space by utilizing deep auto-encoder networks, MTCNN applies the Multi-task convolution network in face alignment. The result shows that the Par-CRELM has a superior learning capability on smaller scaled data. Conversely, the CNN-based methods are prone to be restricted by the size of the dataset. Whereas our approach offers an advantage on HELLEN dataset. On the 300-W Common subset (Table I(c)), the result of Par-CRELM is superior to almost cascade regression methods and certain CNN frameworks like DR-Seq, SCNN DeFA and GECSAN, but lower than the methods including DR, Deep Regression. This dataset has a larger data size than LFPW and HELEN do, which provides sufficient discriminative information for CNN-based methods learning features. This may be more conductive for the CNN-based methods producing better results. Unfortunately, Par-CRELM performs unsatisfactorily in Challenging subset. In contrast, the CNN-based methods, such as SCNN, DeFA, and CECSAN, have highly accuracies. The reason is that they can learn more adequate feature via tuning by supervised information, which is essential for good performance on very challenging samples. While the static model trained by Par-ELM has a poor predictive capability to handle these challenging situations, it can be tuned with challenging samples to improve its localizing ability.

D. Conclusion and future works

In this paper, we have proposed a incremental learning framework for face alignment, coined incremental cascade regression (ICR), which includes offline and online training procedures. A cascade regression of extreme learning machine is first introduced and its parallel version is developed to train a offline model. Then, we present an efficient method to incrementally update a trained model to make it more generalizable.
or specific. The experimental results demonstrate the validity of online learning. Using our MATLAB implementation, the entire incremental learning procedure takes over 110fps, 33fps, 24fps on LFPW, HELEN, and 300-W dataset respectively, on an Intel Single Core i5-4570@3.2GHz CPU computer. Possible future works include replacing the hand-crafted SIFT features with deep features [16], [43] and new optimization strategy [44], [45].

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