Resampling for Face Detection by Self-Adaptive Genetic Algorithm

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Motivation

- The performance of all of the statistical methods highly depends on the training set, and they suffer from a common problem of data collection for training.
Include these samples in our training set?
How about these samples?
Motivation

- propose a re-sampling method to generate more samples from existing ones by using genetic algorithm (GA) operations.
The outline of the algorithm:

- **The current generation**
- **The GA operations**
- **The next generation**
- **Good samples**
- **Evaluate based on SNoW**
- **Garbage can**
- **Bad samples**
- **Negative samples**
- **Train the SNoW**
- **The last generation**
Face-Samples Preprocessing

alignment

rotation

Translation

Scaling
Face-Samples Preprocessing

30,000 faces

6,000 faces

Training set 15,000

Validation set 5,000

Test set 10,000
The outline of Genetic algorithms

1. Create an initial population
2. Selection
3. Crossover and mutate
4. Evaluate
The main procedure

- (1). Encoding
- (2). Initial Population.
- (3) Crossover and Mutation.
- (4) Evaluation function:
Mutation

- sharpening, blurring or re-lighting

As to the re-lighting of mutation operator, we use two kinds of strategies.
- One is to simulate linear point light source;
- the other is to simulate more complex diffuse light fields by a configuration of nine point light source directions.
Re-Lighting

- Assuming a face is a convex Lambertian surface, we get the face image:

\[ I(x, y) = \rho(x, y)\hat{n}(x, y)\hat{s} \]

- \( \rho(x, y) \) is the albedo of the point \((x, y)\)

- \( \hat{n}(x, y) \) is the surface normal direction

- \( \hat{s} \) is the point light source direction whose magnitude is the light source intensity.
Re-Lighting

A set of images of a Lambertian object under varying lighting can be approximated by a 9D linear subspace spanned by harmonic images. The harmonic images are defined as:

\[ b_{lm}(x, y) = \rho(x, y) A_l Y_{lm}(\theta(x, y), \phi(x, y)), \]

where \( Y_{lm} \) is spherical harmonic at the surface normal, \((\theta, \phi)\) corresponding to pixels \((x, y)\) and \( A_l \) is the spherical harmonics coefficients.
The image under arbitrary lighting can be written as:

\[ I(x, y) = \sum_{l=0}^{2} \sum_{m=-l}^{l} L_{lm} b_{lm}, \]

\( L_{lm} \) is the spherical harmonic coefficients of the specific lighting.
Re-Lighting

- **Illumination ratio image** between the canonical image and original image the is defined as:

\[
IRI(x, y) = \frac{I_{can}(x, y)}{I_{org}(x, y)} = \frac{E_{can}(\theta(x, y), \phi(x, y))}{E_{org}(\theta(x, y), \phi(x, y))}
\]

- the subscripts are index of illumination, and \(E\) is the incident irradiance.
Re-Lighting

Image relighting with illumination ratio image can be written as:

$$I_{can}(x, y) = IRI(x, y) \times I_{org}(x, y)$$
The self-adaptive probability

- In order to search the solutions effectively, the probability $P_c$ and $P_m$ are modulated self-adaptively.

- The modulation scheme is:

$P_c = \begin{cases} k_1 (f_{\text{max}} - f_c')/(f_{\text{max}} - \bar{f}), & f_c' \geq \bar{f} \\ k_3, & f_c' < \bar{f} \end{cases}$

$P_m = \begin{cases} k_2 (f_{\text{max}} - f)/(f_{\text{max}} - \bar{f}), & f \geq \bar{f} \\ k_4, & f < \bar{f} \end{cases}$
The self-adaptive probability

- $f'_c$ is the bigger one of two parents’ fitness value;
- $f$ is the fitness of the mutated parent;
- $f_{\text{max}}$ is the maximum fitness value of the current population and is its average fitness $\overline{f}$;
- $K_1 = k_3 = 1$, $k_2 = k_4 = 0.5$. 
The self-adaptive algorithm reduces the $P_c$ and $P_m$ of those individuals whose fitness value are bigger than the average of the current population.

- It can make the GA operations converge quicker.

- The $P_c$ and $P_m$ of those individuals whose fitness value are smaller than the average are increased to avoid the local solutions.
Re-sampling

- Divide The initial population.
- Choose individuals
- Crossover these selects with \( P_c \)
- Mutate with \( P_m \)
Selection

- After every 10 generations, the population will be cut down and keep only 85,000 solutions.
- All of them are sorted in a sequence according to their fitness value. And we pick out 85,000 individuals evenly along this sorted sequence.

$$15,000 \times (1+0.3)^{10} = 206,787$$
The process GA operations

Current Generation $t$

[10, 15]

[-10, -5]

[10, 15]

[-15, -10]

Next Generation $t+1$

$\omega_1$

$\omega_2$

$\omega_3$

$\omega_4$

$\omega_5$

$\omega_6$

GA Operations

Mutation
Face samples generated by GAs
Experiments

- Comparing the solutions performance of the different generations

- The generalization performance
The ROC curves on the validation set
ROC curves for Adaboost based detectors on the CMU test set.

ROC curves for face detectors on CMU database

Correct Detection Rate

False Positive

- GA40
- NoGA
Some detected
Some detected
Thank you!

Questions?