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Improved Harr-like algorithm in all optical environment

Le Thi Vui[1], Phan Huy Anh[1]

[1]Hanoi University of Natural Resources and Environment, Vietnam[1]

Abstract: To build flexible systems that work in a variety of lighting conditions and run on mobile phones or handheld PCs, robust and efficient face detection algorithms are required. Appearance-based methods are mainly employed to achieve high detection accuracy. They solve a two-class problem by using a probabilistic framework or finding a discriminant function from a large set of training examples. To solve this problem, it is necessary to find more distinctive features, which can capture the structural similarities within the face class. In this paper, I'm propose a new feature, called joint Haar-like feature, for detecting faces in images. This is based on co-occurrence of multiple Haarlike features. Feature co-occurrence, which captures the characteristics of human faces, makes it possible to construct a more powerful classifier. The joint Haar-like feature can be calculated very fast independently of image resolution and has robustness against addition of noise and change in illumination.

Keywords: algorithms detection, probabilistic framework, finding a discriminant function, Haar-like feature.

I. INTRODUCTION

One of the usages of computer vision is detecting faces in images is a fundamental task for realizing surveillance systems or intelligent vision-based human computer interaction [1]. In this case, we can point to some problems such as the variety , the variety in size and color transforming in respect to position and distance in ratio of camera. Different algorithms are used to detect . In [6] used Haar-like features, which are similar to Haar basis functions. The features encode differences in average intensities between two rectangular regions, and they can extract texture without depending on absolute intensities, provides both robustness and computational efficiency. Many improvements or extensions of this method have been proposed. I'm will improved Harr - like algorithm in all optical environment. A face detector is learned by stagewise selection of weak classifiers based on the Haar-like features using [3]:

$$H(x) = sign\{\textstyle\sum_{t=1}^{T} \alpha_t \, h_t(x)\} \qquad (1)$$

Inside:

$h_1(x) = |z_{1,1} \dots z_{1,f} \dots z_{1,F}|$

$h_T(x) = |h_1(x) \dots Z_{T,1} \dots Z_{T,F}|$

The final strong classifier $H(x)$ is a linear combination of weak classifiers $h_1(x)$ to $h_T(x)$, $h_1(x)$ observes F features in total and evaluates joint statistics of these features. The structural similarities of faces, which cannot be evaluated using a single feature, are extracted from $z_{1,1}$ (eye regions darker than neighboring regions), $z_{1,f}$ (nostrils are dark) and $z_{1,F}$ (the region between the eyes is brighter than the eyes) [4]. These combined features are selected in each round of the boosting process, such that the error on the training set is minimized. I'm first describe the t Haar-like features. Then, improved Harr-like algorithm in all optical environment our method yields higher classification performance than method other.

II. ALGORITHM

Haar-like features have scalar values that represent differences in average intensities between two rectangular regions [5]. They capture the intensity gradient at different locations, spatial frequencies and directions by changing the position, size, shape and arrangement of rectangular regions exhaustively according to the base resolution of the detector. In [7], a weak learning algorithm is designed to select the single feature that best separates the face and nonface. Even the best feature selected from 80,160 features cannot provide good classification performance. The training error and the generalization error are plotted against the number of weak classifiers. The training error converges to zero when the number of features reaches about 500 [8]. However, the generalization error is no longer reduced after 1,000 features are selected. This means that no effective features remain and further improvement cannot be expected. In [11] divided the range of the feature values into 64 partitions to express complex densities.

A, Feature Value

To improve the generalization performance, we use weak classifiers that observe multiple features. Feature cooccurrence makes it possible to classify difficult examples that are misclassified by weak classifiers using a single feature. We represent the statistics of feature co-occurrence using their joint probability [9]. To calculate the joint probability, we quantize the feature value $\boldsymbol{z}$ to two levels. By doing so, each feature value is represented by a binary variable $\boldsymbol{s}$, which is 1 or 0, specifying face or nonface respectively.

Calculate:

$$\boldsymbol{s}(\boldsymbol{x}) = \begin{Bmatrix} \mathbf{1} \; if \; \boldsymbol{p} \cdot \boldsymbol{z}(\boldsymbol{x}) > \boldsymbol{p} \cdot \boldsymbol{\theta} \\ \mathbf{0} \qquad otherwise \end{Bmatrix} \quad (2)$$

Where θ is a threshold and p is a parity indicating the direction of the inequality sign. The values of θ and p are determined so that the error rate is minimized. The Haar-like features are not limited to the case of using binarized feature values. Multi-level quantization of the feature value fits more complex distributions than binarization.

B, The Haar-like Features

The Haar-like features are represented by combining the binary variables computed from multiple features, an example of the Haar-like feature, which is based on the co-occurrence of three Haar-like features [10]. When the variables are 1, 1 and 0, the value of the Haar-like feature is calculated by:

$$j = (110)2 = 6 \quad (3)$$

The feature value j as a binary number specifies an index for 2F different combinations, where F is the number of combined features. The feature represents the feature cooccurrence between different positions, resolutions and orientations. For each class, statistical dependencies between the features are obtained by observing j for each example. I'm use such dependencies for classification. The subwindow is classified to be face or nonface by evaluating from which class the feature value is likely to be observed. The combined features are selected to capture distinctive structural similarities of faces. In the subsequent section, I'm will improved Harr-like algorithm in all optical environment.

III. IMPROVED HARR-LIKE ALGORITHM

A, The learning algorithm:

A set of N labeled training examples is given as $(x_1, y_1), \ldots, (x_N, y_N)$, where $y_i \in \{+1, -1\}$ is the class label associated with example x_i. $D_t(i)$ is a weight of example x_i. The weights are initialized by $D_t(i) = 1/N$.
The final strong classifier $H(x)$ is a linear combination of T weak classifiers $h_t(x)$:

$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t \, h_t(x)\right) \quad (4)$$

B, **Algorithm progress:**

1	Given example images $(x_1, y_1), \ldots, (x_N, y_N)$, $y_i \in \{+1, -1\}$ for face and nonface examples respectively.	
2	Initialize weights: $$D_t(i) = 1/N$$	(5)
3	For $\boldsymbol{t} = 1, \ldots, \boldsymbol{T}$: (A) For each feature, calculate a feature value. (B) Binarize each feature value and assign a binary variable according to Eq (C) Train a weak classifier based on a combination of features. The error is evaluated with respect to $D_t(i)$. $$\epsilon_t = \sum_{i:\, y_i \neq h_t(x_i)} D_t(i)$$ where j is a feature value of the joint Haar-like feature. $$P\,(y = +1\|j) and \; P\,(y = -1\|j)$$ are probabilities observing feature co-occurrence represented by j. They are evaluated with respect to weights $D_t(i)$ of examples as follows: $$P\,(y = +1\|j) = \sum_{i:\, y_i \in j \,\wedge\, y_i = +1} D_t(i)$$	(6)

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	$P\ (y\ =\ -1\|j) = \sum_{i:\, y_i \in j\ \wedge\ y_i = -1} D_t(i)$	
4	Choose $h_t(x)$:with the lowest error ϵ_t $\forall x\ \in\ j,$ $ht(x)\ = \begin{cases} +1 & if\ \ P\ (y\ =\ +1\|j) > \ P\ (y\ =\ -1\|j) \\ -1 & otherwise \end{cases}$	
5	Update the weights: $D_{t+1}(i) = \dfrac{D_t(i)\exp - (\alpha_t y_i\, h_t(x_i))}{\sum_i D_t(i)\exp - (\alpha_t y_i\, h_t(x_i))}$ where $\alpha_t\ = \frac{1}{2}\log\frac{1-\epsilon_t}{\epsilon_t}$	(7)
6	The final strong classifier is: $H(x) = sign\left(\sum_{t=1}^{T} \alpha_t\, h_t(x)\right)$ $H(x) = \begin{cases} 1\ object, & f.p \geq \theta.p \\ -1\ clutter & otherwise \end{cases}$ Here, $\boldsymbol{p}\ \in\ \{1,-1\}$ is a polarity term, which can be used to invert the inequality relationship between $\boldsymbol{f}$ and θ.	(8)

IV. EVALUATE THE COMPLEXITY OF THE ALGORITHM

To construct a weak classifier, need to find distinctive feature co-occurrences. The best feature combination can be found by exhaustive search from all possible feature combinations. However, it is not feasible for a limited training time. The computational complexity for selecting F from M features is $O(M^F)$. Several solutions for efficient feature selection have been proposed, but without the guarantee of optimal selection [12]. I'm use the well-known Sequential Forward Selection. Features are added one by one to improve the classification performance. The computational complexity becomes $O(M\ \cdot\ F)$.

How determine F is also important. Choosing F too large leads to overfitting. Furthermore, the range of j becomes twice as large by adding one feature. To avoid statistical unreliability due to long histograms, we limit F by,

$$2F\ max\ \times\ 10\ <\ N$$

The following two methods for determining F are considered:

(1) Select the best classifier from multiple classifiers trained using different $\boldsymbol{F}$. Since a fixed F is used for each classifier, all weak classifiers observe the same number of features.

(2) Choose the best F in each boosting round using the hold-out method

However, it does not run in realtime since a large set of feature combinations given in advance is used for evaluating joint statistics. In algorithm automatically selects a small number of distincitve feature combinations

V. CONCLUSIONS

In this paper, I'm describe a new visual feature, called Haar-like feature, for face detection and show how it can be selected. The feature captures the characteristics of human faces and improves the performance of each weak classifier.

The results also indicate that 'too weak' classifiers used in the conventional method do not contribute to improving the generalization performance. The proposed method gives a new framework for feature selection and it is not restricted to the use of only Haar-like features.

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BIOGRAPHY

Le Thi Vui is a Lecturer at Hanoi University of Natural Resources and Environment (Hanoi, Vietnam).
College graduated at Hanoi University of Mining and Geology.
Graduated master's degree at Military Technical Academy
Her research interests include cryptography, communications, and algorithm.

Phan Huy Anh is a Lecturer at Hanoi University of Natural Resources and Environment (Hanoi, Vietnam).
College graduated at Hanoi University of Industry
Graduated master's degree at Military Technical Academy
His research interests include cryptography, communications, and information system security

