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# TECHNICAL SCIENCES

## ALGORITHMS FOR DETECTING THE FACE AREA IN THE IMAGE

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**Abstract**

his research work is dedicated to the description of algorithms for identifying the face area in the image, where the existing algorithms are studied, and divided into the categories of empirical recognition and human face image modeling methods. Among face recognition methods in images, features such as local binary templates and directed gradient histograms were highlighted as important in feature recognition. Also, the work presents the problems that arise in the creation of an automatic face recognition system and describes the achievements and shortcomings of face recognition algorithms.

**Keywords:** face image, localization, recognition, computer vision, method of principal components, neural networks, Viola-Jones algorithm, basis vector machines, video stream, local binary template.

Determining the face region in an image is considered the "first step" of a recognition system and can be applied before or after pre-processing the image. Face detection in computer vision is widely used in two modifications, face localization and face motion tracking. Face localization is a simplified version of face detection, as it relies on detecting the presence of only one person in an image. The problem of tracking face motion in a video stream can be expressed as the problem of localizing a face in the current frame based on information about its position in previous frames.

The issue of face detection in an image is a very simple problem for a person, but the following problems arise when creating an automatic face detection system:

– a strong change in the appearance of the faces of different individuals;

– even a small change in the position of the face with the camera can cause a serious change in the image of the face;

– the presence of distinctive features in the image, such as mustache, beard, glasses, and wrinkles, significantly complicates automatic recognition;

– changing the facial expression can strongly affect its appearance;

– if a part of the face is not visible in the image, that is, it is blocked by other objects, it leads to a decrease in the quality of recognition;

– recording conditions, for example, lighting, camera color balance, and image distortions caused by system optics significantly affect the captured face image;

Since the emergence of the problem of face detection, many algorithms have been developed and researched [1-5] that allow the extraction of face images in an image or video stream. Each of the existing algorithms has its advantages and disadvantages.

The problem of face detection in an image can be expressed as follows. Suppose we are given an image I with face regions. It is required to form a list of rectangles that enclose the faces in the image.

Existing algorithms designed to solve the problem of face detection are mainly divided into the categories of empirical recognition and human face image modeling methods. The first category of algorithms relies on human experience in solving the face recognition problem and tries to put this experience into practice. Researchers using this approach try to identify the conditions and cues that are used as a basis for deciding whether a face is a face or not. Many heuristics are formed and based on their presence and compatibility, the automatic system can determine whether there is a face area in the image or not. The following features are used:

– having a certain complexion;

– the face is often symmetrical about the vertical axis;

– the presence of special features on the face, such as eyes, nose, and mouth;

– the fact that facial features have a strictly determined ratio of size and mutual location.

The second category of algorithms does not seek to formalize the processes occurring in the human brain, but they are based on the apparatus of mathematical statistics. This class of methods relies on well-developed pattern recognition theory, or more generally, classification problem-solving theory. Here, the problem of face detection is considered a special case of the problem of classification with a predetermined class "face" and "not a face". Determining whether the image belongs to one of the classes uses a vector of features representing the reflection of the analyzed image in a space with a larger size compared to the given size. Since the total number of features is very large, various methods and algorithms of feature selection are used to reduce the size and extract important features [6-14]. Many methods of this category use two stages of training. At the training stage, the most important ones are extracted from the set of features, and the threshold values of the features used in deciding whether the image belongs to one or another class are determined. At the classification stage, the feature values are calculated and the image belongs to the class. Since the stage of training and selection of the most important features does not require human intervention, the results of the methods of the second category have a significant advantage over the results of empirical methods of determination.

In recent years, work has been actively carried out in the field of recognition of a person based on a face image and is based on such approaches as the principal component method of the second category [15], neural networks [16], the Viola-Jones algorithm [17,18], support vector machines [19, 20]. Many methods have been proposed. An important breakthrough in solving the problem of face recognition was the use of deep learning neural networks [21]. The main disadvantages of this class of methods are that the training phase requires a lot of time and a large sample size, and in most cases, it only trains objects from their rectangular images and discards some information related to color.

Face recognition methods based on Local Binary Patterns (LBP - Local Binary Patterns) have an effective ratio of accuracy, time, and resource requirements [22]. LBPs are used to represent textural characterizing features of images. LBP is a binary representation of the area of a point in an image, where the LBP operator applied to an image pixel takes the central pixel as a threshold and uses N pixels around it. Surrounding pixels whose intensity is greater than or equal to the intensity of the central pixel receive a value of 1, and the rest receive a value of 0, and an N-bit binary code representing the pixel's surroundings is generated:

$$\mathrm{LBP}(x_c, y_c) = \sum_{i=0}^{N-1} s(g_i - g_c)2^i,$$

where $x_c, y_c$ are pixel coordinates; $g_c$ is the central pixel intensity; $g_i$ are the intensities of surrounding pixels, $i = 0, \dots, N-1$; s is a threshold function, which is defined as follows:

$$s(x) = \begin{cases} 1, x \geq 0, \\ 0, x < 0. \end{cases}$$

Typically, six-bit LBP is widely used in image processing. If the LBP contains no more than three series of 0 and 1, the LBP is called flat. For example, 000000000, 0011100000, and 111000001. Only the most important local features of the image can be determined by flat LBPs, and it allows to significantly reduce the code sets. A histogram of codes is used to represent the image area through LBP. Face detection using this approach requires a training sample with additional face images. Each of them is divided into rectangular areas and corresponding LBP-coded histograms are constructed. The resulting histograms are combined into a single histogram to represent the image.

One of the most popular approaches to identifying individuals in an image is based on histograms of oriented gradients (HOG, Histogram of Oriented Gradients) [23]. The idea behind this approach is that the image of the object is sufficiently well described by the distribution of gradients of pixel intensities. The main unit of image representation using HOG features is a block, i.e., a rectangular area of the image. The block, in turn, consists of cells containing pixels. A histogram of the directions of the gradients obtained from the given number of channels is applied to each cell, in which the signs of the angles are not taken into account, that is, the angles α and -α are considered equivalent. To do this, each pixel in the cell participates in weighted voting for direction histograms based on gradient values. In the distribution of weights in voting, the pixel weight can be given by the absolute value of the gradient or some function of it. After the histograms are calculated in each cell of the block, they are combined to form a vector of block features, and then the vector is normalized. Such features are calculated for all blocks of the image. In this case, the blocks overlap each other, that is, it is taken into account that the pixel gradient represents several blocks. The HOG representation of the image is formed by concatenating the feature vectors of all the blocks.

One of the best classification methods is the support vector machine (SVM) [21], which has many unique features:

1) training is reduced to a quadratic programming

problem that has a single solution that is sufficiently efficient even in selections of several hundred thousand objects;

2) the solution is sparse, that is, the state of the optimal separating hyperplane depends only on a small number of teaching objects, called base vectors, and the rest of the objects practically do not affect their state;

3) by introducing a kernel function, the method is transferred to the case of non-linear separating surfaces.

Below is a detailed description of the SVM method.

Suppose we are given a set of training samples $\{(X_i, Y_i), i = 1, \dots, L\}$. Here $X_i$ is the n-dimensional feature vector of the i -th object of the training sample, $Y_i$ is the target of the i -th object, $Y_i \in \{-1, +1\}$. In the case of linearly separable classes, the separating hyperplane equation is expressed as follows:

$$W^T X + b = 0, \quad (1)$$

where W is a vector of weights, b is a threshold value defining the classification decision rule:

$$\begin{cases} W^T X + b \geq 0 \rightarrow Y_i = +1, \\ W^T X + b < 0 \rightarrow Y_i = -1. \end{cases} \quad (2)$$

The hyperplane constructed on the basis of the vector of given weights the threshold value and the distance between the closest point of the data set is called the partition boundary. The main problem to be solved by the method of basis vectors is to find an exact hyperplane that maximizes the partition boundary, and the solution surface satisfying these conditions is called an optimal hyperplane.

Assume that $W_o$ and $b_o$ are the optimal vectors of weights and threshold values, respectively. Then, the solutions in the feature space of the optimal hyperplane equation with a multidimensional linear surface can be written as:

$$W_o^T X + b_o = 0 \quad (3)$$

In this case, the discriminant function is obtained as follows:

$$g(X) = W_o^T X + b_o = 0 \quad (4)$$

The discriminant function defines an algebraic measure of the distance from point X to the optimal hyperplane. A point X in the character space can be expressed as:

$$X = X_p + r\frac{W_o}{\|W_o\|} \quad (5)$$

where $X_p$ is the normal projection of the X point to the optimal hyperplane, r is the distance from the point to the optimal hyperplane. In this case, r can be negative or positive, depending on which side X is located relative to the hyperplane. From equations (4) and (5) we get:

$$g(X) = W_o^T\left(X_p + r\frac{W_o}{\|W_o\|}\right) + b_o = W_o^T X_p + r\frac{W_o^T W_o}{\|W_o\|} + b_o = = r\frac{W_o^T W_o}{\|W_o\|} = r\frac{\|W_o\|^2}{\|W_o\|} = r\|W_o\| \quad (6)$$

or

$$r = \frac{g(X)}{\|W_o\|} \quad (7)$$

The points closest to the separating hyperplane are called base vectors. The maximum bandwidth that can be passed between two classes of support vectors is called the geometric gap. The geometric notch is a value that is twice the minimum value of r calculated by the formula (7). Taking into account that the scaling of parameters $W_o$ and $b_o$ do not change the value of the geometric slot, the following conditions can be introduced:

$$\begin{cases} W_0^T X_i + b_0 \geq 0 \rightarrow Y_i = +1, \\ W_0^T X_i + b_0 < 0 \rightarrow Y_i = -1. \end{cases} \quad (8)$$

The solution of the system of inequalities (8) is equivalent to the solution of the following inequality:

$$Y_i(W_0^T X_i + b_0) \geq -1 \quad (9)$$

As a result, inequality (9) is fulfilled for all points, and there are support vectors that transform it into equality. The distance $r_i$ from the point $X_i$ to the hyperplane is calculated by the following formula:

$$r_i = Y_i\left(\frac{W_0^T X_i + b_0}{\|W_0\|}\right) \quad (10)$$

Since the distance between the base vectors and the hyperplane is equal, the geometric slot is obtained as follows:

$$\rho = \frac{2}{\|W_0\|} \quad (11)$$

In general, in the SVM method, it is required to find the values of parameters W and b that satisfy the following conditions:

1) the maximum value of the geometric slot: $\rho = \frac{2}{\|W\|}$,

2) the inequality $Y_i(W^T X_i + b) \geq 1$ holds for all pairs $(X_i, Y_i)$ taken from the set of teaching samples.

The problem of maximizing $\frac{2}{\|W\|}$ is equivalent to the problem of minimizing $\frac{\|W\|}{2} = \frac{1}{2}\sqrt{W^T W}$ and the problem of minimizing $\frac{1}{2}W^T W$. This leads to the formulation of the optimization problem in the basis vector method, that is, to determine the values of parameters W and b that satisfy the following conditions:

1) $\frac{1}{2}W^T W$ magnitude reaches a maximum.

2) the inequality $Y_i(W^T X_i + b) \geq 1$ holds for all pairs $(X_i, Y_i)$ taken from the set of teaching samples.

This formulation of the problem corresponds to the quadratic optimization problem, and its solution requires the formulation of a dual problem. In this case, the correct problem depends on the Lagrange multiplier $\alpha_i$ corresponding to each linear constraint $Y_i(W^T X_i + b) \geq 1$. It is required to find $\alpha_1, \alpha_2, \dots, \alpha_n$, satisfying the following conditions:

1) $\sum_{i=1}^{L} \alpha_i - \frac{1}{2}\sum_{i=1}^{L}\sum_{j=1}^{L} \alpha_i \alpha_j Y_i Y_j X_i^T X_j$ size reaches a maximum.

2) $\sum_{i=1}^{L} \alpha_i Y_i = 0$,

3) $\alpha_i \geq 0$, $i = 1, 2, \dots, L$.

The solution looks like this:

$$\begin{cases} W_0 = \sum_{i=1}^{L} \alpha_i Y_i X_i \\ b_0 = Y_k - W_0^T X_k \forall X_k : \alpha_k \neq 0 \end{cases} \quad (12)$$

In the solution, some parameters $\alpha_i$ are equal to zero, and each non-zero value of $\alpha_i$ means that the vector $X_i$ is the basis. In this case, the classification function will look like this:

$$g(X) = \mathrm{sign}\left(\sum_{i=1}^{L} \alpha_i Y_i X_0^T X + b_0\right) \quad (13)$$

In cases where the classes are separated linearly, the points being classified are shifted to a higher dimension space:

$$\Phi: X \to \phi(X). \quad (14)$$

This means the transition from the scalar multiplication $X_i^T X$ in the expression (13) to the kernel $K(X_i, X)$:

$$K(X_i, X) = \phi(X_i)^T \phi(X) \quad (15)$$

The kernel K must be continuous, symmetric, and have a positive definite Gram matrix. These conditions guarantee the reflection in the generating kernel of the Hilbert space (Hilbert space - vector space, complete space with respect to the scalar product), that is, the space in which the scalar product overlaps with the function value K. The most common families of kernels are:

- polynomial kernel:

$$K(u, v) = (1 + u^T v)^d, \quad (16)$$

- radial basis functions:

$$K(u, v) = \exp(-\beta \|u - v\|^2) \quad (17)$$

The support vector method has many advantages and disadvantages, and in order to overcome the disadvantages, the method has been developed such as Relevance Vector Machine (RVM), 1st norm SVM (LASSO SVM), Doubly Regularized SVM (ElasticNet SVM) and Support Features Machine (SFM). Many modifications have been developed.

Face detection in video sequence frames and their identification using the methods described above require considerable time. Compared to the methods described above, a less resource-intensive and effective method is the mean shift method known as MeanShift [24].

The idea behind the MeanShift method is the kernel estimation of the distribution density:

$$f(x) = \frac{1}{n}\sum_{i=1}^{n} K(x - x_i) = \frac{1}{n}\sum_{i=1}^{n} ck\left(\left\|\frac{x-x_i}{h}\right\|^2\right), \quad (18)$$

where $x_i$ $(i = 1, \dots, n)$ are vectors of features of distribution points, K is a distribution kernel, k is a kernel function (or parzen window), h is the size of a parzen window.

The gradient of the function $f(x)$ is calculated by the formula:

$$\nabla f(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n} \nabla K(\mathbf{x} - \mathbf{x}_i) =$$

$$= \frac{c}{n}\left[\sum_{i=1}^{n} \mathbf{x}_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)\right]\left[\frac{\sum_{i=1}^{n} \mathbf{x}_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - \mathbf{x}\right] \quad (19)$$

where $g(r) = -k'(r)$ is the function of the first derivative of the kernel function.

In the expression (19), the average displacement vector with a kernel $G(x) = cg\left(\left\|\frac{x-x_i}{h}\right\|^2\right)$ also participates as a multiplier:

$$m(x) = \frac{\sum_{i=1}^{n} x_i g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)}{\sum_{i=1}^{n} g\left(\left\|\frac{x-x_i}{h}\right\|^2\right)} - x. \quad (20).$$

From the expression (20), it can be seen that the mean displacement G consists of the normalized density gradient given by the kernel.

In general, the moving average algorithm can be expressed as follows:

1. The position and features of the center of gravity of the area where the given object is in the first frame of the video sequence are determined;

2. For each subsequent frame, the following is performed:

2.1. Calculation of the average displacement vector relative to the previous center of gravity;

2.2. Moving the center of gravity according to the new position;

2.3. If the center of gravity does not change, then proceed to analyze the next frame, otherwise, proceed to step –2.1.

The stability of the algorithm can be increased by clarifying the position of the intended area of the image by tracking the object based on the methods described above. It does not significantly slow down the procedure, as the refinement can be performed less frequently (not at each step of the processing cycle). For example, there is a lot of information in the literature about algorithms based on the application of Bhattacharya distance. As a modification of the mentioned algorithms, it is possible to propose the use of histograms of codes obtained using the LBS operator. Another development of the MeanShift method is related to the SVM method and adaptive learning. This object can help to identify in cases where information is lost in a particular frame.

The Viola-Jones method is the most promising method in terms of high efficiency and low frequency of false starts, as well as a large percentage of correct face detections [17]. The main principles underlying the method are as follows:

• use of images in integral representation. This allows you to quickly calculate the necessary objects;

• Using Haar features. The search for the desired object is carried out using Haar features;

• using busting to select the most suitable features for the desired object in a given part of the image;

• passing all features to the input of a classifier that returns the result "true" or "false" ("face" or "not face");

• using feature cascades to discard undetected windows.

The integral representation of an image is a transform of a grayscale image in which each (x, y) point is the sum of the intensities of the image pixels to the left and above that point, including that pixel.

Haar features (Figure 1) consist of mixed rectangular areas [25] and these areas are placed in the image, then the pixel intensities in the areas are summed, the difference between the sums is calculated. The advantage of using Xaar features is that they are faster to calculate than other features. Using the integral representation of images, the Haar features can be calculated at the present time. In the detection step, the Viola-Jones method uses a window of a certain size that moves over the image. A Haar feature is calculated for each area of the image corresponding to the current window. The presence or absence of the searched object in the image window is determined by the difference between the feature value and the trained threshold.

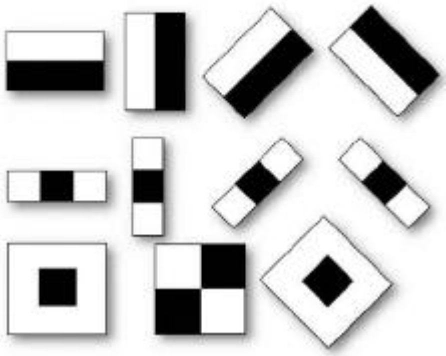

***Figure 1.*** *Features of Haar*

Haar features are not considered very suitable for teaching or grading. Therefore, it requires a large number of features to describe the object with a sufficient level of accuracy. For this purpose, the Viola-Jones method uses a cascaded classifier, each element of which is a simple (weak) classifier based on one of the Haar features of the following form:

$$h_j(z) = \begin{cases} 1, \text{агар } p_j f_j(z) < p_j \theta_j, \\ 0, \text{акс ҳолда}, \end{cases}$$

where $p_j$ is a parameter indicating the direction of the inequality sign, $\theta_j$ is a threshold value, $f_j(z)$ is a feature value, z is an image window with a size of 24x24 pixels, and the j index identifies a certain Haar feature.

The training of the cascaded classifier is done through a busting scheme. The idea of busting was proposed by Robert Shapiro in the late 90s of the last century when it was necessary to find a solution to the problem of how to get one good one with many bad (insignificantly different from random) training algorithms [20], and it is based on the following assumptions [21]. When solving complex problems of feature recognition, often one of the algorithms cannot provide the required quality of the result. In such cases, the expected results can be achieved by building a composition of algorithms, in which the errors of individual algorithms are mutually compensated. Examples of such algorithms are simple and weighted voting algorithm. In general, the busting scheme has the following structure: at first, class membership ratings of the object to be recognized are calculated, and then a decision rule transfers these ratings to the class target. The probability of belonging to the class of the object, the distance from the object to the separating surface, and the degree of reliability of classification can be taken as the evaluation value. The Viola-Jones method evaluates the recognition of a given person's face in an image window. In this case, training classifiers is very slow, but face detection is fast. The algorithm works well and can recognize facial features at a small angle of about 30 degrees. At angles greater than 30 degrees, the percentage of detection decreases sharply. However, at small angles of up to 15 degrees, the algorithm can reliably detect a human face.

**Conclusion**

Algorithms for face area extraction from images were studied in this research work. In this case, existing algorithms are mainly divided into the categories of empirical recognition and human face image modeling methods. The first category of algorithms relies on human experience in solving the problem of face recognition and tries to put this experience into practice. The second category of methods relies on a well-developed pattern recognition theory or, more generally, on the theory of solving classification problems. Therefore, local binary templates and directed gradient histograms, Haar-like feature descriptions were introduced in the work. It was also recognized that the support vector method, which is popular among machine learning methods, differs from other methods by its specific features.

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