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A Review on Different Techniques of Image Processing

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ABSTRACT:

The human face has always been an attribute of interest of researchers. It is not only an identity feature, but also a unique biological trait of every human being. For this reason, the picture of a person plays an important role in almost every sector. Although face recognition is fairly easy and intuitive task for any human, it requires complex machine learning algorithms to achieve the same. This paper gives a brief overview of different techniques used in image processing and face recognition.

1. INTRODUCTION:

Human face always attracted researchers. It is a unique biological trait of every human being. By this unique biological feature or property one can identify another person uniquely. This characteristic property was noticed by researchers and pioneers of automated face recognition, Woody Bledsoe, Halen Chan Wolf, and Charles Bisson, who developed the first automated face recognition system during 1964 and 1965. Since then, several sectors of security have deployed the use of this technique to add robustness to their security systems. Apart from its traditional use in airports, banks, and other security systems, its most popular impact is now seen in the upcoming trend of using photo tagging in social networking sites.
Face recognition continues to be a strong thrust area in research. One of the many reasons is because the it provides a greater level of security than traditional text based passwords that can be guessed or stolen. Face Recognition overcomes this problem since it tries to recognize the human face that is unique to every human being. This paper discusses debates, confers and considers some popular techniques and ideas of feature extraction in image processing.

2.1 PCA

Karl Pearson in 1901 to improve PCA or Principal Component Analysis. This is a powerful mathematical tool. This tool allows a 2D (two dimensional) image processing and 3D (three dimensional) can be used in image processing. Principal component analysis of a set of linearly uncorrelated variables, the interaction may be a set of observations. Principal component analysis using orthogonal transformation of this conversation. This is the main component. The main elements of the main variables of less than or equal to. This could turn into a way that the first major component is the largest organ in the contravention, and for each succeeding constraint that is orthogonal to the previous item is defined as the maximum possible variance. Main elements to be independent only if the joint is normally distributed data sets are guaranteed. Principal component analysis is sensitive to changes in the relative size of the original variables. Depending on the applied field, it is the discrete Karhunen-Loeve (KLT), Hotelling change or correct orthogonal decomposition (pod) is known. Principal component analysis as a tool for exploratory data analysis and predictive models are used in most cases. Principal component analysis of a data Covariance Matrix Eigen value decomposition or singular value decomposition of the data matrix can be used. Principal component analysis of the results, or sometimes a component of the score is usually discussed in terms of factor scores. Principal component analysis of the eigenvector-based multivariate analysis of a simple form. Principal component analysis using a low-dimensional image, the object is to provide a "shadow" can be informative when viewed from the point of view. This is only a few of the main elements of the transformed data are used to reduce dimensionality. [1][2][3][4]

2.2 ICA

Independent component analysis ICA is another powerful mathematical tool. This tool allows a 2D (two dimensional) image processing and 3D (three dimensional) can be used in image processing. Independent component analysis and higher - the second order and the second input data and results for the data minimizes the dependency of the statistical information for the try. When the independence assumption is correct, a mixture of blind signal separation is the result of the ICA. This signals that are generated by the analysis of a mixed use is not permitted. The independence of mutual information and the broadest definition for ICA), the minimization of non-Gaussianity b) Maximization of the use of the content analysis of centralization, white, and pre-processing step in order to reduce the dimensionality and to reduce the complexity of the problem for the iterative algorithm. Whitening or singular value decomposition and the reduction of the main elements of the analysis can be achieved with. Make sure that the same level of whitening is considered a priori before the algorithm runs. Blind signal separation by ICA and has many practical applications. It is (or even a special case) for a factorial code to search for information on closely related. [5][6]

2.3. LDA

Linear Discriminant Analysis LDA to complete the form. This is a powerful mathematical tool. This tool allows a 2D (two dimensional) image processing and 3D (three dimensional) can be used in image processing. Discriminant analysis of the underlying linear vector space that best discriminate between classes to find out. Linear discriminant analysis, statistics, pattern recognition and machine learning is used. This is a feature that characterizes the object, or a linear combination of two or more different classes to help people find. The combination of a linear classifier, for example, or may be used, usually after the dimensionality reduction for classification. Linear Discriminant Analysis of the ANOVA (analysis of variance) and regression analysis, which is a linear combination of dependent variable from the other property, or the size of closely related efforts. In the other two methods, depending on the amount of a numerical variable, when the LDA is an independent variable (ie class label). Logistic regression and probit regression is more similar to the LDA, such as an independent variable to explain that. Other applications of this method is that it is normally distributed independent variables, a Linear Discriminant Analysis method, which is not reasonable to assume that it is recommended that the basic assumption. Linear Discriminant Analysis is to closely analyze the main components (PCA) and factor analysis of the data that they interpreted as a linear combination of variables, both for appearance. Linear Discriminant Analysis of the differences between the model and try to clear from the data. While PCA does not consider, take a class in the factor analysis of the differences and similarities rather than differences based on the features and the combinations. Discriminant analysis is also different from factor analysis, it is not an interdependence technique: the independent variable and the dependent variable (also known as criterion variables) must be the difference. Linear Discriminant Analysis of the observations for each independent variable is measured on a continuous scale. Categorical independent variables with the behavior, equivalent to correspondence discriminant analysis method. [7][8][9][10][11][12]

2.4 EP

Evolutionary pursuit EP complete the form. This is a powerful mathematical tool. This tool allows a 2D (two dimensional) image processing and 3D (three dimensional) can be used in image processing. Principal component analysis of the projection method for realization of an evolutionary adaptation to the generalization property. Evolutionary pursuit of the white image data transformation is applied to reduce the level of reduction of the primary component analysis. Convert image datas that have the same variance as the whitening of the original group was created, but is uncorrelated. Whitening transformation matrix is a diagonal matrix of corresponding eigenvalues. Whitened space, then the image will be converted to a rotation. According to the pair of spins in the two axises. Then, genetic algorithms, evolutionary accomplishment, and a rotation vector to vector conversion in various combinations to find the optimal subset. Genetic algorithms to solve a string of bits to be represented in the form of the chromosomes. A solution with a pair of angle and vector. Each angle is to be published by 10bits. [13][14][15][16][17]

2.5 EBGM

Elastic bunch graph matching EBGM complete the form. It is a mathematical tool. This tool allows a 2D (two dimensional) image processing and 3D (three dimensional) can be used in image processing. Elastic bunch graph matching, a local feature based methods. I have a label on a graph that identifies the nodes and edges. Node is selected, the mouth, ear, eye, like the fiducial points from the corners and edges are connected by. Jet node, which is near the gray values of a given pixel of an image using the patch are labeled. This change is based on a small wave. Or two-dimensional vector with the edge distance is known. The fiducial point of a jet from a group called a cluster. This cluster graph is created semi-automatically. Appropriate fiducial points and the selected nodes are drawn in by the end user. Edge labels are automatically computed as the difference between nodes. Finally, Gabor wavelet jets to change the node is available. Different faces in different poses for a group of a graph and a pointer to the node connection is used in various poses. [18][19]

2.6. KM

Full form the kernel method. It is a mathematical tool. This tool allows a 2D (two dimensional) image processing and 3D (three dimensional) can be used in image processing. Kernel methods are algorithms for the analysis of a pattern class, which is famous for support vector machine elements (SVM). The kernel method uses a kernel function, which places their property without ever computing the coordinates of the location information from active management owe their name, but only the data for all pairs of images by computing the inner product feature space. Coordinates are often computationally cheaper than the explicit computation of this operation. The kernel function of order data, graphs, text, photos, as well as a high-dimensional feature space vectors.Kernel method, where each coordinate is a feature of the data by mapping data from a similar problem has been on the transfer of a Euclidean space is a set of data points. The location, method of use of the information can be found in the relationship. Since the mapping can be very common, very common, according to the relationship found in this manner. This method is called the kernel trick. Algorithm enables the operating system kernel with support vector machines Kernek (SVM), Gaussian processes, linear discriminant analysis of Fisher's (LDA), the main component analysis (PCA), canonical correlation analysis, ridge regression, spectral clustering, linear adaptive filtering, and many other . [20][21][22][23][24][25][26]

2.7 TT

Full form of TT is trace Transform. This is a powerful mathematical tool. This tool allows a 2D (two dimensional) is used for image processing. Trace changes, changes Radon is a generalization, the effectiveness of the straight line along which the image is an image of the functional are calculated. Functionals used in the production of the same image can be transformed from a different trace. Each trace is a trace line to change the parameters of the 2D image of a function. A line in the plane of two parameters can be identified. A simple example is the trace of the Transform bundle, which is used for line detection, the binary edge maps each trace line along the shank, and is considered the number of edges. The numbers of parameters, then the two lines are plotted as a function of the bunch. Trace changes, for each parameter, the two other functionals of a number of methods that apply to the original image, that characterizes the triple product property. [27][28][29]

2.8 AAM:

The full form of AAM Active Appearance Model. This is a powerful mathematical tool. This tool provides 2D (Two Dimensional) and 3D (Three Dimensional) image processing can be used. A new image from the active presence of the model is a statistical model of object shape and appearance matching algorithms for computer vision. They are created during training. A set of images, together with training supervisors to recognize the image of all the coordinates are displayed. Approach for matching and tracking faces and widely used in medical image interpretation. Current estimates from the introduction of an algorithm and optimization techniques to drive the difference between the target image. Strategies to take advantage of least squares, it can match the new image to be very fast. [30][31]

2.9 3-D Morphable Model

Modeling of 3D Morphable automatically generating them using one or more photographs of the faces of a textured 3D modeling techniques. 3D model of an internal model of correspondence from the solid face of computing by automatically registered. 3D face model is represented by a vector space of linear combinations of prototypes can be expressions of the faces in the new issue is received by the shape and texture transfer. [32][33][34][35][36]

2.10 3-D Face Recognition

3-D face recognition system is a powerful mathematical tool. This tool provides 3D (Three Dimensional) image processing can be used. Our real-world 3D (Three Dimensional), all as will be shown in the image. When we try to process it in real-world images using a three dimensional image processing. The main novelty of this method is independent of the surface deformations resulting from the comparison of natural facial expressions. First, range image and the face texture is achieved. Next, the range image sensor, such as a specific part of the hair, which can complicate the recognition process is to remove the pre-processing. Finally, a canonical form of the face surface is computed. Such a representation is insensitive to head orientations and facial expressions, so that simple detection method. Recognition itself is performed on the canonical surface. [37][38]

2.11 Bayesian Framework

Bayesian framework, a process that Bayes' rule to estimate the possibility of additional evidence for a hypothesis is used to update the learned. A Bayesian updating of the statistics, and mathematical statistics, especially the most important strategies: a statistical method based on Bayesian derivation for the viewer to make sure that the method works automatically in some cases, such as a competing process. Updated information is particularly important in Bayesian analysis of a dynamic sequence. Bayesian inference is a science, engineering, medicine, etc., with a range of applications found. [39][40][41]

2.12 SVM

Support vector machine SVM complete the form. This is a powerful mathematical tool. Support vector machine is a supervised learning method for data analysis and statistical patterns, classification and regression analysis used to identify a set and a computer science concept. Standard support vector machine and a set of input data and the predictions about undiscovered maulagulo, for each input, the two possible classes of input forms, creating a non-probabilistic binary SVM classifier raikhika. Examples of training, each belong to one group as a set of two, a support vector machine training algorithm for a class or a model that creates another set of new examples. For example, a support vector machine model as a representation of space points, with a clear space for the different classes that are separated by wide as possible. For example, in the same place with the new, and after they attacked a group based on the spacing of the side that prediction.[42][43][44]

2.13 HMM

complete form is hidden Markov models. This is a powerful mathematical tool. Hidden Markov Model (hmm), where the system is modeled from a statistical Markov model unobserved (hidden) state is assumed to be a Markov process. I make a dynamic Bayesian network can be considered. A hidden Markov model, the state, but is not directly visible in the output, dependent on the state, is visible. The potential distribution of each state can have on the output token. So I generated by a token in the sequence gives information about the state of order. Note that the adjective 'hidden' state order which passes through the means of the model, the model parameters, even if the model parameters are known, the model is still 'hidden'. Hidden Markov models such as the temporal speech, handwriting, gesture recognition, in part - of-speech tagging, the instrument scores, partial discharges and their application to pattern recognition is known as bioinformatics. A hidden Markov model is considered as a mixed model where the hidden variables that control the mix of elements to be selected for each monitor, rather than a Markov process independent of each other can be associated with a comment.[45][46][47]

2.14 Boosting & Ensemble Solutions:

Boosting is a supervised machine learning to perform meta - learning algorithms. Boosting the back of the sample from the sequence of a given training set to generalize a set of classifier on the weak version of the Weighted Student is appointed. A classifier, which is classified as a poor student to be correlated with a small set. Conversely, if a student is classified with a classifier that is arbitrary - correlated. However, a classifier that can be run with little more than random guessing, consists of an ensemble is the (strong) classifier can provide. Boosting algorithmically is not constrained, most of the boosting algorithm iteratively a distribution with respect to the weak classifier learning, and they made a final strong classifier. When they are added, they are usually weak in some ways that students' accuracy is usually associated with the Weighted. After a poor student, is added, the data is reweighted. Boosting and ensemble is very effective and popular solution for a day.[48][49][50][51][52][53]

3. CONCLUSION:

This paper briefly describes the ideas behind different techniques of image processing. Without getting into too many technical details, it modestly glances over the ideas and notions of some popular techniques, for a very basic understanding of the techniques.

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