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Accuracy Driven classification model for Age Prediction

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ABSTRACT:-

Age is an important factor and it's a personal trait of the individual, each individual have distinct patterns emerging from their facial appearance. Technologies derived from rapid advances in computer graphics and machine vision, computer-based age synthesis and estimation via faces have become particularly prevalent topics recently because of their explosively emerging real-world applications, such as forensic art, electronic customer relationship management, security control and surveillance monitoring, biometrics, entertainment, and cosmetology. Age synthesis is defined to re-render a face image aesthetically with natural aging and rejuvenating effects on the individual face. Age estimation is defined to label a face image automatically with the age group (year range) of the individual face. Because of their particularity and complexity, both problems are attractive yet challenging to computer-based application system designers. Here a ground breaking estimation technique was introduced that combines Support Vector Machines (SVMs), to dramatically improve the accuracy of age classification over the current state-of-the-art techniques.

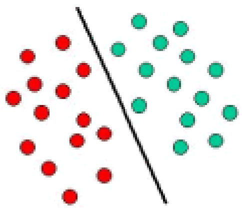
The technique used for age estimation is Support Vector machine (SVM). SVM has emerged as a good classification technique and achieved excellent generalization performance in a variety of applications. Training SVM on a dataset of huge size with millions of data is a challenging problem since it is computationally expensive and the memory requirement grows with the square of the number of training examples.

Keyword:- Age, SVM, classification

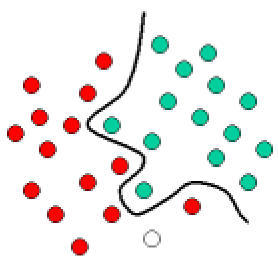
Introduction: For both linear and non-linear data, support vector machine is the absolute choice for age classification. In a high- or infinite- dimensional space, which can be used for classification, regression, or other tasks. It constructs a hyperplane or a set of hyperplanes.

Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

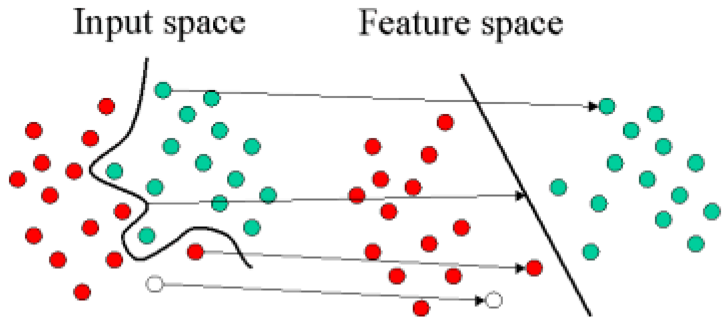
Sometimes it often happens that the sets to discriminate are not linearly separable in that space. For this reason, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space, presumably making the separation easier in that space. To keep the computational load reasonable, the mapping used by SVM schemes are designed to ensure that dot products may be computed easily in terms of the variables in the original space, by defining them in terms of a kernel function $K(x,y)$ selected to suit the problem. The hyperplanes in the higher dimensional space are defined as the set of points whose inner product with a vector in that space is constant. The vectors defining the hyperplanes can be chosen to be linear combinations with parameters α_i of images of feature vectors that occur in the data base. With this choice of a hyperplane, the points x in the feature space that are mapped into the hyperplane are defined by the relation:



The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation, i.e., correctly classify new objects (test cases) on the basis of the examples that are available (train cases). This situation is depicted in the illustration below. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. Support Vector Machines are particularly suited to handle such tasks.



The illustration below shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping (transformation). Note that in this new setting, the mapped objects (right side of the schematic) is linearly separable and, thus, instead of constructing the complex curve (left schematic), all we have to do is to find an optimal line that can separate the GREEN and the RED objects.



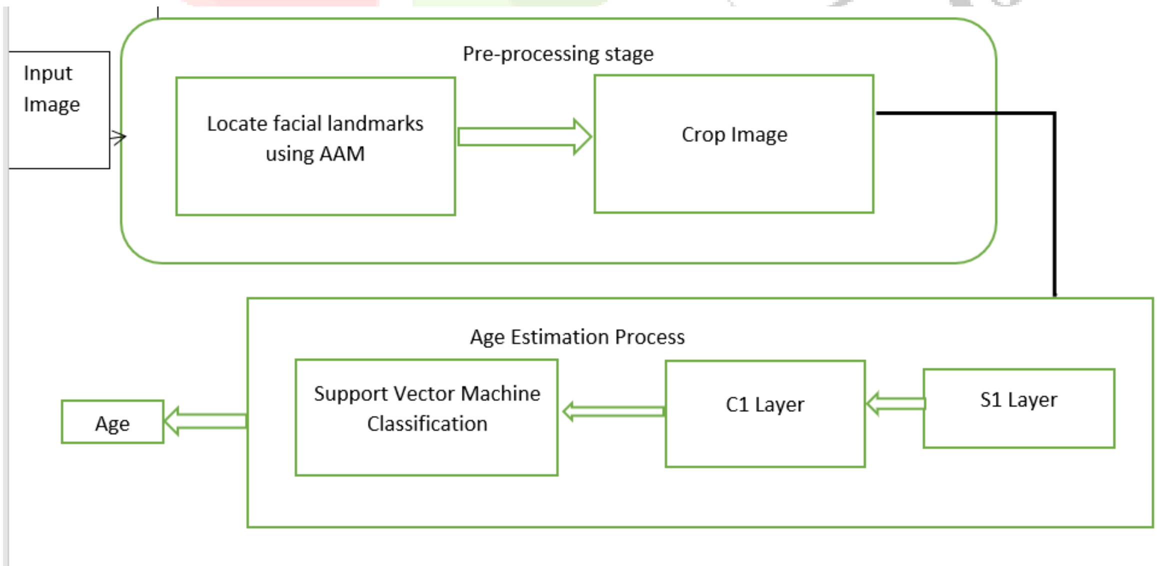
Support Vector Machine (SVM) is primarily a classier method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables.

Proposed Methodology

The proposed method consists of following steps: Face annotated images are read from the database followed by feature extraction using Active Appearance Model (AAM). AAM converts face images into appearance parameters, contains both shape and texture information. This is given as input for training the gender classifier. Depending upon the output from the gender classifier, the appearance parameters are fed into the corresponding age estimator. Gender classification is attempted with two classifiers: Neural network, Support vector machine. Age estimation is performed using Neural networks and the output is given in terms of age range.

Opencv age detection with Linear Support Vector Model

Workflow diagram



There are two fundamental problems inspiring the development of these techniques:

Face image synthesis: Render face images with customized single or mixed facial attributes (identity, expression, gender, age, ethnicity, pose, etc.).

Face image analysis: Interpret face images in terms official attributes (identity, expression, gender, age, ethnicity, pose, etc.).

Age synthesis: Render a face image aesthetically with natural aging and rejuvenating effects on the individual face.

Age estimation: Label a face image automatically with the exact age (year) or the age group (year range) of the individual face.

Actual age: The real age (cumulated years after birth) of an individual.

Appearance age: The age information shown on the visual appearance.

Perceived age: The individual age gauged by human subjects from the visual appearance.

Estimated age: The individual age recognized by machine from the visual appearance.

A Survey on Training Algorithms for Support Vector Machine Classifiers

Learning from data is one of the basic ways humans perceive the world and acquire the knowledge. Support vector machine (SVM for short) has emerged as a good classification technique and achieved excellent generalization performance in a variety of applications. Training SVM on a dataset of huge size with millions of data is a challenging problem since it is computationally expensive and the memory requirement grows with the square of the number of training examples. This paper surveys SVM training algorithms and falls them into three groups. Moreover, recent advances such as finite Newton method and active learning algorithms are described. Support vector machines (SVMs), emerged in the middle of 1990s, are a family of algorithms for data analysis based on convex quadratic programming. Here we focus on their use for binary classification. Although convex quadratic optimization problems are solvable in polynomial time; it is hard to accomplish in practice. Generally, SVM's training time scales quadratically (or worse) in the number of examples, so researches strive all the time for more efficient training algorithms. Convex optimization problems have been extensively studied, a large number of algorithms have been proposed. Earlier, SVMs were trained with ready-made software package such as MINOS, LOQO and MATLAB as well as algorithms mentioned above. For nonlinear kernel SVMs, because the dimension of feature space is typically much larger than the size of dataset, we often solve the dual problem.

Decomposition-based algorithms

Decomposition method is similar to those used in active set strategies. It considers only a small subset of variables in each iteration. The idea is: the variables are split into two parts, the set of free variables called working set, and the set of fixed variables. Free variables are those which can be updated in current iteration, whereas fixed variables are temporarily fixed at a particular value. The advantage of decomposition method is that its memory requirement is linear in the number of training examples. Decomposition method needs an optimization subroutine; also, because of only fraction of variables being considered in each iteration, it is time consuming.

Results:

Inputs

Age estimation confusion matrix on the images

	0-2	4-6	8-13	15-20	25-32	38-43	48-53	60-
0-2	**0.699**	0.147	0.028	0.006	0.005	0.008	0.007	0.009
4-6	0.256	**0.573**	0.166	0.023	0.010	0.011	0.010	0.005
8-13	0.027	0.223	**0.552**	0.150	0.091	0.068	0.055	0.061
15-20	0.003	0.019	0.081	**0.239**	0.106	0.055	0.049	0.028
25-32	0.006	0.029	0.138	0.510	**0.613**	0.461	0.260	0.108
38-43	0.004	0.007	0.023	0.058	0.149	**0.293**	0.339	0.268
48-53	0.002	0.001	0.004	0.007	0.017	0.055	**0.146**	0.165
60-	0.001	0.001	0.008	0.007	0.009	0.050	0.134	**0.357**

Conclusion:

It is easily observable from the results that the use of AAM (Active Appearance Model) steadily increases the performance of gender classification. Experimental results from FG-NET database show further that incorporating gender information for age estimation increases the age estimation performances. Work is in progress to modify the algorithm for age classification into more specific age ranges.

A complete survey of the state-of-the art techniques for age synthesis and estimation via face
images, which became fairly particular in recent decades because of their promising real-world applications in several emerging fields. The explosively comprehensive efforts from both academia and industry have been devoted recently to models and algorithms designing, face
aging databases collecting, and system performances evaluation with valid protocols. Variant solutions to technical difficulties have also been provided by researchers. In general, different age synthesis and estimation techniques and algorithms can be effectively applied to particular scenarios or applications. For face modeling, the appearance-based face model can be considered as a marriage of geometry-based model and image-based model, which shows more photorealistic effects aesthetically for age synthesis purposes. Shape synthesis is more effective for the age progression of young faces whose craniofacial growth and development are more dominant over skin aging.

Texture synthesis is more effective for the face aging after adulthood when skin aging dominates and craniofacial growth slows down. Appearance synthesis is applicable to both cases since, usually, a statistical model will be available built on a large face aging database. Aging cues can be learned statistically for all aging stages and implemented to realistic age synthesis. But the most difficult part of appearance synthesis is the database collection and automatic face correspondence.

Image representation and estimation methods are two key issues in age estimation via face images. The anthropometric model and AAM provide parametric modeling for face image representation. They are flexible to handle both age synthesis and estimation. The anthropometric

model focuses on shape changes, which is mainly for age estimation of young faces. The AAM can deal with all of the age estimation cases and reduce the feature dimension by model parameter representations. It is often combined with regression-based estimation methods. When sequential aging face images are available for individual subjects, the aging pattern subspace might be applied to capture individual aging patterns. Age manifold is pretty useful when a large database spanning a large age range is available. Feature extraction and dimensionality reduction are intertwined in age manifold learning. It can be combined with both regression-based and classification based estimation methods. Appearance model is often a way to consider and handle cases when multiple facial attributes are merged. Patch-based image representation is effective to deal with slight head pose and illumination variations. Bio inspired image representation shows superior discriminant power to capture the general aging patterns.

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