Face Orientation Quantification for Face Sequence Indexing and Matching: The Case of Smartphone

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Abstract

In recent years, there has been a lot of research into Face Orientation Quantification for Face Sequence Indexing and Matching. There are two primary reasons to write this thesis paper: the first is to provide an up-to-date analysis of the current literature; the second is to reveal some technical terms that describe Face Orientation Quantification for Face Sequence Indexing and Matching. Face Orientation Quantification is a well-developed topic of software engineering, so it is no wonder that we were inundated with academic articles. We tried to review several such articles and initiatives, many of which we found immediately applicable in our thesis of interest. The use of Face orientation Quantification in social life indicates the embrace of recreational principles by its detractors, as well as spontaneity. Face Orientation Quantification enables the emergence of new categories; these are essentially matrices of complicated behaviors, but during the Quantification process, they are transformed into measurable value.

However, in domains such as close relationships and identities, these attempts frequently change the nature of the category and disappear. Simultaneously, the dominant Quantification obliterates existing objects and relationships, leaving many social processes fundamentally invisible and unmeasurable. Finally, orientation Quantification contends that it is commonly addressed in sectors where arithmetical significance is lacking.

Keywords*: Face Orientation Quantification, Face Sequence Indexing and Matching, Local Binary Pattern, Principal Component Analysis.*

1 Introduction

Communication and information technologies are becoming increasingly ubiquitous in many parts of our lives and enterprises. Ushering in a world of previously unseen scenarios in which People engage with technological gadgets implanted in sensitive surroundings, to and sensitive to their existence Indeed, since the first instances of "smart" buildings with computer-assisted security and fire safety mechanisms were introduced, demotic research has been characterized by a demand for more sophisticated services tailored to each user's specific needs. The role of person sensing and recognition becomes of fundamental importance in an ecosystem regarded as a "community" of smart objects driven by computational capabilities and high user-friendliness, capable of detecting and responding to the presence of various persons in a smooth, non-intrusive, and frequently undetectable manner.

Face Orientation Quantification has become one of the most important smartphone vision challenges explored in the literature thus far. In / out rotations are frequently generated by natural head movement. When the face is rotated along the axis from the face to the observer, in-plane movement is observed (rotation with respect to z axis), applying face Orientation Quantification for face sequence indexing and Face matching is an essential step in the development of automatic face analysis research.

Face Orientation Quantification for Face Sequence Indexing and Matching is an issue that has been discussed It has been around for almost 20 years, but it is still unsolved in terms of speed and accuracy. A conventional face detection method splits an image into tiny sub-windows and use a qualified classifier to determine whether or not a face is there. or not each sub-window contains a face image. There has been a rapid development of predicting the face image size of the sub-windows in the last decade.

The traditional Face Orientation Quantification (FOQ) can be categorized into two categories: holistic features and local feature approaches. The holistic category is further subdivided into linear and nonlinear prediction techniques. Since not all of the faces in an image are the same size, predicting the size of the sub-windows is difficult. As a result, the Face Orientation Quantification step must be replicated several times at various resolution levels. Color models are used in many Face Sequence Indexing and Matching (FSIM) projects.

According to the values of the pixels concerning the image pixels can be classified as skin or non-skin pixels. Although color diversity is a valuable indication of the existence of faces in photos, it should not be relied on alone to locate them.

Smartphones have evolved into the most simple and pervasive interface for accessing Internet services. They come with a variety of sensors that can greatly increase the user's cognitive abilities. Thanks to the broad variety of possible applications, face recognition is one of the fastest growing applications in the smartphone domain. Face Orientation Quantification, on the other hand, is a computationally intensive method that necessitates resources that are beyond the capabilities of even modern mobile devices.

2 Related Works

Face Orientation Quantification issues have been the subject of several studies [16]. Face Sequence Indexing and Matching, on the other hand, has received little attention. Most currently available face recognition approaches run into the orientation problem [14], which makes neutral faces difficult to be identified when photographs of them appear with various facial expressions. Some previous studies have attempted to predict the success or failure of the Face Orientation Quantification verification result, which is akin to the pursuit of a verification method.

[21] identify the most recent findings and study patterns in their survey on the state of the art in multi-modal face recognition, noting that "the variety and complexity of algorithmic techniques investigated is growing." Enhancing identification accuracy, increasing resilience to facial expressions, and, more recently, improving algorithm performance are the main problems in this field.

2.1 Projection Methods

The principal component analysis (PCA) which is a dimensionality reduction approach is one common methodology underlying several face recognition projection algorithms. The PCA technique traditionally employed by Turkey and Pentland in the Eigenfaces approach [6] calculates the own vectors and values of a covariance matrix and resolves a problem of a value of its own. This approach does not discriminate but instead the vectors that meet the highest individual values are utilized in a low-dimensional space as the basic vectors. Then the picture may be projected onto this smaller area and the closest match can be found via Euclidean distance. Also investigated was the merging of Eigenfaces and Eigen modules into a hybrid approach known as modular Eigenfaces. Results are coupled with proprieties, eyes and eyes which, in addition to their own surfaces, are computed in a similar way.

2.2 Statistical methods

This approach uses the breakdown of space in high-dimensional picture areas to assess the full density functions. The matching is then made in the maximum probability formulation utilizing these density estimates rather than using the normal distance metric. The Independent Component Analysis (ICA), which seeks to calculate separate properties of things such as the human face, is another approach comparable to PCA.

Hidden Markov models are the most popular statistical method based on features (HMM). It is based on a Markov chain with a limited number of states, a State transition probability matrix, a distribution of the starting state probability and a collection of probability density functions for every state. The first thing is to scan pictures in 1D or 2D and extract a collection of blocks. Features are retrieved from top to bottom as they are naturally present, and a status is assigned to each face area in the HMM. Finally, the most likely match is to be found with a maximum selection process. The computational complexity of earlier techniques of this was significantly reduced by [20]

2.3 Graph matching methods

Elastic Graph Matching (EGM) is a genetic algorithms object identification method used in computer vision. It is biologically inspired by two sources: (I) the visual characteristics utilized are based on Gabor wavelets, which have been shown to be a suitable model of early visual information in the brain, namely simple cells in the primary visual cortex. (ii) The matching algorithm is an algorithmic version of dynamic link matching (DLM).

EGM represents visual objects as labeled networks, with nodes representing local textures based on Gabor wavelets and edges representing distances between node positions on an image. As a result, a picture of an item is represented as a collection of local textures arranged in a certain spatial arrangement. When a new item in an image has to be identified, the labeled graphs of previously recorded objects, known as model graphs, are matched onto the picture. The locations of the nodes in the picture for each model graph are adjusted such that the local texture of the image matches the local surface of the model and the distances between the locations match the distances between the nodes of the model.

2.4 Neural network methods

Neural networks such as the probabilistic- based neural network (PDBNN) and evolving pursuit Expression Point (EP) were also explored for greater generalization in face classes . These kinds of learning methods enhance the decision-making line using fitness functions. Rowley H., Baluja. [3] deployed the PDBNN, which consisted of three modules: face detector, eye locator and face detector. It employs the hierarchical network structure with non-linear effects in order to recognize the intensity of features and the edge information.

Neural networks provide data processing similar to that seen in biological systems such as the human brain, where information is processed. Its key strengths are their ability to learn from examples, their tolerance for failure, and their strength.

They may be used to recognize a wide range of face images while requiring little modification to the recognition algorithm.

3 Face Sequence Extraction

A series of faces corresponding to the picture is retrieved for the face image. The size of the extracted face in the image is a significant consideration in this situation. In general, we utilize a basic tracking approach between adjacent Index-frames in some of the collected face images, which checks the overlapping of the bounding boxes of the retrieved faces. If the faces are almost in the same position and more than 30% of the area overlaps, they are thought to belong to the same individual. Face detection is applied first to every frame within a specific interval of frames. The system employs a neural network-based face detector that identifies primarily frontal faces of varied sizes and positions.

Sequence indexing and matching performed with the nearest pair of the face sequence and class can be used to index and match the face. A facial class can be found inside a face class that was incorrectly classified and is notoriously far from the rest. This face may be incredibly close mistakenly to a sequence that does not meet the face class but is matched due of the incorrectly classified face. In this case, we may be able to steal the erroneous face by taking advantage of the fact that the wrong face does not constitute a statistical majority. This problem may thus be solved by extracting and using face-class prediction techniques.

Using facial feature extraction for face orientation quantification, the face sequence extraction approach could be greatly improved, and outliers could be avoided by using temporal redundancy within subsequent picture frames. We are aware that our method is incapable of dealing with large changes in picture structure. since the underlying PCA is affected by scale, rotation, and changing illumination conditions Our preliminary face clustering attempts have been positive, and we want to examine the potential of enhancing our face orientation Quantification by modelling the distribution of face sequence indexing and matching.

4 Solution Design

A face is a typical non-rigid object, and its shape changes dramatically as a result of its expression, lighting, and occlusion. As a result, face orientation Quantification should be capable of reliably drawing out the distinguishing feature from facial pictures with varied disruptions. The outputs of face orientation are usually the face pictures to be accurately identified. In the face pictures, the orientation of the facial organs is generally stable and precise. As a result, we adopt a technique based on face orientation Quantification for face sequence indexing Matching.

4.1 Face orientation Quantification representation

Face Orientation Quantification may be used to index and match the face by applying it to the face sequence and class. A facial orientation can reflect a face class that was misidentified and is famously different from the others. This face might be mistakenly matched to a sequence that does not belong in the face class but is matched because of the improperly identified face. In this situation, we may be able to detect the incorrect face by using the fact that the incorrect face does not form a statistical majority. By extracting and employing face-class orientation Quantification, this problem may be overcome, methods for representation of face orientation Quantification to facial classes include defining the difference between different orientation angle using the face orientation model. The basic idea is taken from the face's closest pair-based sequence; nevertheless, this might be less sensitive to curves. This is due to the fact that the method relies on statistical models for face classification and is expected to be less effective for groups with statistically tiny outliers

4.2 Face orientation Quantification model

A Face sequence indexing and matching based on face orientation Quantification is the core module in this design. On this section, we've summarized the key design considerations. A distance metric will be used in order to estimate the distance between the trained face orientation and the proposed Quantification. The face image is finally given with a list of the shortest distances. A face orientation Quantification application requires the user to assert their identification

Preliminary Face alignment has few options, and the most of them are computationally difficult to accomplish. Even if it isn't centered, rotated, or scaled properly all at once. You might be able to identify a common strategy to align them by using a variety of facial images. Each pixel stack in a set is assigned a probability value, and a series of translations, rotations, and scaling are iterated to discover the best transformation that minimizes the difference between a set of face images. The alignment is accomplished by transforming each image one at a time while reducing the total entropy sum.

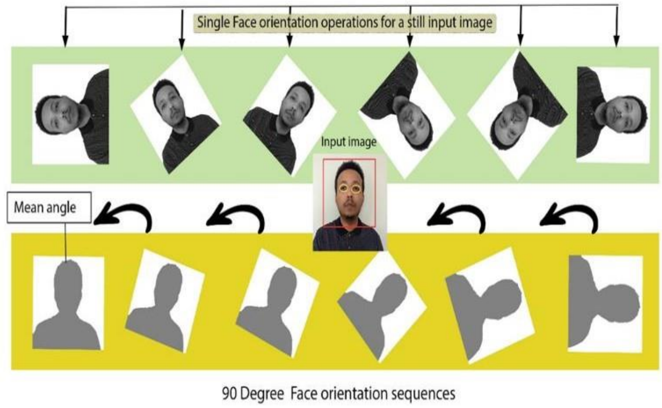

***Figure 1**, A processing diagram demonstrating*

4.3 PCA and Cascade classifier

A feature-based method is used to train the cascade classifiers. The cascade classifier is made up of a series of tests on input properties. Selected attributes are divided into stages, with each step being trained as a strong classifier using the best weak classifiers. For weak classifiers, the tested approach uses a high number of LBP.

Each stage is in charge of determining whether or not the detection window contains a face. If the window fails at any point, it will be deleted immediately. As a consequence of the cascading, regions without faces will be removed at each level, allowing for speedier processing. During the learning process, the number of phases is determined and set in order to reach a certain detection accuracy.

From face photographs, the algorithms extract a set of geometrical attributes and distances that can then be compared. A feature-based algorithm like local feature analysis is an example. Methods for Measuring Face Orientation.

4.4 Proposed System Architecture

Face Orientation Quantification has adopted state-of-the-art techniques from domains including different orientation factor processing, computer vision, pattern recognition, and machine learning, among others. All approaches have their own pros and limitations, making it difficult to choose the optimal one for a given task. To perform the Face Orientation Quantification, efficiency and low complexity are key considerations.

Feature-based approaches have made significant steps in our study, and holistic methods, it is believed, still perform better overall. To normalize orientation Quantification, however, facial characteristics must be detected and used. Performance is also affected by variations in scale, head posture, and partial occlusion. However, most of these approaches are partially adaptable enough to function in all situations, while others are too sophisticated or inefficient for the case of smartphone. it is possible to process the database pictures such that the training data is at least standardized.

This might result in a obtaining of discriminant information when matching a new Face, depending on the Face Orientation Quantification technique. we cannot assume that the training set would include every conceivable variation that might appear in the Quantification Face pictures. The precise set of potential modifications would be helpful, however that depends on the user and varies from camera to camera. When estimating approaches, the major concern was that the algorithms would operate within the constraints of smartphone.

Our knowledge of the Face orientation Quantification is challenged by the extraordinary effectiveness of human face recognition.

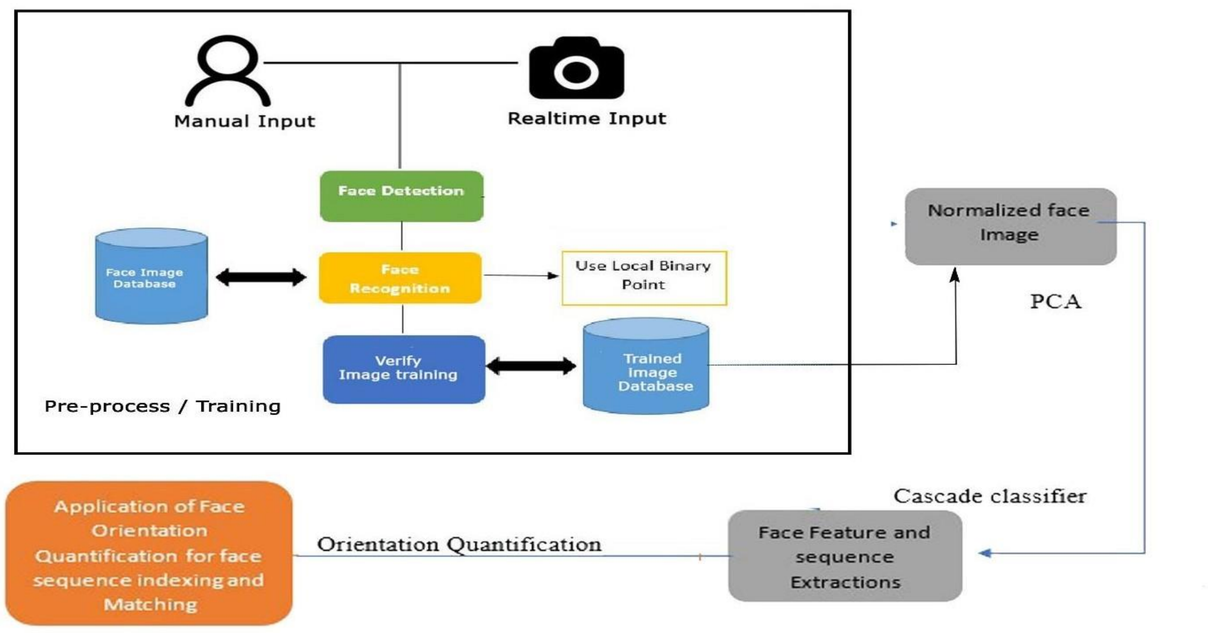

Figure 2, *Face Orientation Quantification Architecture Model*

And our efficiency comes from observer- driven biases at high-level levels of orientation Quantification processing that favor upright faces' higher-order characteristics features like eyes, nose, and mouth and their orientation spatial arrangement within the face.

Face orientation Quantification in the face sequence indexing and matching with the encoding of local edge orientation in the primary visual cortex. Face image pattern responses generally indicate a preference orientation with a peak level of response, with diminishing responsiveness for edges oriented away from the desired orientation. The function that connects face orientation Quantification responses to direction is a sequence indexing with a bandwidth that represents the sharpness of the face orientation.

5 Implementation and Evaluation

There are few algorithms for face alignment available, and the most of them are computationally costly to implement. Even if it is not properly cantered, rotated, and enlarged at the same time.

Using a variety of facial images, you may discover a common strategy for aligning them. Iteratively apply a set of translations, rotations, and scaling to discover the best transformation that minimizes the difference between a set of face images. Each pixel stack in the set is assigned a probability value. The alignment is accomplished by transforming each image one at a time while reducing the total entropy sum.

We must first authenticate a face picture from a captured image before we can employ face orientation Quantification to face sequence indexing. Then start adjusting the face's orientation. One way is to use Eigen to compare selected facial picture Principal Component Analysis (PCA). The simplest and quickest algorithm is PCA. PCA is a technique for turning a set of possibly associated parameters in a sample face image into a set of uncorrelated variables known as principal components. The primary goal of PCA is to find correlations in data.

The change in the values of two or more variables at the same time is quantified by correlation. In this instance, the linear correlation is used. Consider our dataset, which comprises n parametric variables retrieved from the observations (x1,x2,...,xn). PCA's purpose is to choose k n (typically k = 2 or 3) new variables (that will turn out to be the main components) that characterize a significant portion of the orientation Quantification captured in the face picture by accounting for the biggest covariations imaginable in it. We'll look at n = 3 variables obtained from m = 9 different orientation angles to demonstrate the manner of representation. the initial variables and the face-orientation technique Face Orientation Quantification for Indexing and Matching of Face Sequences

5.1 Analysis and Image processing filters

The Quantification 's flexibility to data collection scenarios is supported by the underlying fundamental assumption, which is supported by the artefact and design methods, as well as Orientation Map Matching Orientation and Map Extraction pixel-based edge orientation. This is to collect data on Face Orientation Quantification from multiple sources using Face Sequence Indexing and Matching.

The most essential techniques to illumination normalization are what are known as quasi illumination-invariant image filters. High- pass and locally scaled high-pass filters are examples of these, which are frequently based on fairly simple picture creation models, such as modeling light as a spatially low-frequency band of the Fourier spectrum and identity-based information as a high-frequency band.

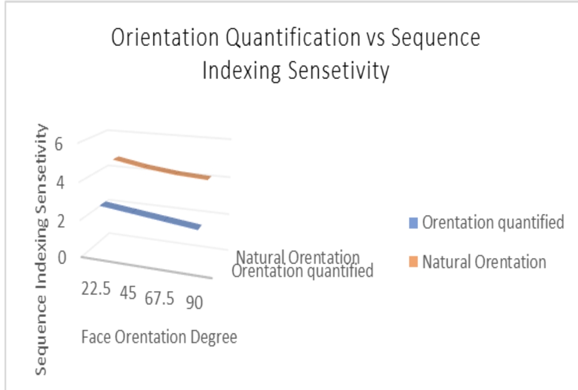

Figure 3, *Line graphs depict the Orientation Quantification versus Sequence Indexing Sensitivity*

The amplitude values at all spatial frequencies inside each of these orientation ranges were added together and divided by the overall maximum total for each picture. Face picture stimuli is being used Greyscale face photos were filtered in 22.5° increments from 0° to 90° vertical orientations and back. The outlines of filtered faces were examined using face orientation quantifications or natural orientation and describes the hypothesized pattern of human face index sensitivity to face orientation quantifications as a function of orientation range, for both vertical and inverted faces in the image plane

5.2 Testing and Evaluation

Throughout the image capture process, face photos are cropped and changed to grayscale images, which are then saved in the same folder to construct face databases for extraction operations. Following that, the standardization technique is used to all photographs in order to minimize noise and establish the correct image scaling position in order to obtain the recognition result as quickly as possible.

A face sequence indexing application based on face orientation measurement is envisioned in this technique. We've put up a list of the most pressing design issues in this area. A distance meter will be used to determine the distance between the taught face orientation and the suggested quantification. Finally, a list of the shortest distances is included with the face image. The user must identify their identification in order for a face orientation Quantification system to work. A threshold is typically used to determine if the distance between the input face and the face in the database is near enough. As a result, prior to authentication, Face Orientation Quantification is performed.

Consider a dataset with m observations and n parametric variables (x1,x2,...,xn). The purpose of PCA is to identify new variables (that will turn out to be the primary components) that decide a large percentage of the information stored in it by accounting for the maximum covariations conceivable in the data.

5.3 Performance and speed results

We acknowledge in our study that the LBP face recognition algorithm's capacity is largely dependent on the accuracy of the feature extraction and comparison stages, which is also highly dependent on the quality of both the input and training/reference pictures used in the face comparison phase. To increase the LBP algorithm's face recognition accuracy, lighting, sharpness, noise, resolution, scale, and posture were used to create the best match pictures, which revealed more details of image characteristicsfor more accurate feature extraction and comparison.

6 Results and Discussion

The majority of the methods indicated in the literature review essentially use many face orientation strategies in parallel, each specialized to one view and based on the PCA methodology described above for face orientation of the same views. The subsystem that is most equipped to describe the image data in terms of its orientation scale is generally the one that is specialized for a perspective that is closest to the view of the facial picture. As a result, it may be chosen automatically to execute the face orientation quantification. The face sequence and indexing show how well a system can perform if it does not adjust for the impacts of rotation in depth and instead depends solely on the robustness of the subsystem nearest to the look at the probe image Because matching is done with a local binary pattern, our fundamental orientation quantification only adjusts for rotation in depth.

Before we can use Face Orientation Quantification for face sequence indexing and matching, we must first prepare the face dataset for training. The face dataset was created using face recognition technology, which identifies and records faces in real- time cameras. The images are kept in a dataset folder and may be used in the future for face recognition, feature extraction, and training. The gadget will first collect information about the user, such as eye, noise, and mouth movements, before opening the camera and photographing the person in 42 different face expressions and moods. The images are saved in a dataset folder with the same unique ID as the individual's information, which is stored in a database.

	Number of Cycles (x 106)	Computation Time (With a CPU at 500Mhz)	Performance Memory Consumption for Data
Face detection	1116	1.92 sec	~ 442 KB
Eye localization	475	1.17 sec	~ 336 KB
Face normalization	46	1.11 sec	~ 112 KB
Face classification (PCA & LBP)	21	0.12 sec	~ 253 KB
Face classification	1	0.11 sec	~ 1044 KB

Table 1 *Performance and speed result*

The Face orientation measurement regarding community participation reveals the opponents' support of leisure ideals and spontaneity. The facial expression Quantification enables the creation of new categories; these are essentially matrices of complicated behaviors that are transformed into 'things' via the Quantification process. These attempts, on the other hand, usually have an impact on the substance of the category and vanish in domains such as close connections and identities. At the same time, the dominant Quantification obliterates existing objects and relationships, leaving many social processes invisible and unmeasurable. Lastly, critics of orientation Quantification claim that it is widely used in businesses where statistical significance is absent. Despite these difficulties, face orientation quantification is an inescapable technique

7 Conclusion and Future Work

We utilized the Local Binary Patterns histogram technique to recognize faces in the proposed Face Orientation Quantification for face sequence indexing and matching. Image-based face identification, facial feature extraction, and image-based sequence index classification are the three aspects of the method. Face Orientation Quantification is a technique for determining the orientation of a person's face in a picture. In the feature extraction phase, facial landmarks are detected and used to create an LBP histogram that delivers a totally unique output, and in the identification phase, the input image's histogram is compared to the database histogram using a classifier. The results demonstrate that the system can distinguish between known and unknown individuals.

In real-time, our algorithms can identify and recognize faces with great accuracy. When compared to other detection methods, it has a faster detection speed. The identification of eyes is used to improve face detection accuracy. Face component alignment, picture smoothing, and contrast modulation all help to improve face detection performance. Face images are taken in real time as training samples and identified in a variety of situations, including amid other faces. New classifiers will be learned in the future to broaden face recognition across a wider variety of facial positions. In order to fine- tune the face picture and sustain effective evaluation, the system may foresee head rotation.

Finally, while some attempts have been made to deal with face Orientation quantitative processes, other forms of Face orientation quantitative applications necessitate the use of specific digital approaches in the most efficient manner possible. While certain approaches have been addressed in research, additional effort must be done to enhance face orientation quantification techniques that accommodates the image factors mention in the scope limitation of theses study includes such as image-specific issues, or subject-specific factors such as, image demographics and frontmost part of the eye such as the cornea furthermore, it is suggested that still there remains a gap in terms of study in video image recognition that requires Similarly to the face image orientation quantification, which is more complicated that needs to be researched

References

[1] T. Sim, S. Baker, and M. Bsat. The CMU Pose, lumination, and Expression (PIE) database of human faces. Technical Report CMU-RI-TR-01-02, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA,January 2001.

[2] Kelly M. D., Visual Identification of People by Computer. Stanford AI Project, Stanford CA, Technical Report, 1970,

[3] Rowley H., Baluja S., and Kanade T., Neural network-based face detection, IEEE Trans. Pattern Anal. Mach. Intell, 20, 1998,

[4] T. Fromherz, P. Stucki, M. Bichsel, "A survey of face recognition," MML Technical Report, No 97.01, Dept. of Computer Science, University of Zurich, Zurich, 1997.

[5] T. Riklin-Raviv and A. Shashua, "The Quotient image: Class based recognition and synthesis under varying illumination conditions," In CVPR, P. II

[6] Turk, M. A., Pentland, A. P., Eigenfaces for recognition, 1991, Cognitive Neurosci., V.

[7] K. Jonsson, J. Matas, J. Kittler, and Y. Li, "Learning support vectors for face verification and recognition," In Proc. IEEE International Conference on Automatic Face and Gesture Recognition, 2000.

[8] R. Brunelli and T. Poggio, "Face recognition: Features versus templates," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 15, no. 10, pp. 1002–1112, 1993.

[9] C. Schneider, N. Esau, L. Kleinjohann, and B. Kleinjohann 2006. Feature based face localization and recognition on mobile devices. Control, Automation, Robotics and Vision,

[10] Lu, H. et.al. (2008). Mpca: Multilinear principal component analysis of tensor objects. IEEE Transactions on Neural Networks, 19.

[11] Wang, J. et.al. (2010). Multilinear principal component analysis for face recognition with fewer features. Neurocomputing, Elsevier

[12] S. Lawrence, C. L. Giles, A. C. Tsoi and

[13] A. D. Back, "Face recognition: a convolutional neural network approach," IEEE Transactions on Neural Network, vol. 8, no. 1, Jan 1997.

[14] M. Black and Y. Yacoob. Tracking and recognizing rigid and non-rigid facial motions using local parametric models of image motion. In Proc. of International conference on Computer Vision, pages 354– 381, 1995.

[15] P. Viola and M.J. Jones, "Rapid object detection using a boosted cascade of simple Features," IEEE Transactions on Computer Vision and Pattern Recognition, vol. 1, 2001.

[16] Kelly M. D., Visual Identification of People by Computer. Stanford AI Project, Stanford, CA, Technical Report, 1970, AI- 130

[17] A. Lanitis, C. Taylor, and T. Cootes, "Automatic interpretation and coding of face images using flexible models," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19, no. 7, 1997.

[18] Pentland A. and Moghaddam B., Probabilistic Visual Learning for Object Representation, IEEE Trans. Pattern Analysis and Machine Intelligence,19(7), July 1997,

[19] Rapha el Feraud, Olivier J. Bernier, Jean-Emmanuel Viallet, and Michel Collobert, A Fast and Accurate Face Detector Based on Neural Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 23, No. 1, January 2001.

[20] Wiskott L., Fellous J.-M., and Von dermalsburg C., (1997), Face recognition by elastic bunch graph matching. IEEE Trans. Patt. Anal. Mach. Intell. 19, (1997) 725-779..

[21] Fasel B., and Luettin J., "Automatic facial expression analysis: A survey," Pattern Recognit.,36(1), 2003.

[22] Kittler J., Hatef M., Duin R.P.W., and Matas J., On combining classifiers. IEEE Trans. Pattern Analysis and Machine Intelligence, 20(3), 1998,

[23] Bowyer, K.; Chang, K. & Flynn, P. (2004). A survey of 3D and multi- modal 3D+2D face recognition, in Proc. Int. Conf. on Pattern Recognition (ICPR).