We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,300

Open access books available

172,000

International authors and editors

190M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Adaptive Fitness Approach - an Application for Video-Based Face Recognition

Alaa Eleyan¹, Hüseyin Özkaramanli² and Hasan Demirel²

¹*Mevlana University*

²*Eastern Mediterranean University*

¹*Turkey*

²*Northern Cyprus*

1. Introduction

In the last two decades face recognition has emerged as an important research area with many potential applications that surely ease and help safeguard our everyday lives in many aspects (Zhao et al., 2003; Kirby & Sirovich, 1990; Turk & Pentland, 1991; Martinez & Kak, 2001; Belhumeur et al., 1997; Philipps et al., 2000; Eleyan & Demirel, 2007, 2011; Brunelli & Poggi, 1993; Wiskott et al., 1997). The face recognition problem from still images has been extensively studied (Sinha et al., 2006; Eleyan et al., 2008). Face recognition from video has recently attracted the attention of many researchers (Zhou et al., 2003; Li & Chellappa, 2002; Wechsler et al., 1997; Steffens et al., 1998; Eleyan et al., 2009). Video is inherently richer in information content when compared with still images. It has important properties that are absent in still images. Some of these important properties are the temporal continuity, dynamics and the possibility of constructing 3D models from faces. On the other hand, it should also be noted that video acquired facial data are normally of very low quality and low resolution, which make recognition algorithms very inefficient. The temporal continuity and dynamics of a person captured by a video makes it easier for humans to recognize people. Humans are usually able to recognize faces in very low resolution images. This is not the case for the computer based techniques which have been shown to be quite capable in recognizing faces from still images. Utilization of these properties for more efficient and high performance face recognition algorithms requires approaches that are different than the traditional approaches.

There are many reasons why humans are so successful in recognition of faces in video while computers are not. Some of these are: 1) Humans use a collection (flow) of data over time rather than an individual video image during both training and testing. 2) Humans are superbly capable of tracking objects. And in so doing can make excellent use of flow of data. In the training stage, when a new person is to be “memorized” many features such as appearance, gestures, gait etc. are encoded. Each person in the human memory (gallery) is encoded differently and there are quite a number of people memorized by humans. In the testing (recognition) stage human beings compare these features and make a decision on the identity of a person. This process however is not a “one shot” comparison, but it is continually made based on the flow of data. When the person is far a way for example, it is difficult to discern the facial features. However from the gait and gestures the human brain

is able to extract important information to identify an approaching person. Based on this information the human brain automatically deems some of the people in the memory as unlikely candidates to match the approaching person and thus those candidates are not considered in further comparisons/associations. As the person approaches closer, the human brain restricts the comparison to reduced set of likely candidates in the memory.

Inspired by this biological process of making comparisons and making decisions based on a reduced set of candidates at testing stage, we propose in this chapter to design an analogous structure for computer based face recognition from video whereby the gallery is continually updated as the frames of the probe video is processed. In order to demonstrate the effectiveness of the proposed approach we employ features derived from PCA or LBP. After every probe frame, the feature vector is compared with the feature vectors of the gallery images, the unlikely images in the gallery are discarded based on the accumulated fitness of the gallery images. An update set of features are derived using remaining image in the gallery. The update set of features are used to test the next frame in the probe video. The results obtained using the idea of updated gallery set indicates that significant improvement in recognition performance can be achieved. The adaptive fitness approach (AFA) is also tested without updating the gallery set. Again, this scheme with fixed gallery set gives comparable performance results as the scheme with updated gallery set.

The rest of the chapter is organized as follows. Section 2 briefly reviews feature extraction. Section 3 presents the face video database. Section 4 introduces the adaptive fitness update approach. Section 5 reports our experimental results and discussions, and Section 6 concludes this chapter.

2. Feature extraction

Feature extraction is a very crucial stage of data preparation for later on future processing such as detection, estimation and recognition. It is one of the main reasons for determining the robustness and the performance of the system that will utilize those features. It's important to choose the feature extractors carefully depending on the desired application. As the pattern often contains redundant information, mapping it to a feature vector can get rid of this redundancy and preserve most of the intrinsic information content of the pattern. The extracted features have great role in distinguishing input patterns.

In this work, instead of using more biologically oriented features, for the reasons of simplicity we employ features derived from principal component analysis (PCA) (Kirby & Sirovich, 1990; Turk & Pentland, 1991) and local binary patterns (LBP) (Ahonen et al., 2004; Ojala et al., 2002). However the recognition framework does allow the incorporation of other features. In PCA case, one needs to prepare a projection space using the training set and use it to preparing the feature vectors of both training and tested sets. In LBP every image is processed independently to form its feature vectors. So if the size of the training set changed as it does in AFA, new space has to be prepared if PCA is used to form the feature vectors while feature vectors will stay same if LBP is used.

3. Video face database

In this study we used the BANCA database (Popovici et al., 2003), which is a multimodal database designed with various acquisition devices (2 cameras and 2 microphones), and under several scenarios (controlled, degraded and adverse). The videos were collected for 52

individual (26 male and 26 female) on 12 different occasions (4 recordings for each scenario). In our work we will be using the video sequences for the 52 individual with the three different scenarios. In the degraded scenario a web cam was used, while higher quality camera was used in the controlled and adverse scenarios. Figure 1 shows samples from the database for the three scenarios.

Fig. 1. Samples of the BANCA database images *Left: Controlled, Middle: Degraded, Right: Adverse* scenarios.

Fig. 2. Example of using face detection algorithm to crop the face region from the whole frame.

As it was computationally expensive to use all the frames in each individual's video sequence, we selected 60 frames which correspond to every other frame in the video sequence. The face images from the first n frames ($n=\{1,2,...,10\}$) of each video sequence were used to form the gallery set to train the system, while the rest were used for testing. It was essential to run face detection in the pre-processing stage on the extracted frames in order to prepare them for the face recognition process. For this reason, the local Successive Mean Quantization Transform (SMQT) (Nilsson et al., 2007) has been adopted for face detection and cropping due to its robustness to illumination changes. Cropped faces were converted to grayscale and histogram equalized to minimize the illumination problems.

Bicubic interpolation was used to resize the resulting face images to the same size of the reference resolution (size of gallery images 128×128). Figure 2 shows an example of the face detection cropping and resizing preprocess for one of the image in BANCA database.

4. Adaptive fitness based updating

4.1 Adaptive Fitness Approach (AFA)

The features of each subject in the gallery are derived from the first n frames ($n=\{1,2,\dots,10\}$) of each subject's video sequences using PCA and LBP. Each frame in the test/probe video is treated as a single still image. Feature vectors of each test frame are formed using PCA or LBP techniques. Each feature vector encodes the similarity of the test frame to each of the gallery images. It is natural to expect that some of the gallery images will have high similarity with the frame under the test while others will have low similarity. One can thus establish with some confidence that those gallery images with very low similarity measures will very likely not be the match for the probe frame. Thus when processing the next frame in the test video, one can reduce the size of the gallery by discarding those unlikely candidates. This enables one to make the gallery set smaller after each tested frame. It is a well known fact that the discriminating power of algorithms such as PCA improves when the gallery set that is reduced. The algorithm of discarding images from the gallery set enables in a way the mechanism employed by human brain in recognizing an approaching person. When the person is far away (low resolution) the human brain uses global features to identify for example the approaching person and it does so by eliminating people in its gallery who are unlikely to form a match. When the person gets closer there is an automatic update of the gallery and the approaching person is compared against smaller number of people in gallery. Eventually when the person is very close, the gallery images are reduced to just a few.

Inspired by this biological process which is employed by human brain in recognition tasks, we propose a simple approach to adaptively shrink the size of the gallery set after each frame of the test video is processed. A fitness measure $\Phi_{i,k}$ is defined using the Euclidean distance as

$$\Phi_{i,k} = \begin{cases} \frac{\bar{\delta}_{i,k} - \delta_{i,k}}{\delta_{i,k}}, & k = 1 \\ \Phi_{i,k-1} + \frac{\bar{\delta}_{i,k} - \delta_{i,k}}{\delta_{i,k}}, & 2 \leq k \leq N \end{cases} \quad (1)$$

where $\delta_{i,k}$ is a vector denoting the Euclidean distance between the i^{th} gallery image and the k^{th} test frame. $\bar{\delta}_{i,k}$ is the mean distance value of the vector $\delta_{i,k}$, and $\Phi_{i,k}$ denotes the accumulated fitness between the i^{th} gallery image and the k^{th} test frame. At the first frame of the test video the fitness is set to be just the normalized distance as the first line in equation

(1) indicates. The normalization is achieved by subtracting $\delta_{i,k}$ from the mean distance $\bar{\delta}_{i,k}$ and dividing by the corresponding element $\delta_{i,k}$, in order to reduce the effect of outliers.

The accumulated fitness measure forms the basis for shrinking the size of the gallery by discarding the candidates in the gallery that are unlikely to form a match with the probe

video frame. After eliminating unlikely candidates from the gallery, a new set of features is formed from the remaining more fit candidates. For example, if PCA is used for feature extraction, after eliminating images from the gallery the existing eigenspace is updated and new feature vectors are formed for the remaining images. On the other hand if LBP is used, throwing out an image accounts to throwing out the corresponding feature vector; thus there is no need to recalculate a new set of feature vectors. Eventually the continuous updating of the gallery promises to leave behind few candidates that are very likely to form a match with the person under test.

This approach has several advantages. Its resemblance to the recognition by human beings is the first to note. Second, it promises to speed up the recognition process due to the discarding of the unfit images from the gallery. However it should be pointed out that due to the discarding of images from the gallery this approach may lead to, even though very unlikely, throwing out some of the correct images in the gallery.

The number of discarded images from the gallery set at each processed frame depends on the standard deviation of the accumulated fitness values at that particular frame. The standard deviation of this distribution is used to establish a fitness threshold θ_c for discarding gallery images. The critical fitness value θ_c is picked conservatively to ensure with almost 100% confidence that the correct gallery images are not eliminated. This forces one to process almost all the frames in order to come up with a decision since with a low θ_c one discards few images from the gallery. This also leads to higher computational burden. This undesirable situation can be avoided by picking a higher threshold θ_c .

The adaptive fitness approach can also be used without updating the gallery. In this scheme one simply processes all the frames in the probe video and accumulates the fitness measure with the originally prepared feature vectors. This approach where the gallery is fixed and no updating is required is computationally more efficient compared with the scheme where one updates the gallery and the feature vectors. However, this advantage is not significant since the updating of feature vectors after the gallery is reduced in size can be done incrementally without much computational burden. Furthermore, in the scheme with gallery updating one does not need to process all the video frames to come up with a decision. Figures 3 and 4 give step by step the algorithms of these two schemes.

```
Initialize gallery set  
For frame= 1, 2, ... N  
    Compute feature vectors  
    Project probe image  
    Compute fitness measure  
    Accumulate fitness measure  
    Discard gallery images with lowest  
    fitness values  
    Update gallery set  
End  
Identify using highest accumulated fitness value
```

Fig. 3. Pseudo code for Adaptive Fitness Approach (AFA) with updated gallery set, $N = 50$.

```
Initialize gallery set
Compute feature vectors
For frame= 1, 2, ... N
    Project probe image
    Compute fitness measure
    Accumulate fitness measure
End
Identify using highest accumulated fitness value
```

Fig. 4. Pseudo code for Adaptive Fitness Approach (AFA) with fixed gallery set, $N= 50$.

An example of how the accumulated fitness measure is employed in the video recognition process with updating of the gallery is depicted in Figures 5 and 6. The feature vectors in Figure 5 are derived from PCA where in Figure 6 feature vectors come from LBP. In this example the probe video belongs to person # 1. The accumulated fitness measure in both figures show clearly that the accumulated fitness corresponding to person # 1 increases while for all other people it is insignificant. Number of training images for each person in this example was $n=1$ using the controlled scenario (see first row in table 1).

Fig. 5. Example of fitness accumulation through the frames for 1st video sequence of person number 1 using AFA with PCA.

4.2 Adaptive Fitness Fusion Approach (AFFA)

To recognize an individual human beings use more than one feature such gait, face, body shape and even wearing. A simple fusing technique is employed. The individual fitness

Fig. 6. Example of fitness accumulation through the frames for 1st video sequence of person number 1 using AFA with LBP.

measures coming from PCA and LBA are simply added. The recognition system based on feature vector fusion is the same as before. In the same manner, at the end of processing all the frames the individual with the highest fitness value is declared to be the correct subject. Figure 7 and 8 show the pseudo codes for the proposed fitness fusion idea with fixed and updated gallery set respectively.

```

Initialize gallery set
Compute feature vectors using PCA
Compute feature vectors using LBP
For frame= 1,2,...N
    Project probe image using PCA
    Project probe image using LBP
    Compute fitness measure  $\Phi_{PCA}$ 
    Compute fitness measure  $\Phi_{LBP}$ 
    Sum  $\Phi_{total} = \Phi_{PCA} + \Phi_{LBP}$ 
    Accumulate fitness measure  $\Phi_{total}$ 
End
Identify using highest accumulated total fitness value
  
```

Fig. 7. Pseudo code for AFFA approach with fixed gallery set, $N=50$.

Fig. 9. Performance in controlled scenario with 1 training image per video with updated and fixed gallery set using PCA.

Fig. 10. Performance in controlled scenario with 1 training image per video with updated and fixed gallery set using LBP.

Fig. 11. Performance in adverse scenario with 1 training image per video with updated and fixed gallery set using PCA.

Fig. 12. Performance in adverse scenario with 1 training image per video with updated and fixed gallery set using LBP.

Fig. 13. Performance in degraded scenario with 1 training image per video with updated and fixed gallery set using PCA.

Fig. 14. Performance in degraded scenario with 1 training image per video with updated and fixed gallery set using LBP.

Scenario	# of gallery images per individual (<i>n</i>)	Recognition Performance (%)		
		AFA updated gallery set	AFA fixed gallery set	PCA/LBP
Controlled	1	95.67 / 97.12	97.60 / 100	66.25 / 85.62
	2	97.60 / 98.56	98.56 / 100	77.17 / 90.51
	3	98.08 / 99.04	99.04 / 100	82.13 / 93.28
	5	99.04 / 100	99.52 / 100	89.14 / 96.58
	10	100 / 100	100 / 100	96.16 / 98.38
Degraded	1	90.39 / 94.23	89.90 / 97.60	63.06 / 84.09
	2	95.67 / 95.67	96.15 / 98.08	73.48 / 88.30
	3	96.63 / 98.56	96.63 / 98.56	78.25 / 91.30
	5	98.08 / 99.52	97.12 / 99.04	84.76 / 94.43
	10	100 / 100	100 / 100	97.15 / 97.63
Adverse	1	91.83 / 96.63	92.31 / 97.60	68.17 / 87.24
	2	95.19 / 99.52	96.63 / 98.56	78.65 / 92.76
	3	98.56 / 100	98.08 / 99.56	84.25 / 95.41
	5	99.52 / 100	99.04 / 100	90.35 / 97.39
	10	100 / 100	100 / 100	99.04 / 98.89

Table 1. Performance of the adaptive fitness approach (AFA) using different number of training images from BANCA database with fixed and updated gallery set.

Scenario	# of gallery images per individual (<i>n</i>)	Recognition Performance (%)					
		updated gallery set			fixed gallery set		
		AFA _{PCA}	AFA _{LBP}	AFFA	AFA _{PCA}	AFA _{LBP}	AFFA
Controlled	1	68.27	80.77	83.77	68.75	80.77	84.25
	2	79.33	88.94	89.90	78.85	88.94	89.90
	3	83.66	90.87	92.79	83.17	90.87	92.79
	5	89.90	93.27	95.67	90.38	93.27	96.15
	10	95.67	97.60	100	94.23	97.60	100
Degraded	1	70.67	75.85	78.85	71.15	75.85	79.33
	2	80.29	84.62	87.50	78.85	84.62	87.02
	3	83.17	89.90	90.38	83.65	89.90	90.87
	5	89.90	92.79	94.71	88.46	92.79	94.23
	10	91.83	95.19	100	92.31	95.19	99.52
Adverse	1	68.75	74.04	78.85	69.23	74.04	79.33
	2	73.08	77.88	83.25	73.56	77.88	83.73
	3	80.29	85.10	89.54	79.81	85.10	89.54
	5	86.06	90.87	95.67	84.62	90.87	95.19
	10	93.27	96.63	100	92.79	96.63	100

Table 2. Performance of the adaptive fitness Fusion approach (AFFA) using different number of training images from BANCA database with fixed and updated gallery set.

scenarios. This is far more challenging since the 4 recordings of each individual are quit similar in terms of feature vectors. The results of this modification in the database size together with the adaptive fitness fusion approach (AFFA) results between LBP and PCA with updated and fixed gallery sets are shown in table 2.

The graphs in figure 15 to figure 20 show examples of the performance results of the proposed fitness fusion in the three different database scenarios (controlled, degraded, adverse) with 1 and 5 training images. The results shown in these figures are obtained using the scheme with fixed gallery set. It is clear in all figures that the fusing of separately obtained the fitness values Φ_{PCA} and Φ_{LBP} using the PCA and LBP feature vectors helped to improve the performance of the system. For example, in figure 15 the performance of AFA approach in the degraded scenario with 1 training image was 71.16 % and 75.85% using PCA and LBP, respectively. When fusion technique AFFA was applied the performance increased to 79.33 %. In figure 16, the training images were increased from 1 to 5 images in the same scenario. With AFA the performance was 88.46 % and 92.79% using PCA and LBP, respectively, and with AFFA it reached 94.23%. Same observation can be made for the other two database scenarios with different training images in figures 17 to 20.

Fig. 15. Performance in degraded scenario with 1 training image per video with fixed gallery set.

Fig. 16. Performance in degraded scenario with 5 training image per video with fixed gallery set.

Fig. 17. Performance in controlled scenario with 1 training image per video with fixed gallery set.

Fig. 18. Performance in controlled scenario with 5 training image per video with fixed gallery set.

Fig. 19. Performance in adverse scenario with 1 training image per video with fixed gallery set.

Fig. 20. Performance in adverse scenario with 5 training image per video with fixed gallery set.

6. Conclusion

In this chapter a new biologically inspired approach called Adaptive Fitness Approach (AFA) for identifying faces from video sequences is proposed. The fitness value of each image in the gallery set is calculated and accumulated as the probe video frames are processed. Two schemes are used with the AFA approach. First scheme employs discarding of unfit images from gallery followed by an update of the feature vectors. In the second scheme gallery and thus the feature vectors are kept fixed.

In order to demonstrate the proposed AFA approach with updated and fixed gallery schemes, PCA and LBP derived features are employed for convenience. Performance of both schemes is far superior to single frame based PCA or LBP approaches. Even for very small number of training images. The adaptive fitness framework is also shown to conveniently accommodate fusing of different feature vectors with further and significant improvement in recognition performance over the AFA with single feature.

7. References

- Ahonen, T.; Hadid, A.; & Pietikainen, M. (2004). Face Recognition with Local Binary Patterns, in: *Processing European Conference on Computer Vision*, pp. 469-481
- Belhumeur, P.; Hespanha, J. & Kriegman, D. (1997). Eigenfaces vs. Fisherfaces: Recognition using Class Specific Linear Projection, *IEEE Transaction on pattern analysis and machine learning*, Vol. 19, No.7, pp.711-720
- Brunelli, R. & Poggio, T. (1993). Face Recognition: Features Versus Templates, *IEEE Transaction on pattern analysis and machine learning*, Vol. 15, No. 10, pp. 1042-1052

- Eleyan, A. & Demirel, H. (2007). PCA and LDA Based Neural Networks for Human Face Recognition, In: *Face Recognition*, Kresimir Delac and Mislav Grgic (Ed.), pp. 93-106, ISBN: 978-3-902613-03-5, I-Tech Education and Publishing, Croatia
- Eleyan, A.; Ozkaramanli, H. & Demirel, H. (2008). Complex Wavelet transform-based Face Recognition. *EURASIP Journal on Advances in Signal Processing*, Vol. 2008, Article ID 185281, 13 pages
- Eleyan, A.; Ozkaramanli, H. & Demirel, H. (2009). Adaptive and Fixed Eigenspace Methods with a Novel Fitness Measure for Video based Face Recognition, *24th International Symposium on Computer and Information Sciences*, pp. 636-640
- Eleyan, A. & Demirel, H. (2011). Co-Occurrence Matrix and Its Statistical Features as a New Approach for Face Recognition, *Turkish Journal of Electrical Engineering & Computer Sciences*, Vol. 19, pp. 97-107
- Kirby, M. & Sirovich, L. (1990). Application of the Karhunen-Loeve Procedure for the Characterization of Human Faces. *IEEE Transaction on pattern analysis and machine learning*, Vol. 12, pp. 103-108
- Li, B. & Chellappa, R. (2002). A generic Approach to Simultaneous Tracking and Verification in Video, *IEEE Transaction on Image Processing*, Vol. 11, pp. 530-544
- Martinez, A. M. & Kak, A. C. (2001). PCA versus LDA, *IEEE Transaction on pattern analysis and machine learning*, Vol. 23, pp. 228-233
- Nilsson, M.; Nordberg, J. & Claesson, I. (2007). Face Detection using Local SMQT Features and Split up Snow Classifier, *ICASSP 2007* 2 pp: II-589-II-592
- Ojala, T.; Pietikainen, M.; Maenpaa, T. (2002). Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns *IEEE Transaction on pattern analysis and machine learning*, Vol. 24, No. 7, pp. 971-987
- Philipps, P.J.; Moon, H.; Rivzi, S. & Ross, P. (2000). The Feret Evaluation Methodology for Face-Recognition Algorithms, *IEEE Transaction on pattern analysis and machine learning*, Vol. 22, pp. 1090-1104
- Popovici, V.; Thiran, J.; Bailly-Bailliere, E.; Bengio, S.; Bimbot, F.; Hamouz, M.; Kittler, J.; Mariethoz, J.; Matas, J.; Messer, K.; Ruiz, B. & Poiree, F. (2003). The BANCA Database and Evaluation Protocol, in: *Proceedings of the International Conference on Audio- and Video-Based Biometric Person Authentication*, pp. 625-638
- Steffens, J.; Elagin, E. & Neven, H. (1998). Personspotter—Fast and Robust System for Human Detection, Tracking, and Recognition, in: *Proceedings of the International Conference on Automatic Face and Gesture Recognition*, pp. 516-521
- Sinha, P.; Balas, B.; Ostrovsky, Y. & Russell, R. (2006). Face Recognition by Humans: Nineteen Results All Computer Vision Researchers Should Know About, *Proceedings of the IEEE 94*, Vol. 11, pp. 1948-1962
- Turk, M. & Pentland, A. (1991). Eigenfaces for Recognition, *Journal of Cognitive Neuroscience*, vol. 3, pp. 71-86
- Wechsler, H.; Kakkad, V.; Huang, J.; Gutta, S. & Chen, V. (1997). Automatic Video-Based Person Authentication using The RBF Network, in: *Proceedings of the International Conference on Audio- and Video-based Biometric Person Authentication*, pp. 85-92
- Wiskott, L.; Fellous, J.M.; Kruger, N. & Malsburg, C. (1997). Face Recognition by Elastic Bunch Graph Matching, *IEEE Transaction on pattern analysis and machine learning*, Vol. 19, No. 7, pp. 775-780

- Zhao, W.; Chellappa, R.; Rosenfeld, A. & Phillips, P.J. (2003). Face Recognition: A Literature Survey, *ACM Computing Surveys*, pp. 399-458
- Zhou, S.; Krueger, V. & Chellappa, R. (2003). Probabilistic Recognition of Human Faces from Video, *Computer Vision and Image Understanding*, Vol. 91, pp. 214-245

IntechOpen

IntechOpen

New Approaches to Characterization and Recognition of Faces

Edited by Dr. Peter Corcoran

ISBN 978-953-307-515-0

Hard cover, 252 pages

Publisher InTech

Published online 01, August, 2011

Published in print edition August, 2011

As a baby, one of our earliest stimuli is that of human faces. We rapidly learn to identify, characterize and eventually distinguish those who are near and dear to us. We accept face recognition later as an everyday ability. We realize the complexity of the underlying problem only when we attempt to duplicate this skill in a computer vision system. This book is arranged around a number of clustered themes covering different aspects of face recognition. The first section presents an architecture for face recognition based on Hidden Markov Models; it is followed by an article on coding methods. The next section is devoted to 3D methods of face recognition and is followed by a section covering various aspects and techniques in video. Next short section is devoted to the characterization and detection of features in faces. Finally, you can find an article on the human perception of faces and how different neurological or psychological disorders can affect this.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Alaa Eleyan, Hüseyin Özkaramanli and Hasan Demirel (2011). Adaptive Fitness Approach - an Application for Video-Based Face Recognition, New Approaches to Characterization and Recognition of Faces, Dr. Peter Corcoran (Ed.), ISBN: 978-953-307-515-0, InTech, Available from: <http://www.intechopen.com/books/new-approaches-to-characterization-and-recognition-of-faces/adaptive-fitness-approach-an-application-for-video-based-face-recognition>

INTECH
open science | open minds

InTech Europe

University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

© 2011 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the [Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License](https://creativecommons.org/licenses/by-nc-sa/3.0/), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen