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Improvement of a facial recognition system based on one shot camera

Médégnonmi Eléonore Elvire HOUSSOU[1,2], Amadou Tidjani SANDA MAHAMA[1,2], Pierre GOUTON[1], Guy DEGLA[2] ;
[1]ImVia, University of Bourgogne Franche-Comté, Dijon, FRANCE;
[2]IMSP, University of Abomey-Calavi, Dangbo, BENIN

Abstract

In recent years, one-shot cameras that integrate Multispectral Filter Arrays (MSFA) are used to acquire multispectral images. In a previous paper, we have proposed a multispectral image recognition system based on this type of camera. The images acquired with these cameras are then demosaiced. Multispectral facial images acquired with our MSFA one-shot camera present information redundancy which leads to a strong correlation between bands. A dimensionality reduction is necessary to reduce information redundancy. Dimensionality reduction is a set of techniques that allow to project an initial image of dimension n into a final image of dimension p, while preserving its relevant information. This paper proposes an improvement of facial recognition system using the Multispectral Filter Array one shot camera. A dimensionality reduction module has been added to the system. A comparison of the performance of different dimensionality reduction methods based on the eigenvalues, and VGG19 classification results are conducted. Experimental results on the EXIST database made up with our camera indicate a good decorrelation of the bands leading to the reduction of bands from eight to three with the Karhuen-Love transform and an accuracy of 100% with VGG19. The application of the dimension reduction method resulted in a 15 % gain in processing time always reaching an accuracy of 100%.

Keywords—MSFA, one shot camera, Dimensionality reduction, EXIST database.

Introduction

Multispectral Imaging (MS) [1] is a technique for image acquisition of the same scene in several spectral bands. At each capture, the number of images acquired depends on the spectral bands covered by the acquisition system. Multispectral images contain richer information than color images. MS imaging systems can be classified into three broad categories:

-Multi-camera systems that capture images with multiple single-shot cameras. Thus, each camera captures images in a given spectrum;

-Single-camera systems with multiple shots: it is a single camera that captures images in several shots and according to the number of spectral bands;

-MSFA one-shot systems: these consist of a single camera that integrates the spectral filter arrays. This camera captures images simultaneously on several spectral bands in a single shot. MSFA cameras are fast and able to capture moving scenes. At the end of each acquisition, the MSFA one-shot cameras produce a raw image. This image is then demosaiced according to the number of filters integrated into the MSFA.

In [2] a MSFA camera has been proposed. Despite its advantages, the multispectral images acquired with this camera are highly correlated. They also present information redundancies like most hyperspectral images. The MSFA one-shot camera covers the spectral range from 650 nm to 950 nm. Each MS image acquired with this camera consists of 8 image bands of size 2072 x 1104. An analysis of the acquired facial images shows a high correlation between bands. It is therefore obvious that processing all the whole images is a waste of time. A reduction of the dimensions of the images is then necessary to decrease this redundancy and to find a set of uncorrelated data while preserving the information necessary for the optimization of the recognition system. Dimensionality reduction is a set of methods aimed at selecting or extracting an optimal subset of relevant features according to well-defined criteria. It not only reduces information redundancy but also improves the posterior processing of the reduced data. During the last decades, many dimensionality reduction methods have been developed. Among them, are the Karhuen Loeve Transform (KLT), Factorial Analysis (FA), and Curvilinear Component Analysis (CCA). KLT and FA are linear projection methods based on the calculation of eigenvectors while CCA is a non-linear projection method that uses the topology of the data. This paper proposes an identification of the optimal band reduction method based on KLT, FA, and CCA for facial recognition using Multispectral Filter Array camera one shot to improve the facial recognition system.

The remainder of this paper is structured as follows: Section 2 briefly presents our facial recognition system and then reviews various linear and nonlinear dimensionality reduction methods. The selected dimensionality reduction methods are described in section 3. Section 4 presents the method evaluation. Results and discussion are reported in Section 5, followed by the conclusion and future works in Section 6.

Related works

MS facial recognition systems have been developed in recent years [3]. A face recognition system is mainly represented by four essential modules: capture, feature extraction, matching, and decision.

The capture module uses one or several cameras for image acquisition.

The feature extraction module extracts the relevant information from the acquired images. The features extracted give a new data representation.

The matching module uses the set of extracted features to find the most with the features of those images stored by the system in the database during enrollment.

Finally, the last module checks if the current subject corresponds to a subject in the database and the degree of similarity.

The following figure shows the relationship between the different modules of a face recognition system.

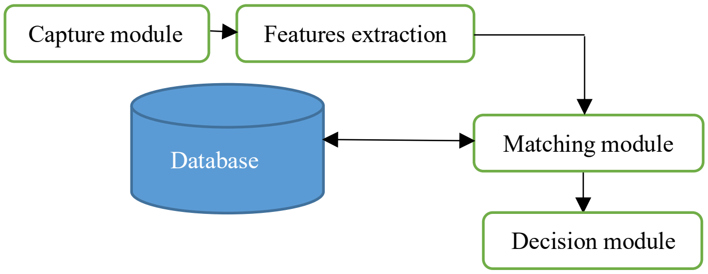

Figure 1: Facial recognition system

EXIST Database

In [3] authors present a number of facial recognition systems and propose a one-shot camera used to make up the EXIST database. It is a set of images collected with a MSFA one-shot camera that covers the spectral range from 650 nm to 950 nm. It is a light and compact acquisition system developed in the Laboratory of Electronics, Informatics and Image (LE2I) which is now ImViA (Imaging and Artificial Vision) in the framework of the EU H2020 project called EXIST (EXtended Image Sensing Technologies) [2], [4]. This one-shot camera is composed of a single Viimagic 9220H sensor covered by an MSFA of eight filters, optical lenses, an electronic board to drive the sensor, and a camera board for image acquisition. The MSFA has been carefully selected considering a regular distribution of pixels in the moxel. With the MSFA system, the camera works in real time application with 30 fps. The choice of filters is an important step in the design of MSFA one-shot cameras. It is composed of 8 optimal filters selected in the wavelengths {685, 720, 770, 810, 835, 870, 895, 930} (in nm) with genetic algorithms thanks to a study carried out at LE2I laboratory[2], [5]. Figure 2 illustrates the spatial distribution of moxel.

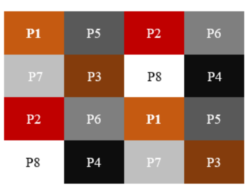

Figure 2: Final moxel of MSFA

The MSFA one-shot cameras produce the raw images which are then demosaiced before being processed. The bilinear interpolation method was used to demosaic the multispectral images acquired on eight bands. EXIST dataset consists of 2000 raw face images of 105 subjects. Each multispectral image (2072 x 1104 x 8) consists of 8 demosaiced image bands which correspond respectively to the wavelengths {685, 720, 770, 810, 835, 870, 895, 930}.

Dimensionality reduction methods

Dimensionality Reduction (DR) methods are used to reduce information redundancy in multispectral images. Various projection-based data dimensionality reduction methods have been proposed in recent years [6]. Generally, projection methods look for the best optimal subspace by minimizing the projection error. The images of an initial space of dimension R^n are projected into a final space of dimension R^p such that $p < n$. Projection methods make the data set more representative. The literature distinguishes two categories of projection methods: linear and non-linear projection methods.

Linear projection methods

The linear projection methods are those based on the projection of the pixels of the initial image on new linear axes in the final subspace. The literature presents several linear projection methods including Karhuen Loeve Transform (KLT), Principal Component Analysis (PCA) and its variants, Linear Discriminant Analysis (LDA), Source Separation (SS), Locality Preserving Projections (LPP), Multidimensional Scaling (MDS) and Factor Analysis (FA). Karhuen and Loeve proposed a linear method named Karhuen Loeve Transform [7]. It is based on the computation of the eigenvectors. KLT converts a set of correlated variables to a set of uncorrelated variables. PCA [8] is a well-known classical statistical method for exploring the structure of multidimensional data. Based on eigen values computation like the KLT, PCA aim to maximize the variance of the projected data. LDA [9] extracts discriminant information by searching projection directions that maximize the ratio of the between-class and the within-class scatter. SS uses moments of order greater than 2 to achieve statistical independence of sources. Several algorithms based on source separation have been developed including Second order blind Identification (SOBI)[10]. The principle of LPP [11] is to construct a neighborhood graph of the data set using the notion of a Laplacian graph, and a transformation matrix that maps the data points to a subspace. FA [12] describes covariance relationships among many variables by defining the intercorrelations between n variables considering a set of common factors. MDS [13] generates coordinates that result from an optimal linear fit to the given dissimilarities between points in the least squares direction if the distance used is metric. MDS is the basic algorithm of the non-linear methods Sammon'Mapping, ISOMAP, and CCA.

Linear projection methods do not allow highlighting the non-linearity that exists in some multidimensional data. Linear DR methods can only be successfully applied to data when they are linearly separable.

Non-linear projection methods

The non-linear projection methods are based on the topological relations of the neighborhood between the pixels in relation to each other in the projection space. The nonlinear RD methods are Sammon's Mapping, Local Linear Embedding (LLE), Isometric Feature Mapping (ISOMAP), Laplacian Eigenmaps, Curvilinear Component Analysis (CCA) and its variants. Sammon Mapping [11] is a variant of MDS. It preserves the neighborhood topology through the conservation of Euclidean distances by minimizing the error function through gradient descent. Roweis et al.[12] introduced LLE which determines the weight-based representation of each point and its neighbors by using the local linearity of the data manifold. Tenenbaum et al. [13] developed Isomap. This method uses the geodesic distance between the data while the MDS uses the Euclidean distance. Mikhail Belkin[14] developed the Laplacian Eigeimaps(LE) which uses local linearity to find the weight-based representation of each point and its neighbors. Pierre Demartines et al. [15] had proposed Curvilinear Component Analysis (CCA) to deal with multidimensional data. Initially named Vector Quantization and Projection (VQP), CCA is based on the MDS algorithm, it reproduces and preserves the local topology of the distribution of individuals in a reduced subspace.

L.Journaux et al. proposed a variant of CCA named CCAint(PCA) to reduce Landsat images from 8 to 3[16]. J. Ma et al.[17] used PCA to reduce the dimensionality of features extracted with deep learning for facial recognition. The feature vectors were reduced from 3727 to 887 with an improvement of the SVM classification accuracy from 87.97 to 90.35.
The authors in [18] had used the 2DPCA to reduce the size of the images (112x92) of the ENT database and the SVM and KNN classifiers. The accuracies obtained vary according to the size of the reduced images and the classifier used.

Selected dimensionality reduction methods

Linear DR methods can only be successfully applied to images when they are linearly separable. Also, the observation of some multispectral or hyperspectral images shows that they can present nonlinearities. This motivated us to use in this paper the linear projection methods KLT, FA, and the CCA a nonlinear method. KLT is a very efficient technique for the dimensionality reduction of hyperspectral images without loss of relevant information[19]. It is a suitable transformation for the removal of redundant information. The KLT is more suitable for spectral decorrelation, compared to other transforms[20]. A Curvilinear Component Analysis is one of the most widely used nonlinear dimensionality reduction methods. It is a technique that uses data topography and weighted distances[21], [22]. Indeed, KLT seeks to maximize the variance of the new components while FA finds the latent variables in a data set. Therefore, we have chosen these three DR methods because of this motivation, the running time, and the results obtained.

Karhuen Loève Transform

The Karhuen Loève transform (KLT) is an optimal linear method of data dimensionality reduction. Its specificity is to transform correlated components into uncorrelated components while preserving the main information. This transformation takes place in two main steps: the computation of the covariance matrix and the determination of the eigenvalues of this matrix. The covariance matrix is a square matrix of dimensions equal to the number of spectral bands.

Let X be the matrix representing the n image bands such that each image band X_i $i \in \{1,..,n\}$ is the column i of X and each of its rows represents an observation. To determine the covariance matrix, we must first calculate the mean of the variables, it is described by the following equation

$$\bar{X} = \frac{1}{N}\sum_{j=1}^{N} X \quad (1)$$

Where N denotes the number of pixels of the image X. The covariance matrix is defined in equation 2

$$C_x = E[(X - \bar{X})(X - \bar{X})^T] \quad (2)$$

Where E represents the mathematical expectation and T denotes Transpose. The objective of the Karhuen-Loeve transform is to find a linear transformation Y that allows determining a square matrix $A(nxn)$, such that $Y = AX$, where the row vectors $a_i(i\epsilon\{1,2,..,n\})$ of the matrix A are the eigenvectors respectively associated with the eigenvalues $\lambda_i(i\epsilon\{1,2,..,n\})$ of the covariance matrix. The row vectors a_i are the final components. This defines then equation 3

$$C_x X = \lambda_i X \quad (3)$$

A diagonal matrix C_y of the eigenvalues is obtained after transforming the covariance matrix.

$$C_y = \begin{bmatrix} \lambda_1 & 0 & 0 & 0 & \dots & 0 \\ 0 & \lambda_2 & 0 & 0 & \dots & 0 \\ 0 & 0 & \lambda_3 & 0 & \dots & 0 \\ 0 & 0 & 0 & \ddots & 0 & 0 \\ \vdots & \vdots & \vdots & 0 & \ddots & 0 \\ 0 & 0 & 0 & 0 & 0 & \lambda_n \end{bmatrix}$$

Curvilinear Component Analysis

Curvilinear Component Analysis is a nonlinear DR method based on MDS. It is a self-organizing neural network that performs the vector quantization of the submanifold in the data set (input space) and nonlinear projection (P) of these quantizing vectors toward an output space, providing a revealing unfolding of the submanifold. CCA is a network of N neurons consisting of two layers: an input and an output. This network takes as input the vector $x_i, i \in \{1,2,..N\}$ with n the dimension of multispectral image (n = 8 in the case of this study) and the output is a vector y_i of dimension p such that ($p \ll n$). The Euclidean distance between x_i: $X_{ij} = d(x_i, x_j)$and y_i: $Y_{ij} = d(y_i, y_j)$ are calculated. According to the author [15], mathematically there exists an error function that characterizes the difference of topologies between the initial space and the final projection subspace. The main objective of the CCA is to minimize this error function defined by:

$$E = \frac{1}{2}\sum_i \sum_{j(i\neq j)}(X_{ij} - Y_{ij})^2 F(Y_{ij}, \lambda_y) \quad (5)$$

Where λ_y denotes scale deployment and $F(Y_{ij}, \lambda_y)$ is decreasing function such

$$F(Y_{ij}, \lambda_y) = \begin{cases} 1 \; if \; Y_{ij} \leq \lambda_y \\ 0 \; if \; Y_{ij} > \lambda_y \end{cases} \quad (6)$$

Factor Analysis

Factor Analysis is a dimensionality reduction method that determines the underlying variables or factors that define the intercorrelation of a set of observed variables. These variables are then defined as linear combinations of the factors. Mathematically, the factor analysis method can be described as follows:
Let P denote the number of variables$(X_1, X_2, \dots, X_P)$,m the number of underlying factors $(F_1, F_2, \dots, F_m)$ and X_j the variable that represents the latent factors

$$X_j = a_{j1}F_1 + a_{j2}F_2 + \dots + a_{jm}F_m + e_j \quad (7)$$

Where $j = 1, 2, \dots, P(P = 8)$, e_j unique factor and a_j the factors loading defined by the correlations between the variables, and the factor. For all pairs of variables (X_i, X_{i+1}), the objective of the factor analysis is to find the factors such that the correlation between the pairs is zero. Once a correlation matrix is computed, the factor loadings are then analyzed to see which variables load onto which factors. Essentially, Factor Analysis is described in the following equation

$$R_{mxm} - U^2_{mxm} = F_{mxp}F'_{pxm'} \tag{8}$$

Where R_{mxm} refers to the correlation matrix, U^2_{mxm} denotes the diagonal matrix of unique variances of each variable, and F_{mxp} represents the common factor loadings.

Evaluation of the reduction methods

The improved facial recognition system is as follows:

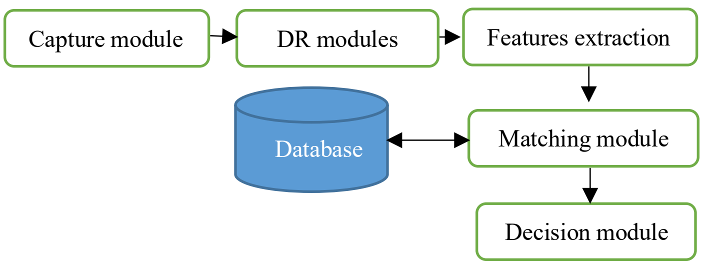

Figure 3: Modified facial recognition system.

The evaluation of the method is described in two steps: spectral band reduction and the use of the VGG19 neural network for feature extraction and classification.

In the first step three dimensionality reduction methods namely Karhuen Loeve Transform (KLT), Curvilinear Component Analysis (CCA), and Factor Analysis (FA) were applied to each of the images in the database. Each method takes as input a multispectral image X made up of 8 bands X_i, $i \in \{1,..,n\}$,n=8. It returns after transformation an output image X made up of p bands X_i, $i \in \{1,..,p\}$,p<n. A comparison of the three DR methods used is performed. To do this, the eigenvalues of the principal components are first calculated to determine the intrinsic dimension of the p components. The correlation between the reduced p components is calculated to evaluate the band reduction method that provides the uncorrelated components.

The second step is based on feature extraction and classification of the reduced images. The convolutional neural network VGG19 is used for feature extraction and classification of the reduced images. It consists of stacked convolutional and max pooling layers. VGG19 is an architecture of VGGNet which contains 19 weight layers consisting of 16 convolutional layers with 3 fully connected layers and the same 5 pooling layers. The accuracies obtained with VGG19 for KLT, CCA, and FA are compared to determine which DR method provides better accuracy.

Results and discussion

Before going to the results, figure 4 shows one of the images from the EXIST database after the demosaicing process.

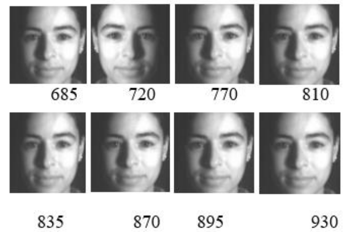

Figure 4: Sample of initial images

As described above, EXIST database images are a set of 8-bands demosaiced faces multispectral images. These images have redundant information, so they are highly correlated. Table 1 shows the average correlation coefficients of the images(80) in the EXIST database.

Table 1. The average of the correlation coefficients of 80 images in the EXIST database.

Bands	1	2	3	4	5	6	7	8
1	1	0.98	0.97	0.97	0.97	0.97	0.96	0.95
2	0.98	1	0.98	0.97	0.98	0.97	0.96	0.95
3	0.97	0.98	1	0.98	0.98	0.98	0.97	0.96
4	0.97	0.97	0.98	1	0.98	0.98	0.97	0.96
5	0.97	0.98	0.98	0.98	1	0.98	0.97	0.96
6	0.97	0.97	0.98	0.98	0.98	1	0.97	0.9676
7	0.96	0.96	0.97	0.97	0.97	0.97	1	0.97
8	0.95	0.95	0.95	0.96	0.96	0.96	0.97	1

The results show that the correlation coefficient between bands is very close to 1 which confirms the strong correlation between the 8 bands of images. Each of the three dimensionality reduction methods, namely Karhuen Love Transform, Curvilinear Component Analysis, and Factorial Analysis, was applied to each of the images in the database. The results achieved with these three dimensionality reduction methods in terms of eigenvalues led to the choice of the intrinsic dimension of 3. Figure 5 (a, b, and c) illustrates the resulting images. Table 2, 3 and 4 show the new correlation coefficients obtained after the dimension reduction.

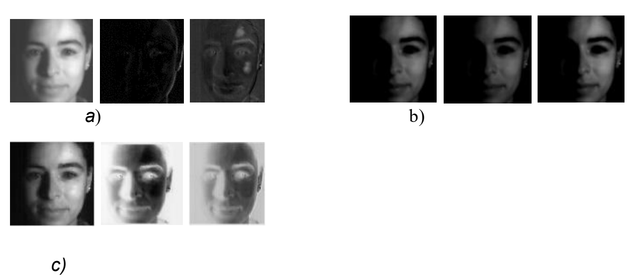

Figure 5. a) Reduced images with the KLT, b) Reduced images with the FA, c) Reduced images with the CCA.

Table 2. Average of the correlation coefficients with KLT

Band	1	2	3
1	1	0.0097	0.0341
2	0.0097	1	0.0861
3	0.0341	0.0861	1

Table 3. Average of the correlation coefficients with FA

Band	1	2	3
1	1	1	0.97
2	1	1	0.9876
3	0.97	0.9876	1

Table 4. Average of the correlation coefficients with CCA

Band	1	2	3
1	1	0.9708	0.9584
2	0.9708	1	0.8630
3	0.9584	0.8630	1

The correlation coefficients between the reduced image bands show that the Karhuen Loeve Transform gives the best decorrelation results.

Then the facial recognition system based on the pre-trained convolutional neural network VGG19 is used to extract features and classify the reduced images obtained with KLT, CCA, and FA. The data sets were identical for all methods. The training and test datasets were separated with random selection. Tables 5 and 6 describe the training parameter of VGG19 and the obtained accuracies.

Table 5. Parameters used in the training procedure

Parameters	Value
Batch size	32
Optimization algorithm	Stochastic Gradient Descent
Learning rate	0.0001
Epoch number	20

Table 6. Results

Methods	KLT +VGG19	CCA +VGG19	FA +VGG19
Accuracy	100%	90%	89,4%

Comparing the accuracies obtained with the different DR methods, the KLT+VGG19 method is the highest and equal to 100%.

To verify the impact of dimensionality reduction on facial recognition with MSFA acquisition systems, we compare the accuracies of reduced images and initial images. Fast Discrete Curvelet Transform(FDCT) had been used in [3] to merge the images from Exist database. It is a family of wavelets that can decompose images into high and low frequencies. We used VGG19 convolutional neural networks to compare the accuracy and recognition time of images reduced by KLT, CCA, FA, and FDCT [3]. Table 7 shows accuracy and time.

Table 7. Results

Methods	KLT +VGG19	CCA +VGG19	FA +VGG19	FDCT+VGG19
Accuracy	100%	90%	89,4%	100%
Time	3 min	6 min	7 min	6min

A validation accuracy of 100% is obtained with the reduced images from the KLT. The recognition time is reduced by 15% compared to the recognition system that was developed.

The band reduction of the multispectral images enabled to optimize the facial recognition system using MSFA one-shot acquisition system.

We also compared the results obtained with those of the state of the art. Table 8 presents this comparison.

Table 8. Comparison with other methods

database	Initial band	DR method	Reduced band	classifier	accuracy
Orl(face database)	112x92	2DPCA	4,3	KNN	92%, 98,3%
orl	112x92	2DPCA	4,3	SVM	90%,90%
Feature vector	3727	PCA	887	SVM	90.35
Exist	**2072x 1104 x 8**	**KLT**	**3**	**VGG19**	**100%**

Dimensionality reduction can be applied to reduce the size of the image or feature vector. Dimensionality reduction methods improve the accuracy of the classifiers and the CNN.

A comparison of the results obtained shows that the accuracy varies according to the classifiers and the size of the images. The results obtained with EXIST database outperform those of the state of the art.

Conclusion and future works

After drawing the conclusion of the need for band reduction of images acquired with our MSFA one-shot cameras, a comparative study of two linear projection methods KLT, FA and a non-linear projection method has been performed. The computation of the correlation coefficients between the 3 bands of reduced images obtained with KLT shows that they are less correlated. The KLT allowed an optimal reduction of the number of spectral bands and gives the best time and accuracy facial recognition results.

Future work will focus on the impact of the demosaicing algorithm on the facial recognition system.

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Author Biography

HOUSSOU Médégnonmi Eléonore Elvire, is a PHD studend and researcher at University of Burgundy Franche-Comte (France) and University of Abomey-Calavi. She works on deep learning and computer vision in IMVIA Laboratory.

Amadou Tidjani SANDA MAHAMA is a researcher. He received his PhD in computer science and image instrumentation at the University of Abomey-Calavi and the University of Burgundy (France) in 2016. His main research fields are multispectral imaging, image segmentation and classification.

Professor, GOUTON Pierre. has obtained a PhD in Components, Signals and Systems at the University of Montpellier 2 (France), 1991. He has integrated the Department of Image Processing in the Laboratory of Electronics, Data-processing, and Images. Since his main topic research carries on the segmentation of Images by Linear methods or None-linear (mathematical morphology, classification), Color Science, Multispectral Images, Micro and Nano Sensor

Professor, Guy DEGLA researcher and lecturer at the Institute of Mathematics and Physical Sciences (IMSP) of the University of Abomey-Calavi (UAC) since 2007. He holds a Ph.D. in Functional Analysis and Applications by International School for Advanced Studies (SISSA),2001 Trieste, Italy.