Discriminative Regions Selection for Facial Expression Recognition

Hazar Mliki[1] and Mohamed Hammami[2]

[1] **MIRACL-FSEG, University of Sfax**
3018 Sfax, Tunisia

[2] **MIRACL-FS, University of Sfax**
3018 Sfax, Tunisia

Abstract

Human Machine Interaction systems are able to perceive facial expressions more naturally and reliably. In this paper, we introduced a new idea to recognize facial expression by selecting the most discriminative facial regions relying on facial expression appearance. The proposed approach is based on the prior knowledge of psychology studies which show that only some facial regions are descriptive in expression revelation. In fact, regions selection seeks to collect the descriptive regions which are responsible of expression divulgence and this was performed using Mutual Information technique. Regarding facial feature extraction, we applied Local Binary Pattern technique to encode facial expression micro-patterns. An experimental study shows that using descriptive regions improved facial expression classification accuracy as well as reduced features vector size. Indeed, we attested the independency of the selected regions of the dataset and the descriptors.

Keywords: *Facial Expression Recognition, Local Binary Patter (LBP), Discrete Wavelet Transform (DWT).*

1. Introduction

Automatic facial expression analysis is a basic step in Human Machine Interaction as the face is a standard communicative tool. In fact, the face shows emotion earlier than people express or even display their feelings. Relying on the shown facial expression, human face plays a major role in communication and interaction that makes machine understand human expression.

Accordingly, facial expression recognition is becoming an area of interest in many research fields such as: human-computer interaction systems, augmented reality and human behavior analysis. Recognizing facial expression has been also used in many areas of life like: supervise patients, investigate the level of concentration and enhance face recognition. Nonetheless, facial expression analysis remains a challenging problem due to the wide variety of facial movements and difficulties in handling illumination and view angle variations.

In fact, facial expression recognition involves two crucial aspects: facial features selection and the classifier design. The facial features selection seeks to define a set of features from the original face images. This set of feature is supposed to minimize the inter-class variations and maximize the intra-class variations. The classifier design makes use of the selected features to perform an accurate recognition results. However, if inappropriate features are used, none classifier will succeed to achieve correct classification. That's why more attention is required while performing facial features selection.

In this paper, we introduce a low-computational approach for automatic facial expressions recognition. The proposed approach makes use of Mutual Information technique to select the most discriminative regions for facial expressions recognition. Psychology studies [1, 2, 3] showed that, through electrical muscle simulation, only some facial muscles are responsible of facial expressions appearance. These facial muscles were located around the mouth, nose and eyes which points out that most of expressive regions for facial expression are around some of face parts. The proposed approach benefits from this psychology finding to select relevant regions describing the best facial expressions. In fact, our approach is composed of two main stages: An off-line stage and an on-line stage. The first stage seeks to define the most descriptive facial expression regions using the Mutual Information technique. Regarding the on-line stage, it uses the already selected regions to classify facial expression via an SVM classifier. In both stages facial features extraction is achieved using Local Binary Pattern (LBP) operator. The idea behind the use of LBP is that the face can be perceived as a combination of micro-patterns which are invariant to grey scale transformation. Thus, LBP encodes the local facial features in multi-resolution spatial histogram and combines local intensity distribution with the spatial information. This helps to cope with noise and local image transformations due to illumination variations. Selecting descriptive facial expressions regions helped to not only decrease facial feature vector size but also to improve facial expression classification accuracy. In fact, the selected regions provided better results while recognizing facial expression than using the whole face regions. Extensive experimental studies were performed to prove the robustness of the selected regions and their independency of the dataset and descriptors. The main contributions of the proposed approach are:

- Proposing a full automatic approach for facial expression recognition where there is no manual initialization or detection.
- Introducing a new algorithm based on Mutual Information technique to select automatically the descriptive regions for facial expressions recognition. This is an enhancement over the manual and imprecise regions selections methods [27, 28, 40].
- Introducing a new approach where the selected regions are independent of the dataset and the descriptors.

The following section is dedicated to a brief study of previous work. The outlines of our proposed approach are presented in details in section 3. The experimental findings and results are reported in section 4. Conclusion and some reflections on our future research studies are given in section 5.

2. Related Works

Based on the way how facial features are extracted for classification, we can categorize the existing methods for facial expression recognition into two main approaches: global approach and geometric approach.

Global methods are essentially based on pixel values and perceive face as a global entity whose characteristics and deformations are learned. They require some prior knowledge about the face structure and are typically based on pixel information or general face data. These data may be encoded as a color vectors, gray scale pixel motion vector or sequence responses of different filters (Gabor Wavelets) [4]. Generally speaking, these methods rely on a training phase wherein different artificial techniques, such as Neural Networks [5, 22, 23] and Support Vector Machines [6, 24, 25], may be applied. Nonetheless, global methods, usually, used part of or the whole image as a high-dimensional vector. Therefore, some subspaces learning methods like principal component analysis [41, 42], independent component analysis [7], locality preserving projection [8], or graph embedding [9], were used to build new subspace representation of the original input. Then, matching is performed in the learned subspace.

Different from the global approach, geometric methods are another significant visual cue for facial expression recognition task. This is because the facial expression usually produces corresponding geometric deformations which have good physical meanings. In view of the fact that people may have different face configurations, the geometric coordinates of facial features cannot be directly used to train the classifier. Therefore, the relative distances [10, 11, 33, 39] are calculated to describe the geometric distance variations. Some methods [12] have used the geometric feature extracted by Active Appearance Model to perform facial expression recognition. In [13], the authors have combined the intrinsic features (geometric information) and the transient features (local texture information) to enhance recognition accuracy. However, manual interactions are required in template-based intrinsic feature extraction, which is inconvenient for users. Geometric methods provide good perceptive justification for facial expression recognition however they depend on the accurate detection of facial features and require space costs for computation. However, global methods inspect the appearance change of the face including wrinkles, bulges and furrows which make them powerful in discovering the discriminative information. Taking all this into account, we introduce in this paper a new global-based approach to recognize facial expression expressions.

3. Proposed Approach

The proposed approach consists of two processing steps: an off-line step and an on-line step. Figure 1 describes the proposed approach.

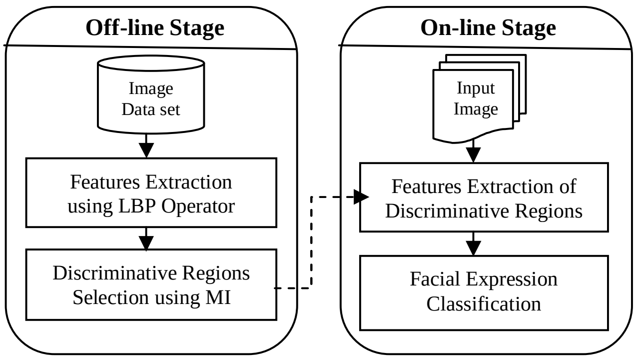

Fig. 1 Proposed approach for facial expression recognition

In fact, the off-line stage is executed one time in order to select the most discriminative facial regions using mutual information technique. The on-line stage intends to identify facial expression class using the already selected regions. The following sub-sections will describe these two stages in detail.

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3.1 Off-line Stage

This off-line stage aims define the most responsible regions for facial expression recognition task. Therefore, we extracted the facial feature vector of every region using the LBP operator. Then, we adapted the mutual information technique to select the most prominent regions.

Feature Extraction using LBP: To extract facial features, we used of psychophysical studies in saccadic eye movements [14] which show that local appearance information is essential for classification step. In fact, people recognize objects when they try to find regions where discriminating information is detected. Our approach availed this finding to recognize facial expression by dividing face images into sub-regions and comparing the similarities between these sub-patterns.
Therefore, the LBP operator is applied to the gradient image in order to characterize the image information. To produce the gradient magnitude image, the image gradients for both X and Y directions must be calculated. This can be achieved by using the Sobel operator as a first order derivative. In our proposed approach, we used only the image gradient for Y direction since it offers a good compromise between the feature vector size and facial expression recognition accuracy [38].
Before computing Gradient image, the face was detected automatically using Viola's face detector [15]. Hence the face is converted to gray scale image level, resized to 64 × 64 pixels resolution and then preprocessed by histogram equalization to enhance the global contrast of the image and reduce the effect of uneven illuminations. Moreover, we applied an elliptical mask in order to get rid of hair, background, neck, and all the noisy objects which can appear jointly with the detected face.
Afterwards, the LBP operator is applied on the Y-image gradient to create the LBP feature map. The LBP operator was first introduced by Ojala et al. [16] for texture analysis task. This operator labels the pixels of an image by thresholding the 3x3 neighborhood of each pixel with the central value and considering the result as a binary number. Based on the operator, each pixel of an image is labeled with an LBP code. The 256-bin histogram of the labels includes the density of each label and can be used as a texture descriptor of the each region. Finally, all LBP histograms blocs are concatenated into a single vector defining accordingly the feature vector of the face.
In our experiment, for a 64×64 feature face image, the region (micro-pattern) is set to 8×8 pixels [38], hence the dimension of the vector feature is 16384.

Regions Selection using Mutual Information: After computing facial feature vector, we move now to select the best discriminative regions using mutual information technique. The Mutual information (also called cross entropy or information gain) is a filter-based method widely used to measure the stochastic dependence of two discrete random features [17, 18, 19]. This dependency is based on the information shared between these two features defined as follow in Eq.(1):

$$I(X,Y) = \iint_{\Omega_Y \Omega_X} p(x,y) \log_2\left(\frac{p(x,y)}{p(x)p(y)}\right) dx\, dy \tag{1}$$

Where Ω_X and Ω_Y are the sample space of X and Y, respectively, $p(x)$, $p(y)$, and $p(x, y)$ in that order are the probability density functions of X, Y, and (X, Y). In case of discrete variables, the integration notation is replaced by a summation notation as below in Eq.(2):

$$I(X,Y) = \sum_{y\in\Omega_Y} \sum_{x\in\Omega_X} p(x,y) \log_2\left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{2}$$

In the pattern recognition applications, we expect a feature set that can remove the uncertainty of the class variable as much as possible. This can be achieved by finding a feature set $S_m = \{X_1, X_2, \dots, X_m\}$ which jointly have the largest dependency on the target class c. This large dependency defines the Max-Dependency which has the following form in Eq.(3):

$$\max D(S_m, c), \quad D = I(\{x_i, i = 1, \dots, m\}, c) \tag{3}$$

Despite the theoretical value of Max-Dependency, it is often hard to get an accurate estimation for multivariate density $p(x_1, \dots, x_m)$ and $p(x1, \dots, x_m, c)$, because of the high-dimensional space. The high-dimensional space is due to the number of samples which is often insufficient and the multivariate density estimation which involves computing the inverse of the high-dimensional covariance matrix that is usually an ill-posed problem. So as the Max-Dependency criterion is hard to implement, an alternative is to select features based on maximal relevance criterion. Max-Relevance searchs features satisfying Eq.(4) which approximate $D(S_m,C)$ in Eq.(3) with the mean value of all mutual information values between individual features x_i and class c.

$$\max D(S_m, C), \quad D = \frac{1}{|S|} \sum_{x_i \in S} I(x_i, c) \tag{4}$$

As one can notice, computing the mutual information of one feature x_i is in other terms computing the relevance score of this feature. So in order to adapt the algorithm to select the most relevant regions, we have computed the relevance score of each facial feature using Max-Relevance criterion. Relying on the relevance score of each facial feature, we have calculated the relevance score of each region by summing up the relevance score of the region features averaged by the number of features. An overview of Mutual Information adapted algorithm for regions selection is detailed below.

Algorithm 1: Regions selection based on Max-Relevance criterion

```
Variables:
NF = Number of all potential features
NR = Number of regions
NF_Reg = Number of features per region
FeatRel[] = Relevance of each feature table
RegRel[] = Relevance of each region table
RegRelSort[] = Sorted table of regions relevance
Sum = Features relevance score sum for every
region, set to 0

1-Compute relevance score of each feature
for i = 1, ..., NF
   FeatRel[i] = MaxRel(Feat_i)
End_For

2-Compute the relevance score of each region.
  for k = 1, ..., NR
    for j = 1, ..., NF_Reg
      Sum = Sum + FeatRelevance[j + (NF_Reg × k)]
    End_For
  RegRel[k] = Sum / NF_Reg
  End_For

3-Sort the RegRel table according to region
relevance score.
  RegRelSort[] = sort(RegRel);
```

3.2 On-line Stage

After defining the most relevant regions, we can then extract facial feature vector of the already selected regions. Such procedure will produce a low-dimensional discriminative feature vector which helps to focus the computational process on the most relevant regions. Relying on the selected regions, we classified facial expressions using an SVM classifier.

Feature Extraction of Discriminative Regions: As far as we know the most significant regions in the face, we can apply LBP operator on these relevant regions. After labeling the selected regions with the LBP operator, a histogram is computed independently within each of the discriminative regions (Figure 2). This LBP histogram contains information about the distribution of the local micro-patterns, such as edges, spots and flat areas, over the discriminative regions, so can be used to statistically describe face characteristics. The resulting histograms are then concatenated into a single which encodes both the appearance and the spatial relations of facial regions.

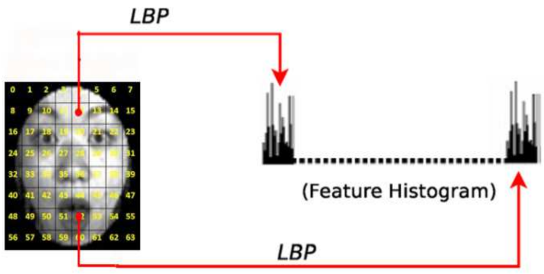

Fig. 2 Computing LBP feature vector on the preselected regions

In this spatially enhanced histogram, we effectively have a description of the face image on three different levels of locality: the labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a discriminative regions to produce information on a regional level and the regional histograms are concatenated to build a global description of the face appearance.

Facial Expression Classification: In the proposed work, we used the six basic expressions defined by Ekman [20] and thus defined seven facial expression classes: Anger, Disgust, Fear, Happiness, Sadness, and Surprise.
To build our facial expression recognition system, we proceeded with SVM classifier thanks to its performance in statistical learning theory and robustness for facial expression recognition task [24, 25]. Support Vector Machine is an efficient technique for classification [21] which carries out an implicit mapping of data into a higher dimensional feature space. Since SVM classifier makes binary decisions, multi-class classification here is accomplished by a cascade of binary classifiers together with a voting scenario. Thereby, we represented every image with an LBP features vector of the selected regions. Then, an SVM classifier is applied to find out the separating plane that has maximum distance to the closest points (support vector) in the training set.

4. Experimental Study

In order to evaluate the performance of the proposed approach, we carried out two series of experiments. The first one seeks to evaluate the performance of the selected regions using mutual information technique and compare its performance with some related works. Regarding the second one, it aims to prove that our proposed approach does not dependent on dataset and descriptor.
The experimental study was carried out on JAFFE database [26] which is the most known database in the current facial expression- research community. This database consists of 213 TIFF images sized 256x256 posed by 10 Japanese models. Each model has two to four

examples for each expression. Each subject has posed seven facial expressions namely: Anger, Disgust, Fear, Happiness, Sadness, and Surprise and one neutral.
We applied cross-validation strategy to measure facial expression classification accuracy and to perform comparison with other related works. Therefore, we randomly divided the database into ten segments in terms of different facial expressions. Each time, we trained nine out of the ten segments and tested the remaining segment. At last, we averaged all the 10 recognition rates to obtain the final performance of the proposed system.

4.1. First Series of experiments

In order to appraise the performance of Mutual Information technique for selecting regions, we inspected the evolution of facial expression recognition rates according to the number of selected regions. Figure 3 shows this inspection study.

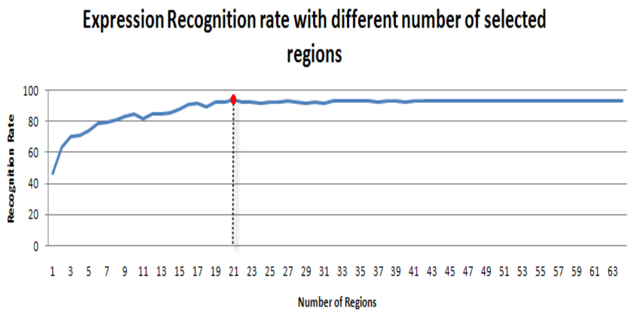

Fig. 3 Facial Expression recognition rates according to the number of selected regions

From this assessment, we perceived how the recognition rate increases promptly with the highest relevance score regions. In fact, we achieved a rate of 93.89% just with 21 regions which are discriminative for all facial expressions. Those selected 21 regions are mainly around the areas of mouth, eyes, eyebrows and nose (Figure 4) which validates the psychology studies [1, 2, 3].

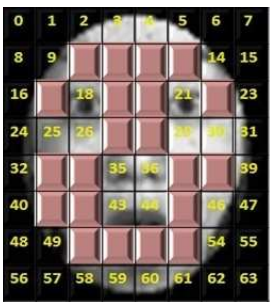

Fig. 4 Regions selection using LBP technique on JAFFE dataset

With the aim of evaluating the selected regions performance, we compared their accuracy with the whole face (64 regions) in terms of facial expression recognition rate, feature vector size and time execution per image.

Table 1: Regions selection evaluation in terms of recognition rate, feature vector size and time execution

Number of regions	Facial expression recognition rate	Feature vector size	Time per image
64	93.42 %	64 * 256 = 16384	19 ms
21	93.89 %	21 *256 = 5376	04 ms

Table 1 shows that we reached a rate of 93.89% with only 21 regions which is three times less than the inputted image regions (64 regions) that achieve 93.42% of recognition rate. This mean that only some relevant information is discriminative within the 21 selected region for facial expressions recognition. Nevertheless, the non-selected regions which have low relevance score bring noises and then affect facial expression recognition accuracy. Moreover, using 21 regions affords a feature vector size three times shorter than using the whole regions. Regarding time execution per image, it was reduced to 4 milliseconds which is five times faster than using the whole face information. Taking all into account, we can assert that selecting relevant regions achieved important gain in terms of facial expressions recognition accuracy, feature vector size and time execution.
To fairly compare our facial expressions recognition results to other related works, we suggest some works using the same JAFFE database under the same 10 cross-validation strategy. Table 2 shows performance comparisons between the proposed method and the existing systems. We can notice that our approach leads to the best result (93,89 %).

Table 2: The performance comparison on JAFFE database

Approach	**Recognition rate**
Lyons *et al* [29]	92.00 %
Zhang *et al.*[31]	90.10 %
Shinohara and Otsu [30]	69.40 %
Zhao and Zhang [32]	81.59 %
Our proposed method	93. 89%

These results prove that proceeding with regions selection on face image provides more discriminating feature to deal with expression classification problem. In fact, relying on 21 discriminative regions our proposed approach succeeded to improve expression recognition accuracy whilst reducing feature vector size and time execution.

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4.2. Second Series of experiments

In this second series of experiments, we aim to study the performance of the selected regions when we change the dataset and when we use another feature extractor technique. In fact, in the first scenario, we applied LBP features extractor technique to KANADE Database [34] and then selected the most relevant regions. In the second scenario, we used DWT (Discrete Wavelet Transform) features extractor technique [35, 36, 37] on JAFFE Database and picked the discriminative regions.

First scenario: In this first test, we kept using LBP features extractor technique but we changed the database by KANADE database. So as to make results comparable with JAFFE Database, we selected 10 subjects randomly from KANADE database, each subject has three samples of each expression: Anger, Disgust, Fear, Happiness, Sadness, and Surprise and neutral.
Applying Mutual Information technique to select prominent regions, 25 regions were selected since they afford the best facial expression recognition rate. (Figure 5)

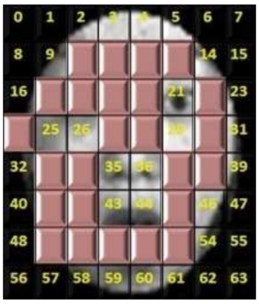

Fig. 5 Region selection using LBP technique on KANADE dataset

The selected regions improved recognition rate while decreasing the features vector size as it is detailed in Table 3. Moreover, we noticed that the 21 regions which were selected with JAFFE database are included in the 25 selected regions which mean that those 21 regions are independent of the database. Furthermore, using only those 21 regions we have attained 97.14% of recognition rate which is not far from the recognition rate while using the 64 regions.

Table 3: Regions selection evaluation on KANADE dataset using LBP technique

Database	Number of regions	Feature vector size	Facial expression recognition rate
KANADE	64	64 * 256 = 16384	98.57%
	25	25 *256 = 6400	99.04%
JAFFE	21	21 * 256 = 5376	97.14%

Notice here that if we change the size of database, in the case where we took all the 97 subjects in the KANADE database (around 1700 samples) the number of selected regions varies since there are more inter-class and intra-class variations. Using the whole KANADE database, the mutual information technique has selected 32 regions which afford a recognition rate of 96.42% whereas with 64 regions we have achieved only 96.05%.

Second scenario: In this second test, we have employed DWT features extractor on JAFFE database. Actually, DWT analyzes the image on various levels of resolution using low-pass and high-pass for decomposing the input image. The low-pass filter gives approximate image however the high-pass filter provides more detailed image. Further, the approximated image could be also divided into a deeper level of details. The chief characteristic of DWT is the multi-scale representation which helps to analyze the image at various levels of resolution. All that makes DWT a suitable tool to extract facial expression features at different levels.
Applying 2-Level DWT on JAFFE database, 25 regions were selected (Figure 6). These 25 regions afforded a recognition rate of 93.33% which is largely higher than using 64 regions. Besides, we noticed again that the 21 regions selected with LBP features extractor on JAFFE database still being included within these 25 selected regions. Additionally, applying 2-Level DWT on these 21 regions, we kept the same recognition rate while using 64 regions (Table 4). This brings us to conclude that these 21 regions are independent of features extractor technique.

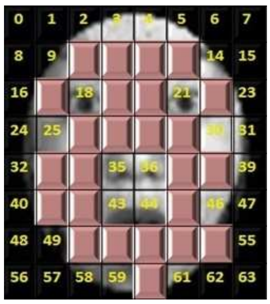

Fig. 6 Region selection using DWT technique on JAFFE dataset

Moreover, this test proved as well that LBP features extractor technique is more efficient than 2-Level DWT features extractor technique. In fact, we have recorded 91.42% with 2-Level DWT technique and 93.42% with LBP technique while using the 64 regions on JAFFE dataset. This is due to the fact that DWT technique provides only multi-scale face description whereas LBP technique describes the face image in three different levels of locality (pixel-level, region-level and face-level) which makes it more robust against face appearance variation.

Table 4. Regions selection evaluation on JAFFE dataset using DWT technique

Descriptor	Number of regions	Feature vector size	Facial expression recognition rate
DWT	64	64 * 208 = 13312	91.42 %
	25	25*208= 5200	93.33 %
	21	21 * 208 = 4368	91.42%

From this second series of experiments, we proved the independency of the 21 selected regions from the database and feature extractor technique. In addition, we proved the robustness of LBP features extractor technique against the 2-Level DWT features extractor technique in facial expression recognition task.

5. Conclusions

In this paper, we presented a low-computational approach for facial expression recognition based on automatic selection of descriptive emotion regions.

In fact, we proposed a new algorithm to select expressive regions based on Mutual Information technique. The selected regions approve the psychology studies since they are located around the mouth, nose, eyes and eyebrows. Through the experimental studies we proved the relevance of the selected regions as well as their independency of the dataset and descriptors. Moreover, the selected regions improved the facial expression classification accuracy since we do not only reduce the size of facial feature vector, but also upgrade recognition rate with the minimum number of regions. As future work, we intend to integrate facial expression recognition module to recognize people under varying facial expressions.

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Hazar Mliki graduated with a master’s thesis in computer science from the University of Sfax in Tunisia. She is a researcher in the MIRACL Laboratory (Multimedia, InfoRmation systems and Advanced Computing Laboratory). Currently, she is preparing her Ph.D at the University of Sfax in Tunisia (FSEGS). Her research interests include biometrics, pattern recognition and image processing.

Mohamed Hammami received a Ph.D in computer science from Ecole Centrale at the Lyon Research Center for Images and Intelligent Information Systems (LIRIS) associated to the French research institution CNRS as UMR5205. He is currently associate professor in the Computer Science Department at the Faculty of Science Sfax-Tunisia. He is a researcher in the MIRACL Laboratory (Multimedia, InfoRmation systems and Advanced Computing Laboratory). His current research interests include data mining and knowledge discovery in images and video, multimedia indexing and retrieval, face detection and recognition, and Web site filtering. He was a staff member in RNTL-Muse project. He has served on technical conference committees and as reviewer in many international conferences.