Portrait Identification Implementing Fuzzy Logic Rules and Neural Network in Digitized Paintings

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Abstract:
The new emerging technologies have successfully been applied to automate the extraction of metadata and make use of it in building various retrieval interfaces in cultural applications. In this paper, the problem of automatic identification of portraits in paintings collections is addressed.
A lot of image processing techniques for face recognition in digital images have been presented and assessed in the literature. However, the applications were mostly restricted in image and video processing for real world images. Therefore, it is quite tempting to investigate the possibility of implementing similar techniques in a retrieval interface for a cultural application.
An approach used for face detection in digital images is now implemented for face detection in digitized paintings. The method is based on fuzzy logic rules especially set for detecting possible skin areas in the paintings on the basis of color information. The candidate regions are then forwarded in a Probabilistic Neural Network (PNN) that is properly trained for the identification of faces from skin areas. Images containing face regions should be classified as portrait images.
Moreover, this paper discusses how these technologies can be adapted to enrich perspectives in exploring and managing digital collections of cultural heritage. The test sample for assessing the proposed method consists of digitized paintings downloaded from the website of the State Hermitage Museum.

Keywords: portrait identification, digital collections, face detection.

1. INTRODUCTION

Museums and Cultural institutions are becoming increasingly aware of how vital the emerging technologies are for reaching and engaging today's new audiences. However, organizations must be capable of offering rich content to fully benefit from new media technologies. This obviously includes high-quality digital images, which have already proven to be tremendously useful in all aspects of museums and other cultural institutions activities. A digital image can be edited, manipulated, e-mailed across the world, deleted, or copied and inserted into other files, World Wide Web pages, MS Powerpoint presentations, document files and publications. Digital images are used for printing, documentation, research and online publishing, most commonly in the service of collections management and preparing catalogues, and promoting exhibits or other events.

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Digitized images are used in a wide range of outreach activities, including Web sites, promotional material, new products for the museum gift shop, and so on. Digitization enhances preservation and conservation strategies, since once digitization has occurred the handling of fragile originals can be minimized. Digital images also play a role in outreach and public access, e.g., the production of exhibitions and the dissemination of information through virtual exhibitions, in galleries and through publications, learning and teaching materials, newsletters, brochures and postcards. Because digital technology makes it possible to search large numbers of records, to modify and manipulate images and text, and to bring together disparate materials in new ways, it can be considered a flexible tool useful throughout the museum CHIN (2000).

The best image collections in the world would be virtually unusable without the facility to search for and retrieve appropriate images. In the context of a digital image collection, content retrieval is usually based around users submitting keyword searches against one or more textual fields associated with each image or group of images. Effective search and retrieval mechanisms can make the difference between a mere aggregation of images and a usable collection. The key to a competent search facility and thus effective searching is to ensure that sufficient metadata is associated with the images. The level of accessibility of images is generally dependent on the amount and type of metadata that has been used to describe the images. An image, because of its visual nature, is less easy to find using traditional text-based searching. If an image is not accompanied by sufficient, meaningful metadata, it is unlikely to be found. (TASI, 2004)

The proposed method belongs to Content - Based Image Retrieval (CBIR) methods. This is the process of retrieving images from a collection on the basis of image features and appearance (such as colour, texture and shape) automatically extracted from the images themselves. The method has been developed for identification of faces in digital images of real world (Anagnostopoulos,2001) and intelligent image retrieval form the world Wide Web (Anagnostopoulos,2002). In this paper this method is implemented in digital paintings for automatic identification of portraits. Iconography characterization is one of the most complex subjects. Some shape recognition seems to be applied to subject such as portrait, landscape, still life, or to themes such as crucifixion, or virgin and child (Lahanier, Aitken et al.,2004). Recently another paper explores the automatic identification of portraits in art images databases (Sikudova, Gavrielides et al. 2003), but their method includes only image processing routines based on color and shape information. In contrast, the proposed method implements artificial intelligence techniques such as fuzzy logic rules for extracting color information and a neural network as a classifier.

Our aim is to classify different digital art images into portraits and non – portraits. We use the assumptions that a portrait is a realistic representation of the sitter (the person in the portrait), showing the subject in mainly frontal view with plain backgrounds or ornate ones with curtains, architectural fragments, landscapes, etc. Image showing the subject standing or sitting and the face is in the focus (i.e. it is a foreground object) of the image.

2. DESCRIPTION OF THE FACE DETECTION METHOD FOR REAL WORLD SCENES

2.1 Fuzzy Logic (FL) System

The color of human skin is distinctive from the color of many other objects and therefore the statistical measurements of this attribute are of great importance for face detection (Belongie, 1998), (Grecu,2000). It is expected that the face color tones will be distributed over a discriminate space in the color planes. So, the first step of the face detection system is the location of potential skin areas in the image, using color information of specific color models. Many approaches in the literature used similar detect procedures either based on the RGB, chrominance (CbCr) (Garcia,1999) or Hue and Saturation (HSV) space (Tsekeridou,1998).

In our face detection method, we used a combination of the Red-Green-Blue (RGB) model as the more generic one and the YCbCr since it is proved to be more representative for modeling the human skin (Bernd,1999), (Saber,1998), (Sobottka,1998), (Chai,1999).

The basic concept in FL, which plays a central role in most of its applications, is that of a fuzzy if-then rule or, simply, the fuzzy rule. In the proposed schema the skin-masking algorithm presented in Umbaugh (1998), is partially used along with RGB cluster groups that represent skin color extracted from experimental tests in a large database of human face images and an additional rule using the YCbCr model. The above measurements and the skin masking algorithm formed the basis for the definition of the fuzzy logic rules. These if - then rule statements are used to formulate the conditional statements that comprise the fuzzy logic-based skin color detector.

Applying fuzzy logic rules the proposed system decides whether a pixel in the inspected image represents or not a potential skin region. However, a skin region does not represent always a face, and therefore the candidate area should be normalized and checked whether it represent a face or not.

The fuzzy logic rules applied for skin area discrimination are the following (R=Red, G=Green, B=Blue in the RGB color model and Cb=Chromaticity blue, Cr=Chromaticity red in the YCbCr color model)

1. If R<100 then no skin (shadow)
2. If R<G then no skin
3. If R<B then no skin
4. If R/G >1.3 and R/B >1.4 then possible skin
5. If R/G <1.3 or R/B <1.4 then no skin
6. If R/G >1.3 and G/B >1.5 then possible skin
7. If 77<Cb<127 and 133<Cr<173 then possible skin

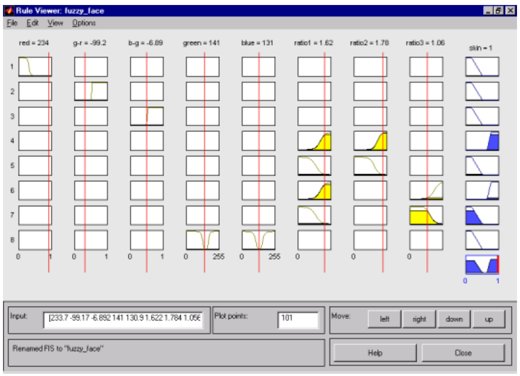

Figure 1. A screenshot of the fuzzy logic rules in Matlab rule viewer

The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. Once the inputs have been fuzzified, the fuzzy logical operations must be implemented. For this application we used the OR operator (max). The weights in every rule were set equal to one. The aggregation method for the rules is the maximum value. Finally, the defuzzification method is the middle of maximum (the average of the maximum value of the output set).

The fuzzy rules were successfully applied to a Fuzzy Inference System (FIS), using the Fuzzy Logic Toolbox of Matlab 6.0 by MathWorks Inc. The inputs of the FIS program are the RGB and CrCb values of the input image. In a Pentium at 1000 KHz , the required time for skin area detection varied from 4 to 6 seconds according the image size. A screenshot of the application is shown in Figure 1. Input and output images are presented in Figure 2 respectively.

Figure 2. Human skin detection

2.2 The Artificial Neural Network (ANN) for image classification

Having collected images with possible skin areas, the next step involves the correct identification of images with human faces. This requires further image processing steps in order to properly feed the image classifier. The image-processing operations consist of four distinct parts.

Firstly, potential skin areas are clustered to form the Region of Interest (RoI), roughly describing its shape, on the basis of the FL output. Every image is transformed in gray scale and in the specific size of 100x100 pixels. Then two morphological operations, which help to eliminate some of the noise in the tested image, are involved. In particular, simple erosion with a 10x10 matrix of ones is performed followed by dilation. Further on, the created image is parsed through a skeletonisation technique, removing simultaneously all the areas that are considered as ‘holes’. As a result of the previously described image processing steps, the RoIs of all the possible skin areas are depicted in Figure 2.

Having defined the RoI in the previous part, in the second step the algorithm is applied to the initial tested image, merging objects that belong to the same area, performing a simple dilation once again, with a structural element, which is a 5x5 matrix of ones. With this technique, segmented pixels in the same neighbourhood, are merged in one region. All the image parts that are included in the defined RoIs, are then transformed to gray scale. In the following part all the segmented images are resizing to a specific size of 225x225 pixels. Finally, the 225x225 pixel images are divided into non-overlapping sub-images of size 15x15 and the mean value for each is calculated, followed by histogram equalization, which expands the range of intensities in the window (Sung,1994). During this procedure, a lower resolution image is created, forming in parallel a descriptor vector that consists of 225 gray scale values from 0 to 255. Figure 3 presents the input for the proposed neural network. The proposed ANN is trained to identify which of the skin regions detected from the FL system represent facial photos. The training set of the ANN consists of a large group of images of the size 15x15, representing face regions or other skin areas. The idea of this approach was motivated by the observation that human faces present a high degree of resemblance when they are sampled in low-resolution (Dai,1998). This is due to the fact that all faces have darker areas, which represent the eyes and the mouth. It is undoubtedly easier for an ANN to recognize the presence of a face, judging from a low quality image. Additionally, the numbers of the computational units are significantly smaller for a low quality image. Artificial Neural Networks have been successfully applied for face detection in images (Rowley,1998), (Dai,1998), (Lin,1997), (Moghaddam,1997).

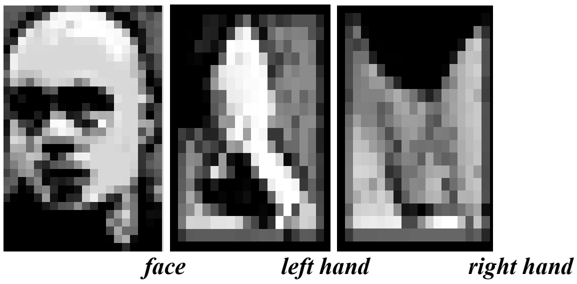

Figure 3. Results from image processing part 1

The ANN is a two layer Probabilistic Neural Network (PNN) with biases and Radial Basis Neurons in the first layer and Competitive Neurons in the second one. Training a neural network for the face detection task is quite challenging due to the difficulty in characterizing prototypical “non-face” images. Unlike in face recognition, where the classes to be discriminated are different faces, in face detection, the two classes to be discriminated are “face area” and “non-face area”. Figure 4 depicts the topology of the proposed PNN as well as the transformation of a face image in the appropriate input vector form, which consists of 225 gray scale values.

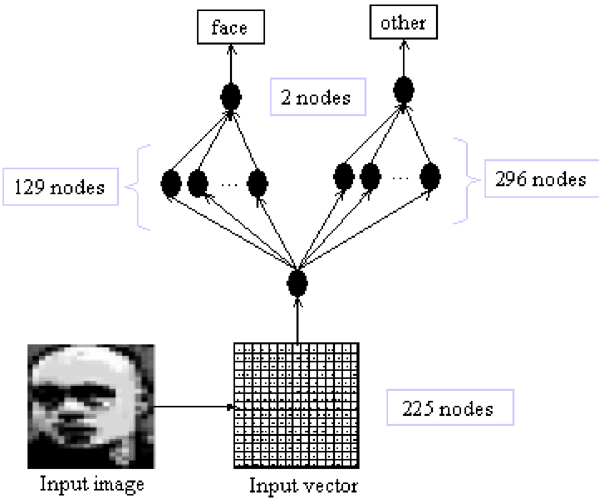

Figure 4. PNN's architecture

A sample of 129 frontal view face images was used as training set for the class ‘Face’, as well as a large sample of 296 images corresponding to other correct or erroneously detected skin areas, such as hands, legs and other objects. Table 2 presents the confusion matrix percentages in terms of the learning ability during the training epoch. The training set consists of 425 sub-images of size 15x15 in a vector form, as these were extracted from 103 color images according the proposed image processing steps. In other words, the neural network ‘learned’ to identify 128 from the

129 sub-images corresponding to human faces as well as 293 from the 296 sub-images corresponding to other skin areas and objects. The time needed for the completion of one training epoch in a Pentium IV at 1.5 MHz with 512 MB RAM, was 22 seconds. The topology of the proposed neural network is 225-425-2. This means that the PNN has a 225-input vector (the 15x15 input image) and a 2-output vector corresponding to the decision of the system (whether it is a face or not). Finally, the system has 425 nodes in the middle layer corresponding to the total training set.

Training Set		
Total color images	Number of faces	Skin areas - Other objects
103	129	296
Testing Set		
Total images		Number of faces
317		482
FL rules		
Segmented areas	841	452 faces + 389 possible skin areas
FL Rules performance	452/482	93.77%
Artificial Neural Network (ANN)		
Faces	397	
No faces	444	
ANN Performance	397/452	87.83%
Total System Performance	397/482	82.36%

Table 1. System's Performance

	Face	Other skin area – object
Face	99.22% (128/129)	0.88% (1/129)
Other skin area - Object	1.01% (3/296)	98.99% (293/296)

Table 2. Training confusion matrix

2.3 Image processing performance

The performance of the system for face detection was tested using 317 color images of various formats, types and size containing human faces. More specifically, the sample of 317 color images contained 482 faces. The system implementing the fuzzy logic rules segmented totally 841 skin areas. However, 30 faces were not selected and therefore the performance of this system is 93.77% (452/482). Following the fuzzy logic system, the ANN received the 841 skin areas and decided that 397 of them represent faces. Thus, the performance of the ANN is 87.83% (397/452). Finally, the overall system performance is 82.36%, since 397 from a total of 482 faces were identified. All the results are shown analytically in Table 1.

3. FACE DETECTION SYSTEM FOR PORTRAIT IDENTIFICATION

The approach, which was described above, is now used implemented for face detection in digitized paintings. The method is based on the fuzzy logic rules especially set for detecting possible skin areas in the paintings on the basis of color information. The candidate regions are then forwarded in the Probabilistic Neural Network (PNN) that is properly trained for the identification of faces from skin areas. Images containing face regions should be classified as portraits.

However, it should be emphasized that there are some restrictions imposed due to the nature of the application. Firstly, the system handles only color and not gray scale digital images. Without the color information, the FL system will not provide any results. Moreover, the system can recognize portraits among realistic representative paintings and not modern artworks (symbolic, abstract or expressionistic portraits). Finally, our current implementation is limited to the detection of human faces in frontal view.

3.1 Testing Set

The testing set of the portrait identification system consist of 150 digitized paintings downloaded from the website of the State Hermitage Museum. This sample set includes 70 portraits and 80 paintings of various themes. The artworks that present one or more human faces are considered to be portraits. Table 3 highlights the recognition rates of the system when the testing set was presented.

Total images	150	
Number of portraits	70	
Number of faces	89	
FL rules		
Segmented areas	178	87 faces + 91 possible skin areas
Neural Network		
Faces in paintings	71	
No faces	107	
Total Performance		
Portraits correctly identified	62	62/70 (88.6%)

Table 3. Portrait identification recognition rates

Some screenshots are presented below highlighting the performance of the system in artworks. Paintings with different themes except portraits have been included in the testing set. In figures 5 and 6 it is demonstrated a correct classification of two paintings, one landscape and a still life, into non-portraits. In figures 7 and 8 you can see a correct classification of two realistic portraits in frontal view in the category portrait. Following, in figure 9 is presented an erroneous classification of a group portrait because the system couldn't isolate the faces from other body parts. And finally in figure 10 in another group portrait the system has identified correctly three of the four faces. PNN failed to identify the boy in the left, probably due to the fact that it is not a frontal view of his face. However, the painting is classified as a portrait.

Figure 5. (a) Original paintings (Rousseau, Theodore, *Landscape with a Sunset*, mid-19th century and Leickert, Charles Henri Joseph, *Urban Landscape*, 1856, Hermitage Collection) (b) FL results, (c) PNN results.

Figure 6. (a) Original painting (Dawe, George, *Portrait of Akim A. Karpov (1767-1838)*, no later than 1827, Hermitage Collection), (b) FL results, (c) PNN results.

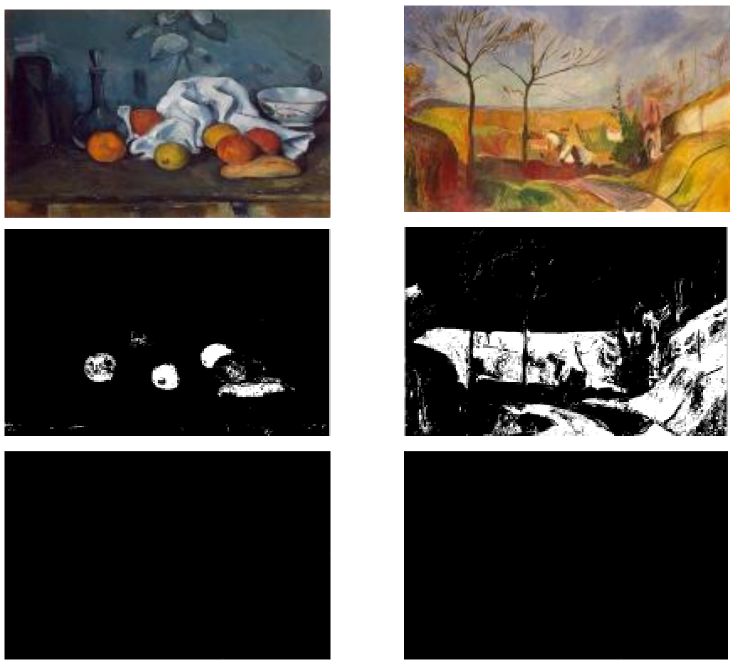

Figure 7. (a) Original paintings (Cezanne, Paul, *Fruit*, circa 1879 and Purrmann, Hans, *Landscape*, between 1910 and 1930, Hermitage Collection) (b) FL results, (c) PNN results.

Figure 8. (a) Original painting (Dawe, George, *Portrait of Alexander I. Gressor (1772-1822)*, no later than 1827, Hermitage Collection), (b) FL results, (c) PNN results.

Figure 9. (a) Original painting (Gronckel, Wital Jean de, *Portrait of Two Children*, 1849, Hermitage Collection), (b) FL results, (c) PNN results.

Figure 10. (a) Original painting (Bruyn, Bartholomaus I., *Portrait of a Man and His Three Sons,* late 1530s - early 1540s, Hermitage Collection), (b) FL results, (c) PNN results.

4. CONCLUSIONS

This paper presented in details the Fuzzy Logic rules joined with a Probabilistic Neural Network for face detection in natural scenes and its application for portrait identification in a collection of digitized paintings. It describes the architecture of both systems applied directly to colour images and identification of portraits in art images database. The method consists from a multistage algorithm, which segments the images based on colour, intensity and edge information. After the image segmentation, the resulting regions are forwarded to a neural network, which is trained to identify face and non-face regions. This classification is then used to identify a painting as a portrait or non-portrait.

So far, the results are very encouraging for further development of the method. However, still a lot of limitations have to be overcome. Our current implementation is limited to the detection of human faces in frontal view. A possible and interesting extension would be the expansion of the Neural Network's training set to include sided-view faces as well.

The proposed method can be used for retrospective documentation, for retrieving images through raw digitized material without proper documentation (images that were created at different periods of time without any registration number), for classification of digital images and publishing them into the category of Portraits on the web site. Actually, the pre-defined categories enables users' search in the digital collection and it is very helpful for browsing a large collection of images on the web, too. Furthermore, the automatic identification of portraits can be combined with the creation of meaningful teaching and learning resources on the web. It could forward the design of a resource pack or an educative web game that introduce students to the vocabulary, history and major themes of portrait and to explore through some examples history, art, stylistic features of an epoch, or an artist, execution techniques, type of portraits, details for the sitter like his position, prestige, profession, etc. Portraiture gives many opportunities for developing rich content education resources and activities and we assume that the proposed application can contribute in exploring different meanings in a portrait image. A portrait does not have to be painted on canvas. It can be many things; it can be tiny (a miniature) or life-size, painted on wood, a sculpture, a drawing or a photograph and all these types in a digital collection can be treated just as digital images. Further, we can expand our sample to include all these different types of portraits.

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Αναγνώριση πορτρέτων από ψηφιοποιημένες συλλογές πινάκων με χρήση ασαφούς λογικής και νευρωνικών δικτύων

ΧΡΗΣΤΟΣ ΑΝΑΓΝΩΣΤΟΠΟΥΛΟΣ, ΣΟΦΙΑ ΜΠΑΚΟΓΙΑΝΝΗ

Οι νέες τεχνολογίες αιχμής έχουν εφαρμοστεί επιτυχώς για την αυτοματοποίηση της επεξεργασίας των δεδομένων και μέτα-δεδομένων σε διάφορες διεπιφάνειες πολιτιστικών εφαρμογών. Η παρούσα εργασία ασχολείται με το θέμα της αυτοματοποιημένης αναγνώρισης πορτρέτων σε συλλογές με πίνακες ζωγραφικής.

Στη βιβλιογραφία έχουν παρουσιαστεί πολλές τεχνικές για αναγνώριση προσώπων σε ψηφιακές εικόνες. Όμως, οι τεχνικές αυτές έχουν εφαρμοστεί κυρίως σε πραγματικές εικόνες και βίντεο. Ως εκ τούτου, είναι αρκετά ενδιαφέρον να ερευνηθεί η δυνατότητα εκτέλεσης παρόμοιων τεχνικών σε πολιτιστικές εφαρμογές.

Μια προσέγγιση που έχει χρησιμοποιηθεί σε παλιότερη εργασία για την αναγνώριση προσώπων σε ψηφιακές εικόνες, εφαρμόζεται τώρα σε ψηφιοποιημένους πίνακες. Η μέθοδος βασίζεται σε κανόνες ασαφούς λογικής που έχουν ειδικά καθορισθεί για την αναγνώριση πιθανών περιοχών επιδερμίδας σε πίνακες ζωγραφικής χρησιμοποιώντας χρωματικές συνιστώσες. Στη συνέχεια, οι πιθανές περιοχές εμφάνισης επιδερμίδας προωθούνται σε ένα Πιθανοτικό Νευρωνικό Δίκτυο που έχει κατάλληλα εκπαιδευτεί για την αναγνώριση προσώπων από τις λοιπές περιοχές επιδερμίδας. Με τον τρόπο αυτό οι εικόνες που περιέχουν πρόσωπα ταξινομούνται ως πορτρέτα.

Επιπλέον, η παρούσα εργασία εξετάζει τους τρόπους με τους οποίους οι νέες τεχνολογίες μπορούν να υιοθετηθούν από πολιτιστικούς οργανισμούς και να συμβάλουν στη διαχείριση των ψηφιακών πολιτιστικών συλλογών. Το δείγμα που χρησιμοποιείται για την αξιολόγηση της προτεινόμενης μεθόδου προέρχεται από ψηφιοποιημένους πίνακες που ανακτήθηκαν από την ιστοσελίδα του Κρατικού Μουσείου Ερμιτάζ της Αγίας Πετρούπολης.

Λέξεις- Κλειδιά: αναγνώριση πορτρέτων, ψηφιακές συλλογές, ανίχνευση προσώπων