Face detection based on invariant moments classified by neural network

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***Abstract*—**Face detection is very important topic in image processing. In this paper we propose a method for face detection based on skin detection for initial potential regions detection and Hu invariant moments as region descriptors. Seven Hu moments present complex relations among different skin regions and neural network is used for face or non-face classification. The utilized network is a multilayer perceptron (MLP) with one hidden layer. The back propagation learning is used for its training. Experimental results demonstrated successful face detection.

***Keywords*—**Image processing, face detection, skin color detection, Hu's moments, neural networks.

I. INTRODUCTION

FACE detection is a very active research field with various applications. Due to technical evolvement numerous of these applications have become an irreplaceable part of our daily lives. To mention some, on cell phones we have systems that recognize that user is looking at them so the screen won't turn off, there are modern human-computer interfaces that recognize body postures, body gestures and even facial expressions. Human eye without difficulty can detect another human face unlike computer vision. For it there are many difficulties (mustaches, glasses, beards hide or change same basic features of the face; technical properties of devices etc.) and even more challenges (pose variance, imaging conditions, face images can become significantly different under various lighting etc.) associated with face localization. Numerous different algorithms have been proposed but the results are still not satisfactory for use in everyday life. Therefore, face detection is still in its infancy, evolving all the time.

Yang, Kriegman and Ahuja [1] proposed classification for face detection, which is generally accepted. According to them, there are four categories of classification algorithms for face detection: knowledge-based, feature-invariant, template matching based and appearance-based.

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Various face detection techniques have been used accomplishing different results [2], [3]. Terrillon et al. [4] presented algorithm for skin color modeling in TSL (tint-saturation-luma) color space that has achieved the best results (in all color spaces for skin color modeling). DeDios and Garcia [5], analyzing YCbCr color space, describe YCgCr color space (use of Cg color component instead of Cb component) that accomplishes better results than YCbCr. Kukharev and Novosielski [7] built skin color model in YCbCr (people of black skin color have not been investigated). They were defining and comparing thresholds for each of Y, Cb and Cr components to identify skin pixels.

In this paper we will describe our algorithm for face detection by neural networks based on invariant moments. First we roughly searched the areas of skin color. On these areas we applied the Hu's moments. For enhancing efficiency of our algorithm, based on the calculated values of Hu's moments, we built neural networks that classify face from other exposed skin body parts.

The rest of the paper is organized as follows: Section 2 describes color space for skin detection. Section 3 shows description of skin color detection algorithm. Section 4 describes briefly Hu's moments and their application in our work. Section 5 describes shortly Neural Networks with an emphasis on Multilayer perceptron (MLP). Section 6 discusses the proposed method in detail. Section 7 reports our experimental results. Section 8 concludes the paper.

II. COLOR SPACE FOR SKIN DETECTION

Colors play an important role for object detection, tracking and recognition, etc. Many models of color spaces have been proposed for skin detection. Some of the most used models of color spaces are YCbCr, HSI, TSL, RGB. There is a proof that if an optimum skin detector is designed for every color space, their performance will be the same. However, it is generally agreed that there does not exist a one color space which is convenient for detection of skin color in all color images [7].

YCbCr color space is utilized by our algorithm of skin detection. In the name of YCbCr color space Y presents the luminance channel and Cb and Cr are the blue-difference and red-difference chrominance components respectively (Fig. 1). It has emerged as a response to the increasing demands for digital algorithms in handling video information. Except YCbCr, in the family of television transmission color spaces belong YUV and YIQ.

YCbCr color space was extensively used in the development of the JPEG standard. This color space is a scaled and zero-shifted version of the YUV, so that the chrominance values are always positive, as shown in following equation

$$Cb = \frac{U}{2} + 0.5 \quad (1)$$

$$Cr = \frac{V}{1.6} + 0.5 \quad (2)$$

for U ranging between $[-0.9, 0.9]$ and for V ranging between $[-0.7, 0.7]$ which are the ranges obtained from the conversion from normalized RGB.

Applying the following formulae we get direct conversion from RGB to YCbCb:

$$Y = 0.299 \cdot R + 0.587 \cdot G + 0.114 \cdot B \quad (3)$$

$$Cb = 128 - (0.168736 \cdot R) - (0.331264 \cdot G) + (0.5 \cdot B) \quad (4)$$

$$Cr = 128 + (0.5 \cdot R) - (0.418688 \cdot G) - (0.081312 \cdot B) \quad (5)$$

We had a problem with some converted value of pixels as they came out of their potential range. Therefore it was necessary to return these values within the interval given sizes. We did it in a way that those values that go below zero we put to zero and those that exceeded 255 we set on 255.

Fig.1. Color image and its Y, Cb and Cr components

III. Skin color detection in YCbCr

Skin color detection is the most important work in the application of face recognition. In this work, we use YCbCr to detect the skin areas of an image. People have different skin colors in appearance. Numerous studies have shown the main difference lies in the intensity rather than the color itself. In contrast to RGB, the YCbCr color space is lumina-dependent, so it is one of the most popular color spaces for skin detection. According to (Hsu et al, 2002), the skin color cluster is more compact in YCbCr than in other color space.

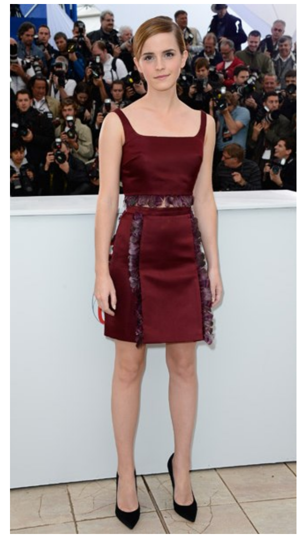

Fig.2. Original image

First what we do in our skin detection algorithm is applying color segmentation on an input image (Fig. 2) by using the threshold for each of the components with the following inequality

$$69 < Y < 215 \quad (6)$$

$$94 < Cb < 126 \quad (7)$$

$$139 < Cr < 17 \quad (8)$$

Our result is a binary image where all pixels are marked either as skin or non-skin. Some noise can take place in both skin and non-skin areas. Therefore, before proceeding to the next step we will used morphological operations.

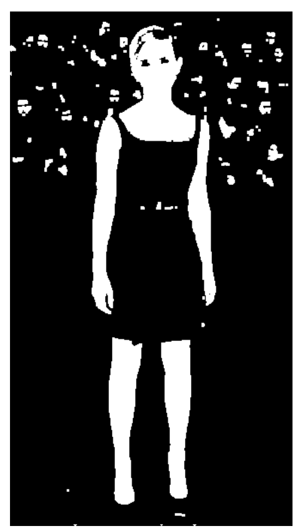

Fig.3. Binary image showing skin areas

A wide set of operations that process images based on shapes is called morphology. Erosion and dilation are two morphological operations. They are used to smooth the boundaries of the object without changing their respective territory. The basic goal of using erosion and dilation is to improve the efficiency of face detection. The dilation process is to add pixels in the boundary of an object where as the erosion is used to remove the boundary pixel from an object. The process when the image is first dilated and then eroded by using the same structuring element is called closing operation. The opening operation performs eroded the image and then dilate the eroded.

IV. Moment invariants. Hu's moments

Moment based methods for object recognition and positioning have been considered by numerous authors, first for two-dimensional, and more recently for three-dimensional objects. Moment invariants were firstly introduced to the pattern recognition field in 1962 by Hu [9], who employed the results of the theory of algebraic invariants and derived his seven famous invariants to rotation of two-dimensional objects.

In pattern recognition, moments and functions of moments have been extensively used as invariant global features of images. An essential feature of pattern analysis is the recognition of objects and characters regardless of their size, position and orientation.

Regular moment invariants are one of the most popular and widely used contour-based shape descriptors, a set derived by Hu (1962) [10]. Later on these geometrical moment invariants have been extended to larger sets by Wong & Siu (1999) and to other forms (Dudani et al 1977; Liao & Pawlak 1998) [11].

Two-dimensional moments of order of digital image of size are defined as:

$$m_{p,q} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} x^p y^q f(x,y) \quad (9)$$

where $p,q = 0,1,2\cdots$.

The corresponding central moment of order $(p+q)$ is defined as:

$$\mu_{p,q} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)(x-x_{avg})^p (y-y_{avg})^q \quad (10)$$

where $x_{avg} = \frac{m_{10}}{m_{00}}$ and $y_{avg} = \frac{m_{01}}{m_{00}}$.

The normalized central moments are defined as:

$$\eta_{p,q} = \frac{\mu_{p,q}}{m_{00}^{\frac{p+q}{2}+1}} \quad (11)$$

The first invariants that appeared in literature were invariants to similarity transformation group. They were a response to the problem of choosing the crucial properties of objects classification regardless of their position, primarily because of its uncomplicatedness in application. Invariants to translation and scaling are trivial – central and normalized moments themselves solve it. So the only non-trivial problem remains finding rotational invariants. The problem is solved by M.K. Hu who defines the following seven rotational invariants which are computed from central moments through order three.

$$h_1 = \eta_{20} + \eta_{02} \quad (12)$$

$$h_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (13)$$

$$h_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (14)$$

$$h_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (15)$$

$$\begin{aligned} h_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})((\eta_{30} + \eta_{12})^2 \\ &- 3(\eta_{21} + \eta_{03})^2) + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) \\ &(3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) \end{aligned} \quad (16)$$

$$\begin{aligned} h_6 &= (\eta_{20} - \eta_{02})((\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) \\ &+ 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \end{aligned} \quad (17)$$

$$\begin{aligned} h_7 &= (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})(3(\eta_{30} + \eta_{12})^2 \\ &- (\eta_{21} + \eta_{03})^2) - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03}) \\ &(3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2) \end{aligned} \quad (18)$$

The Hu's invariants are not demanding for the implementation and therefore they are often used as a basic set of characteristic properties in solving many different pattern recognition problems. The Hu's invariants became classical and despite many disadvantages, they have found numerous successful applications in various areas such as identification of persons, medical applications, objects for robot orientation, recognition of letters, the analysis of satellite images, etc.

Major weakness of the Hu's theory is that it does not provide for a possibility of any generalization.

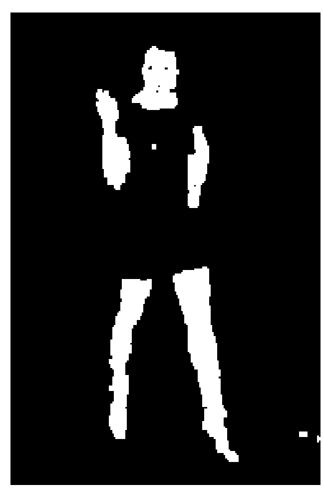

Fig.4. One of binary images on which we applied Hu's moments

V. NEURAL NETWORKS

There are categories of problems for which the algorithm cannot be formulated, problems which require learning to get results, or problems that have exponential time complexity. To solve these kinds of problems we are using swarm intelligence algorithms and/or neural networks. In image processing often problems of selection of some subsets appear like in multiple thresholding [12] (with entropy objective function [13]) or like here selecting the relevant subset of Hu moments. Such exponential combinatorial problems are computationally intractable and successfully solved only by nondeterministic heuristics, where swarm intelligence is prominent. Ant colony optimization [14], [15], [16], artificial bee colony algorithm [17], [18], [19], [20] and other more recent algorithms [21], [22], [23], [24] were successfully applied to different problems, including image processing. Here we first try with neural networks.

At first sight it looks perfect, but on the other side it is very complex, because of complex nature of its calculation, so it is very demanding to find a fault. Usually because of that problem they are being tested on problems for which there are precise solution algorithms or their solution is known in advance.

Artificial neural networks can be characterized as computational models with particular properties such as the capability to adapt or learn to generalize or to cluster or organize data and which operation is based on parallel processing. However, many of the above referred characteristics can be attributed to the existing non neural models. The question is to which scope the neural approach demonstrates to be better suited for certain applications than the existing models. To this day no reliable answer to this question were found.

First beginnings of neural computing is usually associated with the yaer 1943 and neuro-psychologists Warren McCulloch and Walter Pitts, who had produced the first artificial neuron. Technology available at that time did not allow them to do more in this field. The concept of neural networks was first proposed by Alan Turing in his paper "Intelligent machine", 1948. In mid-1960 Minsky and Papert in the book "Perceptron" offered the evidence that neural networks cannot learn the XOR operation. Thus the development of this area slowed down. Their proof was later disproved, of course. Although their beginnings are in the forties, their development began in the eighties when algorithms became good enough to use. Nowadays, development of the field of research has almost been explosive.

Artificial neural networks have the structure, function and process information similar to biological, although the mathematical model of biological network is far more simplified. They are trying to replicate only the simplest elements of this complicated and powerful system. Although they work in a primitive manner, they are very successful in solving many problems.

In this paper, Multilayer perceptron (MLP) is used as a classifier in the face detection system. MLPs are the most popular type of artificial neural networks (ANN). They are feed forward networks of simple processing elements or neurons. Because of their capacity to learn complex non-linear input–output relationships and ability to generalize any given data they have been successfully applied in various pattern recognition problems. The key power provided by such networks is that they admit fairly simple algorithms where the form of the nonlinearity can be learned from the training data.

As the name implies, a Multilayer Perceptron is just that, a network that is comprised of many neurons, divided in layers: input layer, hidden layer or layers and output layer, interconnected by modifiable weights represented by links between layers.

In a Multilayer Perceptron neural network, each neuron receives one or more inputs and produces one or more identical outputs. Each output presents a simple non-linear function of the sum of the inputs to the neuron. Inputs pass forward from nodes in the input layer to nodes in the hidden layer, and then pass from the hidden layer to the output layer. Connections between neurons within a layer are not allowed. If hidden layer is not included (as in a logistic regression model) inputs pass forward directly from nodes in the input layer to nodes in the output layer.

Each neuron has a simple non-linear function assigned to it (known as the activation function) which describes the importance or relevance of a particular neuron to that layer of a neural network. Hidden neurons usually use a hyperbolic tangent function for their activation function, whereas output neurons often use a sigmoid function for activation. Both functions are nonlinear, continuous functions that allow the neural network to model nonlinear relationships between input and output neurons. Threshold function is also frequently used activation function.

In the input layer the number of neurons depends on the number of inputs we want our network to get. In the output layer the number of neurons depends on the problem we want the neural net to learn. MLP can have one or more hidden layers. These layers come between the input and the output and their number can vary. The function that the hidden layer serves is to encode the input and map it to the output.

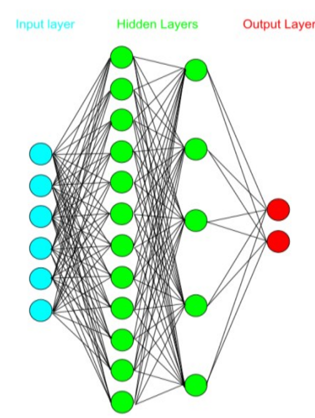

Fig.5. Multilayer Perceptron (MLP)

Although MLP can have more hidden layers, Cybenko has shown that one hidden layer is sufficient for approximating functions [25]. However, the experience has shown that a two hidden layer network will train significantly faster than a one hidden layer network on some classification problems. But there has still not been any specific rule established for selection of the quantity of nodes in the hidden layers.

A diversity of training rules have been developed for setting the weights. The most popular rule to date is back propagation which was originally developed by Paul Werbos [26], rediscovered by David Parker, and popularized by David Rumelhart. The back propagation algorithm is an iterative gradient descent procedure in the weight space which minimizes the total error between the desired and actual outputs of all the nodes in the system.

There are many and various methods of application of neural networks [27], [28], [29], [30]. In the field of neural networks based on the invariant moments we can mention Khotanzad and Hong [31]. They have shown that a neural network classifier using Zernike moments has very strong class separability power. Another method analyzing Pseudo Zernike Moment Invariant and Zernike Moment Invariant for human face recognition in comparison with other moments was used by Haddadnia, Faez, and Moallem [32].

VI. Our face detection system

In this paper we describe the algorithm for locating human faces based on color information and shape analysis based on invariant moments, Hu's moments. With the aim to detect human faces we use MLP as a classifier. The method is divided to three steps: skin / non-skin color classification, characterizing clusters using Hu's moments and head / non-head classification based on neural networks.

After processing the original image to binary image, some noise can take place in both skin and non-skin areas. Therefore it is necessary to perform opening and closing operations before proceeding to the next step. Opening involves morphological operation of erosion, followed by dilation. By this operation, elimination of noise, made by skin pixel is achieved. To eliminate non-skin pixels noise, closing operation is executed, which involves dilation followed by erosion.

On the resulting image we use the method of invariant moments – Hu's moments in order to characterize the shape of each cluster. There are 51 digital images in our data base. For one particular image we calculated values of seven Hu's moments. Analogously, for each processed image in our database, we repeat the procedure and get the values of the seven Hu's moments. Now these values represent the training data set based on which we create neural networks. All data together are saved as a text file in Notepad.

We built our NN in JustNN, neural networks system. Creation of neural networks in this system is quite simplified. It allows the user to produce multilayer neural networks from a grid or from text files and images.

We create multilayer neural networks by the text file of Notepad. Graphic representation of our neural networks can be seen in Figure 6. In the input layer of our neural networks we used seven neurons, seven Hu's moments of every image in training data. We only have one hidden layer which has eight neurons. One neuron is in the output layer. He has a Boolean value, i.e. it returns a true value if the neural networks have recognized a skin patch as head and a false value for not-head.

VII. Experiments

In this section we will present the results achieved with our software that utilizes the proposed method for face detection. Apart from the advantage of simple implementation the method proved to be rather robust.

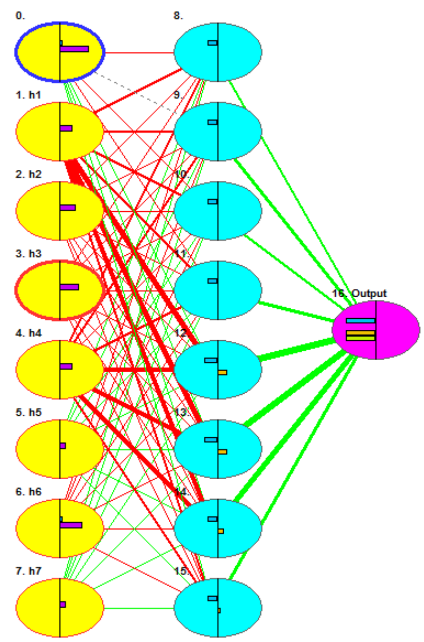

Fig.6. View of our neural network

We applied our algorithm on skin patches which present head and non-head and get values of seven Hu's moments. For example to illustrate these areas of skin, Figure 7 demonstrates image of skin patch which presents head while Figure 8 demonstrate images of skin patches which present non-head.

Fig.7. Image of skin patch which present head.

The first image of skin patches which present non-head shows the leg and the other one arm.

Fig.8. Images of skin patches which present non-head. The first one shows the leg and the other arm.

As we have mentioned before, our method identifies the head or non- head areas, regardless of size, position and point of view. To illustrate this on Figure 9 we showed some images from our database. These images of the non-heads showing hands in different positions.

The values of Hu's moments were our training data set. Based on them we built MLP. In our neural networks we have 32 training example rows and 19 validating example rows.

Our process of learning consists of 1000 cycles. Validating results shows 94.74% correctly identified skin patches with an acceptable number of false detections. So based on the training set we obtained acceptable recognition success percentages.

Table 1. Representation of traning data set with its traning example rows and validating example rows (bold). Hu moments presents inputs while output is 1 or 0 (head or non-head).

	h1	*h2*	*h3*	*h4*	*h5*	*h6*	*h7*	*Output*
Picture 1	*-0,6726*	*-2,00839*	*-3,12629*	*-4,55734*	*8,53241*	*5,60206*	*-8,56843*	*1*
Picture 2	*-0,625782*	*-1,71864*	*-3,34418*	*-4,19423*	*-8,04487*	*5,31498*	*8,21585*	*1*
Picture 3	***-0,429727***	***-1,08855***	***-3,11982***	***-3,08674***	***-6,19057***	***-3,70091***	***7,49117***	***1***
Picture 4	*-0,169418*	*-0,382268*	*-1,52675*	*-1,77146*	*-3,42645*	*-2,01926*	*-4,20681*	*0*
Picture 5	*0,0333326*	*0,0409489*	*-0,120569*	*-0,151143*	*-0,287012*	*-0,133725*	*2,41008*	*0*
Picture 6	*-0,23216*	*-0,514037*	*-1,32716*	*-1,44214*	*-2,82679*	*-1,69919*	*-5,54503*	*0*
Picture 7	***-0,218434***	***-0,478709***	***-1,7374***	***-1,84627***	***-3,63821***	***-2,08884***	***-5,3***	***0***
Picture 8	*-0,695751*	*-2,02854*	*-3,06812*	*-4,45854*	*-8,97904*	*-6,07672*	*8,22862*	*1*
Picture 9	***-0,666956***	***-1,84695***	***-3,01931***	***-4,10628***	***-8,38766***	***-5,51569***	***7,67716***	***1***
Picture 10	***-0,168865***	***-0,369104***	***-1,25723***	***-1,31588***	***-2,60243***	***-1,50045***	***5,55846***	***0***
Picture 11	***-0,131549***	***-0,29527***	***-1,95515***	***-2,10272***	***-4,13219***	***-2,26201***	***-5,43736***	***0***

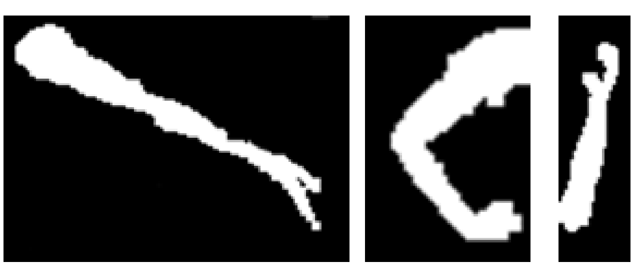

Fig.9. Images of arms that adequately demonstrate that our method is independent of size, position and point of view.

From observing and comparing values in the grid we assumed that the 1th and 4th Hu's moments are playing the key role in recognizing skin patches as a head. On Figure 10 it can be seen the input importance in our program. Because in our case these inputs are Hu's moments, we have the importance scale of all seven Hu's moments in detail.

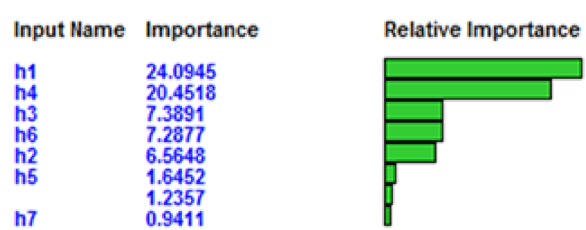

Fig.10. Input importance of NN. In our case importance of seven Hu's moments

As can be seen from the chart first Hu's moment is the most important moment in our classification of skin patches as head or non-head. The fourth Hu's moment is next while the seventh Hu's moment is the last in order of importance.

VIII. Conclusion

This paper presented a novel method for the recognition of human faces in color digital images. After initial detection of skin regions based on skin color in the YCbCr color space we used MLP as a classifier of values of invariant moments, Hu's moments. Invariant-based approach is a significant step towards robust and reliable object recognition methods. It has a deep practical impact because many pattern recognition problems would not be solvable otherwise.

Experimental results show that the proposed method can detect human faces in color digital image regardless of size, orientation and viewpoint. The accuracy of this method is quite good. We have a very large percentage (94.74%) of correctly identified skin patches as the head or non-head.

Further development will include Zernike moments for more versatile approach and improvement in detection rate

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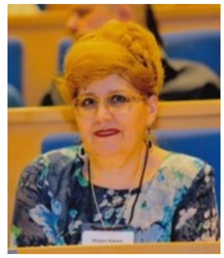

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