Self Organizing Maps for 3D Face Understanding

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Abstract. Landmarks are unique points that can be located on every face. Facial landmarks typically recognized by people are correlated with anthropomorphic points. Our purpose is to employ in 3D face recognition such landmarks that are easy to interpret. Face understanding is construed as identification of face characteristic points with automatic labeling of them. In this paper, we apply methods based on Self Organizing Maps to understand 3D faces.

Keywords: Understanding of images · 3D face recognition · Self Organizing Maps

1 Introduction

Three-dimensional facial recognition appears as to be a powerful approach for biometric person identification outperforming existing two-dimensional approaches. Among numerous approaches to image recognition [5,6,8,9,11,13–15,19] and to 3D face recognition [17,18,24], we have focused on solutions based on the characteristic points (*landmarks*). Automatic understanding of the face landmarks proposed in this paper should significantly speed up the recognition process.

In our previous works, we have presented several approaches to determine three-dimensional facial landmarks [22] and recognition results based on these methods [20,21]. In this work, we move toward understanding of faces, which relies on interpretability of three-dimensional characteristic points. The key idea is to employ a Self Organizing Map (SOM) which preserves a surface topology in the three-dimensional space. By preserving the network topology, we automatically maintain the relationship between face landmarks represented by the network nodes. Such approach provides an immediate and simultaneous identification of characteristic points on faces to be recognized.

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2 Three-Dimensional Facial Landmarks

In this section, we present a new three-dimensional face representation, which is based on our recognition methods. Initially, let the input set be organized in the form of a depth-map. Our task is to examine the possibility of extracting face landmarks (with no explicit relation to anthropometric points) on the basis of extremes. We assume that each row and each column is represented in function forms. Besides, each function can be classified as one of the four types of values:

local minimum of a function at a specified window size,
local maximum of a function at a specified window size,
global minimum of a function,
global maximum of a function.

Therefore, our method consists of two phases (Algorithm 1.1). The first phase extracts characteristic points from columns, and the second one performs the same operation from rows. In each step, only points of the selected range are analyzed.

```
for x = 1 → COLUMNS do
  for y = 1 → WINDOWS_SIZE do
    find_Local_Minimum
    find_Local_Maximum
    if is_Global_Minimum_in_Range then
      save_Global_Minimum
    end if
    if is_Global_Maximum_in_Range then
      save_Global_Maximum
    end if
  end for
end for
for x = 1 → ROWS do
  for y = 1 → WINDOW_SIZE do
    find_Local_Minimum
    find_Local_Maximum
    if is_Global_Minimum_in_Range then
      save_Global_Minimum
    end if
    if is_Global_Maximum_in_Range then
      save_Global_Maximum
    end if
  end for
end for
```

Algorithm 1.1. The first state of landmark extraction

In our algorithm, the height of each point is the smallest distance from the straight line matching the function at the window borders (Fig. 1).

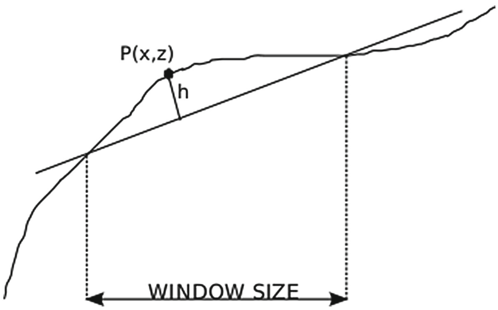

Fig. 1. Determination of the height of the point

Discussed characteristic points have been collected into the following groups:

all, all local and global landmarks from columns and rows,
col-l, local landmarks from columns,
col-g, global landmarks from columns,
glob, global landmarks from columns and rows,
row-l, local landmarks from rows,
row-g, global landmarks from rows.

3 Toward 3D Face Understanding Using SOM Analysis

In this section, we present a new research on 3D face understanding. This research gives the answer for the question whether a Self Organizing Map (SOM) carry information that can be interpreted somehow.

For this purpose, the characteristic points, defined in the previous section, were analyzed using a Kohonen SOM (see e.g. [10]). We made use of a standard rectangular two-dimensional grid of a fixed resolution that was stretched over clusters of points in the three-dimensional space. Figure 2(a) presents a face with marked characteristic points, obtained through the SOM analysis. Our task was to check whether, on the base of obtained points, it is possible to interpret the same part of the other faces.

Figure 2(b) presents a face with marked characteristics points obtained by the SOM. Intentionally we distinguished a group of face characteristic points located close to the nose.

We have compared all groups of points (*all, glob, row-l, ...*). The results we achieved in *glob* group. Figure 3 presents some of the results. In frames, there are marked points which are similar to the previously selected *nose-zone*. This experiment based on 10 3D scans taken from 10 different people. At each scan, we found a group of points that is similar to the selected (nose-zone).

Table 1 shows results of recognition of the nose area in all groups of points. A test set contains 8 faces taken from 6 people. Faces 1a and 1b belong to the same person, differing only in pose. The pattern recognition process is referred

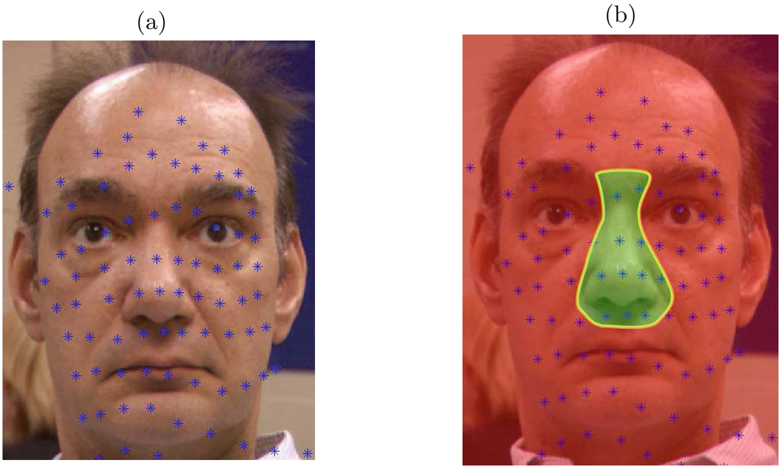

Fig. 2. Face with marked characteristic points: (a) obtained SOM, (b) region of points to be recognized in other faces (nose - middle zone)

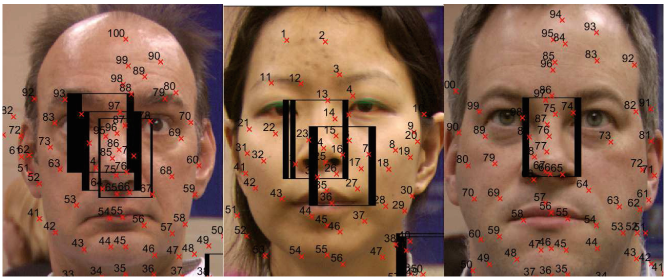

Fig. 3. Face with marked groups of points which are similar to *nose-zone*

Table 1. Search results of nose area in groups. First value determines — correct areas, second — all areas (correct+incorrect)

	Face no.						
Set	1a	1b	2	3	4	5	6
all	6/48	4/43	1/16	2/35	2/12	1/12	3/6
glob	3/4	3/5	2/3	3/5	4/7	2/3	1/1
row-l	9/41	11/36	2/5	1/6	2/5	1/13	4/6
row-g	0/12	0/9	1/5	1/48	1/12	0/28	0/14
col-l	11/43	8/37	1/4	6/15	2/6	3/9	2/6
col-g	6/12	5/8	1/3	2/6	3/8	1/6	1/6

to the face 1a. In our simulations, we make use of a set of biometric three-dimensional images *NDOff-2007* [7]. The advantage of this collection is that, for a single person, there are several variants of face orientation.

4 Understanding of 3D Faces Using Non-regular SOM

As a consequence of previous research, we apply SOMs with labeled nodes to understand face characteristic features. The topology of a proposed SOM have to be non-regular, as the localization of naturally labeled face features is indeed. The proposed here method consist of two stages: generation of an initial SOM, and application of the SOM to new faces without modification of neighborhood coefficients.

In the first stage, the initial SOM has been expanded on a generic 3D face model with prior identification of characteristic points by cluster analysis. Namely, we have made use of the Sobel gradient detector to find more significant changes in the Z-dimension of the face coordinates according to X- and Y-axes separately. Then the both gradients have been used to calculate a magnitude of the resultant vector, hence, we have unified both positive and negative gradients along the two dimensions. In detail, we have applied the following formula:

$$I = \sqrt{\left(conv\left(\mathbf{h}, \mathbf{I}\right)^2 + conv\left(\mathbf{h}', \mathbf{I}\right)^2\right.} \tag{1}$$

where the power has been calculated element-wise and the Sobel mask for the convolutions has been chosen as

$$\mathbf{h} = \begin{vmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{vmatrix}. \tag{2}$$

In order to make SOMs to be sensitive to magnitude of gradients, we have been choosing the training points randomly with the probability proportional to the gradient magnitudes. Such points have been clustered by the standard Fuzzy C-Means algorithm with number of clusters validated by apparent their utility as characteristic points (see e.g. [4]). During multiple runs of the algorithm, we have decided to limit the number of centers to 27 characteristic points. The averaged labeled points are illustrated in Fig. 4.

Then the real distances between the 3D characteristic points on the generic model surface have been used as lateral distances. For simplicity of calculations, we have omitted the distances of 3rd and higher level of neighborhood. Consequently, the Gaussian neighborhood grades could be stored in an array for calculations in the next stage. The resultant SOM, which is plotted in Fig. 5, has been set as the initial map for further identification of 3D face characteristic points.

In the second stage, we have trained the SOM on 6 subsequent 3D faces with an exponentially decreasing learning factor. The result can be observed in Fig. 6.

The trained SOMs in all cases positively localized noses and lips. Moreover, almost in all faces, eye corners have been labeled correctly. The localization of envelope characteristic features, as a *cranium*, *chin* or *zygoma*, depend strongly on the particular shape of the face. Apparently because of the observed thick neck in Fig. 6(d), the *chin* characteristic point has been moved downward. Although the results are very promising, there is still need of further work on training of the SOM. The model should be robust to each kind of uncertainties, especially that

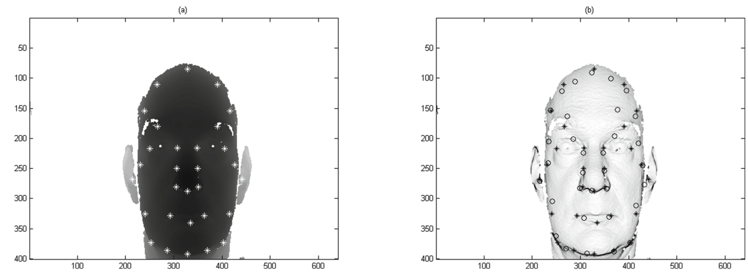

Fig. 4. Interpretable characteristic points (indicated by *stars*) obtained by FCM clustering: (a) shaded representation of the 3D generic model, (b) reference to single-run FCM clusters (indicated by *circles*) on the face model after the Sobel transformation.

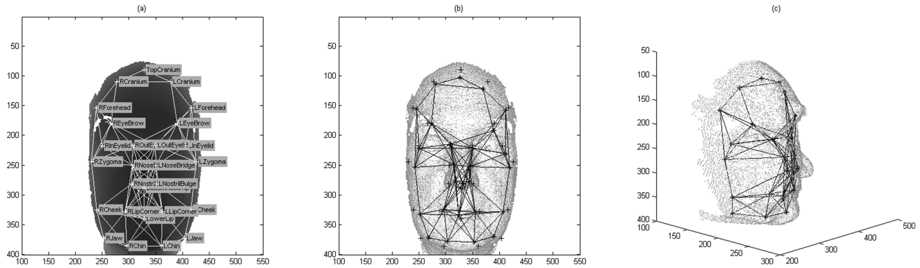

Fig. 5. Face features understanding: (a) initial SOM with labeled features, (b) and (c) expansion of the SOM on a 3D face to be understood (actual features indicated by *plus* sings).

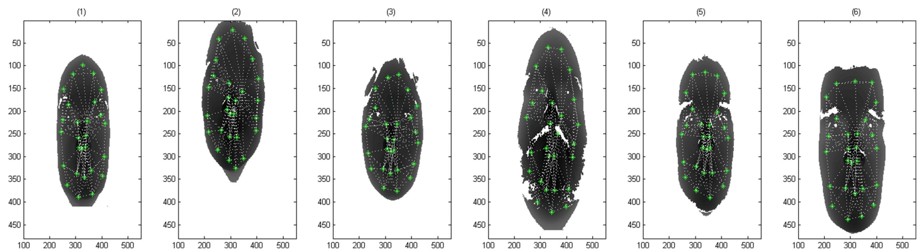

Fig. 6. Understanding of six 3D faces with the labeled version of SOM

localized in the envelope face features. We are positive to solve such problems by introducing uncertainty in the SOM model and processing it with the aid of fuzzy logic, the rough set theory and other kinds of neural networks [1–3, 12, 16, 23].

5 Conclusions

We have demonstrated that SOMs and a new method derived from them are able to interpret obtained nodes as face characteristic points toward understanding of human faces. It has been observed that variability in poses adversely affect the construction of maps. We suppose that the use of surface normals or the Laplacian in the face analysis will reduce this drawback.

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