Nose tip localization on 2.5D facial models using differential geometry based point signatures and SVM classifier

Przemyslaw Szeptycki, Mohsen Ardabilian, Liming Chen
Liris laboratory UMR CNRS 5205,
University of Lyon, Ecole Centrale de Lyon,
FRANCE
{przemyslaw.szeptycki, mohsen.ardabilian, liming.chen}@ec-lyon.fr

Abstract: Nose tip localization is often the basic step for 2.5D face registration and further 3D face processing and as such appears as a side problem of most research works on 2.5D or 3D face recognition. In this paper, we propose to carry out a comprehensive study of four popular rotation invariant differential geometric properties, namely Mean and Gaussian curvature, Shape Index and Curvedness, for the purpose of nose tip localization. For each 2.5D facial model, the set of nose tip candidates is first automatically selected from a shape classification thanks to a priori knowledge of a nose region. A SVM classifier trained on a subset of the data set using the previous four curvature descriptors alone or in combination is then invoked to select the true nose tip from the candidate set. We report extensive experimental results cross-validated in terms of True Acceptance Rate (TAR) and False Acceptance Rate (FAR) in comparison with manually labeled nose tip as the ground truth. A 99.9% Nose Tip TAR with 6.71% FAR is achieved on the FRGC v2.0 dataset when Mean curvature and Shape Index along with Curvedness are used as the input to the SVM.

1 Introduction

With the 3D scanning technology readily available, face processing and analysis in 3D has recently emerged as a major solution to deal with the unsolved issues in 2D, namely lighting and pose variations. While theoretically insensitive to head pose and lighting condition changes, 3D face scans still need to be correctly registered for further processing and analysis, for instance 3D face recognition or 3D facial expression analysis. For this purpose, most works in the literature rely on the availability of the nose tip location to gain insights on the face being analyzed. For instance, nose tip is used for the rotation approximation [FBF08, BKW+08]. Together with the two inner eye corners, nose tip forms the so called three main points which are used for detection of 3D face [NC09, SAC09], face pose estimation [SY08, NC09], 3D face registration [LJC06], face size calculation [NC09, SAC09], 3D face parameterization [SAC+10a, SAC+10b].

Nose tip is one of the most geometric prominent points on 3D face models. Its localization often appears in the literature as a side work for further 3D faces processing and analysis, in particular 3D face recognition, and generally makes use of a priori knowledge of nose shape through convexity/concavity analysis of facial surface [CCS06, SAC09, NC09,
However such an analysis generally leads to many candidate points from a 2.5D facial surface which need to be further sorted out. To identify the true nose tip from the set of candidate points, a mean face model fitting was used in [NC09, SAC09] to check all possible point configurations while using some heuristic. Face reconstruction error was also considered in [CCS06]. While highly effective, these approaches are computationally expensive and suffer from the exponential number of candidate point configurations.

Alternatively, feature points such as nose tip can also be localized using a data-driven approach, by creating some point signatures and thereby enabling fast statistical learning and classification [BKW+08]. Interesting point signatures so far reported in the literature include curvature related descriptors [CSP10], Effective Energy, Spin Images, etc. and record detection rates of 99.3% in [XTWQ06], 98.65% in [CCRA+05] or 99.6% in [Pea08]. Meanwhile, these works did not report the False Acceptance Rate (FAR).

In this paper, we also investigate a data-driven approach and study the relevance of using four rotation invariant curvature-based shape descriptors as a point signature for the task of nose tip localization.

For this purpose, we studied and compared four differential geometry based point properties, namely Mean and Gaussian curvatures, Shape Index and Curvedness in terms of descriptiveness for the nose tip localization. For each 2.5D facial model, the set of nose tip candidates is first automatically selected from a shape classification. A SVM classifier, trained on a subset of the data set, is then invoked to select the true nose tip point. We carried out extensive experiments with cross-validation and in varying the training dataset size. Using the aforementioned four curvature-based descriptors alone or in combination, we compared the achieved results by SVM with the ground truth landmarks. 99.89% Nose Tip TAR with 6.71% FAR was achieved on the FRGCv2 dataset when both Mean curvature and Shape Index were used along with Curvedness as the input to the SVM.

The remaining of this paper is as follows. Section II describes the procedure for locating the nose tip candidate points from a 2.5D face model. Then we introduce in section III the four curvature-based shape descriptors as point signatures for the purpose of the nose tip localization. Section IV discusses the experimental results and section V concludes the paper.

2 Detection of nose tip candidate points

The nose tip is one of the most marked out points in the curvature space, with the similar curvature characteristic for all faces. This property can be used to localize its candidate points. For this purpose, input 2.5D face models are first preprocessed in order to remove holes and large spikes. The main steps for locating nose tip candidate points are summarized in figure 3. We first locate convex regions thanks to the well known HK-Classification. Within each of the located convex regions, a nose tip candidate is searched as a point having the maximum Gaussian curvature. All these nose tip candidate points are then checked out using a SVM classifier.
2.1 Mean and Gaussian curvatures classification

Having a 3D facial surface, the localization of local patches can be carried out through a curvature analysis using a threshold [TV98, CCS06, SAC09, CBF06]. While intuitive and simple, thresholding can also lead to loss of the nose tip region, it can happen in case when people have a flat nose.

In this work, we do not make use of curvature thresholding. Instead, we look for all concave regions thanks to the HK-classification (figure 1) which permits to partition a range data into regions of homogeneous shapes, called homogeneous surface patches based on the signs of Mean (H) and Gaussian (K) curvatures [TV98].

Figure 1: Example of HK-classification, showing decomposition of different patches on the face. Colors show different shape patches based on the signs of Gaussian and Mean curvatures, where: blue - hyperbolic convex, orange - hyperbolic symmetric, yellow - hyperbolic concave, sky blue - cylindrical convex, white - planar, pink - cylindrical concave, green - elliptical convex, black - impossible, red - elliptical concave (figure based on figure 4.11 [TV98] and table 1 [CCS06], better seen in color)

As the approximation of the curvatures over a range data generally is sensitive to a noise [CCS06, SAC09, CBF06], we used the method developed in [SAC09] which incorporates the Gaussian noise rejection in the curvature calculation method. A larger neighborhood for the bi-quadratic surface approximation makes the method more insensitive to the Gaussian noise. Figure 2 depicts such a phenomenon.

A bigger neighborhood in the computation of the curvatures is also useful for the localization of the main facial points. Indeed, an increase of the neighborhood size around a point helps to highlight the most marked out shapes of the local region while ignoring the details. As we can see in figure 2, the most marked out regions remain visible while the less significant patches disappear when the neighborhood size is increased. The first increase in the neighborhood size removes shape details, including noise, the further increase in the neighborhood size enables us to distinct rough shapes of interesting facial regions, such as
Figure 2: The HK-classification and noise reduction on 3D face surface using different neighborhood in surface approximation (neighborhood size is enlarged from top left(5mm) to bottom right(40mm), step 5mm), presented in [SAC09].

the nose tip region or the inner corners of the eyes.

In this work, as illustrated in figure 3b, all the elliptical convex patches, thus with $H < 0$ and $K > 0$, are considered as the nose tip candidate regions. In each of these regions, the point having the maximum Gaussian curvature is then selected and considered as the nose tip candidate point (figure 3c) for which we compute a point signature which is further checked by the SVM classifier. Decomposition of the Gaussian curvature can be seen on figure 4 where the nose tip is clearly seen.

3 Point signatures

Once the set of the candidate points for the nose tip is collected, as described in the previous section, the SVM is invoked to further identify the true nose tip. For this purpose, we simply compute a point signature which gathers several state of the art curvature-based descriptors [CCS06, SAC09, CSP10], namely the Mean, Gaussian Curvatures, the Shape Index, Curvedness and study their discriminative power for the task of the nose tip localization when they are used alone or in combinations.

Curvatures for each nose tip candidate point are computed by a bi-quadratic surface equation approximation using a neighborhood of 25mm. The neighborhood size of 25mm, is a reasonable compromise in removing noises while keeping the rough shape of the local region (fig. 2) as well as achieves stable values of curvatures across different model’s resolution (fig. 5). The derivatives of the bi-quadratic surface equation are then used to calculate
Figure 3: The nose tip localization, a) the face range image, b) the nose tip regions (elliptical convex regions), c) the maximum Gaussian curvature points in each nose tip candidate region.

The Mean ($H$) and Gaussian curvatures ($K$) using the following equations:

\[
H(x, y) = \frac{(1 + f_y^2)f_{xx} - 2f_x f_y f_{xy} + (1 + f_x^2)f_{yy}}{2(1 + f_x^2 + f_y^2)^{\frac{3}{2}}}, \quad (1)
\]

\[
K(x, y) = \frac{f_{xx} f_{yy} - f_{xy}^2}{(1 + f_x^2 + f_y^2)^2}, \quad (2)
\]

where $f_x, f_y, f_{xx}, f_{yy}, f_{xy}$ are the first and second derivatives of the surface $f$ at $(x, y)$ [TV98].

The problem of finding the surface equation can be represented as:

\[
AW = Y, \quad (3)
\]

where matrix $A$ contains $x$ and $y$ values, $W$ is a matrix of estimated function coefficients and matrix $Y$ contains the results.
Shape index \( SI \) at point \( p \) can be calculated using maximum \( (k_1) \) and minimum \( (k_2) \) local curvatures:

\[
SI(p) = \frac{1}{2} - \frac{1}{\pi} \tan^{-1} \frac{k_1(p) + k_2(p)}{k_1(p) - k_2(p)},
\]  

(4)

where \( k_1(p) \) and \( k_2(p) \) are principal curvatures at a point \( p \) of a surface \( S \)[NC09]. Principal curvatures \( k_1(p) \) and \( k_2(p) \), can be extracted from equations:

\[
k_1(p) = H(p) + \sqrt{H(p)^2 - K(p)},
\]  

(5)

\[
k_2(p) = H(p) - \sqrt{H(p)^2 - K(p)},
\]  

(6)

where \( H \) and \( K \) are the Gaussian and the Mean curvature at point \( p \).

The curvedness of a surface at a vertex \( (v) \) can be calculated based on equation [NC09]:

\[
Curv(v) = \sqrt{\frac{k_1^2(v) + k_2^2(v)}{2}}.
\]  

(7)

Extracted from each nose tip candidate point, all these features are then used alone or in combinations to study their descriptiveness for the problem of the nose tip localization.
Figure 5: Example of nose tip curvature stability in case of different resolution of the model; starting from 35000 vertexes to 1000 vertexes. Vertical axis shows the curvature value calculated at the nose tip using 25 mm neighborhood for the surface approximation, horizontal axis corresponds to the different model’s resolution.

4 Experimental results

The experiments were carried out on the FRGC v2.0 dataset using a SVM classifier with a standard Gaussian kernel function. In this section, we first present the dataset and the training of the SVM classifier. Then we compare and discuss the performance of the nose tip localization when different combinations of the features are used for training and testing.

4.1 Testing Data Base

In our work we used FRGCv2 data base [PFS+05] which contains 4007 3D images, acquired between 2003 and 2004. The range data was acquired by a Minolta Vivid 900 range scanner, with a resolution 640x480. The data comes from 466 subjects and contains various facial expressions with various age distribution. The subjects are 57% male and 43% female. For the mentioned data base, 15 landmarks, including a nose tip and eye corners, were manually labeled by our team on the whole dataset. They are publicly available (figure 6) under request.

4.2 SVM Training

Support Vector Machine (SVM) was used to identify the true nose tip from the set of nose tip candidate points. For this purpose, we made use of the publicly available Matlab
LIBSVM\(^1\) library.

For training, the manually marked nose tips were used as the positive samples while negative samples were randomly selected with proportion 1:1. For each training sample, the four curvatures previously described, Mean and the Gaussian curvature, Shape Index and Curvedness, were first calculated. They were fed alone or in combination to the classifier, giving birth to 15 configurations regarding the point signature (see table 1). To verify the localization rate by the SVM, we also varied the learning dataset size, ranging from 100 to 3000 points (figure 4).

Each configuration of the system (different point signature + training set size) was cross-validated 10 times, each time with two folders and reported results are the mean values of all tests. For each cross validation the training set was selected randomly while the remaining models formed the test set.

### 4.3 Nose tip localization

Once learned, the SVM was used for identifying the true nose tip among all the nose tip candidates. If the SVM classifies a nose tip candidate point as a correct one, this point is further checked with the manually labeled one. If the distance between the predicted nose tip and the manually marked one is less than 10mm, the True Acceptance Rate is

\(^{1}\text{http://www.csie.ntu.edu.tw/~cjlin/libsvm/}\)
increased.

Almost all configurations of the point signatures achieved very high True Acceptance Rate (TAR), close to 100%. The highest TAR with the lowest False Acceptance Rate (FAR) was achieved using together the Mean curvature, the Shape Index and the Curvedness where the TAR was 99.9% and the FAR was 6.7%. The lowest localization rate was achieved by single Gaussian Curvature where the TAR was 30.7% and the FAR 3.3%.

Based on figure 7, one can observe that in case of increasing number of the training models the True Acceptance Rate as well as the False Rejection Rate are stable, respectively in a range of 99.9% and 0.1%. The change in the number (from 100 to 3000) of the training examples affects the True Rejection Rate and the False Acceptance Rate, respectively the TRR changed from 85.3% to 93.29% and the FAR changed from 14.7% to 6.71%.

4.4 Discussion

Looking at table 1 and figure 8, one can see that the True Acceptance Rate of the nose tip points is very high for almost all curvature based features, except the Gaussian Curvature which displays a 30.74% TAR for the nose tip. Meanwhile, this result is in line with the conclusion of the state of the art, for instance the one by Ceron et al. [CSP10] who stated that the Gaussian Curvature has the worst descriptiveness for discriminating facial feature

points.

When studying the False Acceptance Rates (FAR) by all these curvature features in table 1, one can see that the lowest FAR 6.7%, was achieved by the combination of the Shape Index, Curvedness and the Mean Curvature which also displays the highest 99.9% TAR. Very similar results were obtained by the configuration using both the Shape Index and Mean Curvature, displaying a 99.7% TAR and a 6.7% FAR respectively.

The False Acceptance Rate at the level of 6.7% means that the SVM classifier incorrectly classified non-nose tip points from the candidate set as the correct nose tips. Those mistakes generally happen when the point candidates have shapes similar to the nose, which occurs sometimes on cloths or hair regions. To exclude these incorrectly classified points one needs to consider further constraints or knowledge. The method guarantees very high True Acceptance Rate (99.9%), which gives reliability that the nose tip will not be missed.

5 Conclusion

In this paper, we study the relevance of four rotation invariant differential geometric properties, namely Mean, Gaussian curvatures, Shape Index and Curvedness, for the purpose of nose tip localization. For each 2.5D facial model, the set of nose tip candidate points was
<table>
<thead>
<tr>
<th>Point Signature combination</th>
<th>TAR [%]</th>
<th>FAR [%]</th>
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</thead>
<tbody>
<tr>
<td>C</td>
<td>99.39</td>
<td>16.72</td>
</tr>
<tr>
<td>SI</td>
<td>94.14</td>
<td>11.98</td>
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<td>SI+C</td>
<td>99.19</td>
<td>7.87</td>
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<tr>
<td>K</td>
<td>30.74</td>
<td>3.35</td>
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<td>K+C</td>
<td>98.58</td>
<td>16.45</td>
</tr>
<tr>
<td>K+SI</td>
<td>95.05</td>
<td>12.45</td>
</tr>
<tr>
<td>K+SI+C</td>
<td>99.19</td>
<td>8.52</td>
</tr>
<tr>
<td>H</td>
<td>99.90</td>
<td>12.49</td>
</tr>
<tr>
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<td>99.90</td>
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<td>H+SI</td>
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</tr>
<tr>
<td>H+SI+C</td>
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<td>6.71</td>
</tr>
<tr>
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<td>99.80</td>
<td>7.59</td>
</tr>
<tr>
<td>H+K+SI+C</td>
<td>99.90</td>
<td>7.15</td>
</tr>
</tbody>
</table>

Table 1: The obtained results (mean value of 10 cross-validations) for different point properties combinations with the fixed number of the training models (3000), (C - Curvedness, SI - Shape Index, H - Mean Curvature, K - Gaussian Curvature)

first automatically selected from a shape classification using a priori knowledge of nose shape. A SVM classifier, trained on a subset of the data set using the curvature features alone or with combinations, was then invoked to select the true nose tip from the set of candidate points. Extensive experiments were carried out on the whole FRGC v2.0 dataset in varying the training dataset size and for each training size 10 times cross-validation using random selection of the training set. The experimental results were evaluated in terms of the True Acceptance Rate (TAR) and the False Acceptance Rate (FAR) using manually labeled nose tip point as ground truth and expressed as a mean value of all cross-validation tests. 99.9% Nose Tip TAR with 6.7% FAR was achieved on the FRGCv2 dataset when the Mean curvature, the Shape Index along with the Curvedness were used as the input to the trained SVM classifier.

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References


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