REAL-TIME HEAD TRACKING AND 3D POSE ESTIMATION FROM RANGE DATA

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ABSTRACT

In this paper a head tracking algorithm using 3D data is described. The system relies on a novel 3D sensor that generates a dense range image of the scene. By not relying on brightness information, the proposed system guarantees robustness under various illumination conditions, and content of the scene. The main novelty of the proposed algorithms, with respect to other head tracking techniques, is the capability for accurate tracking of the 6 degrees of freedom of the head by explicitly utilising 3D head-shoulder geometry. A Bayesian tracking framework is also proposed for continuous 3D head pose estimation. The proposed system has been tested in a real-time application scenario.

1. INTRODUCTION

Capturing and understanding human motion has become one of the most active research areas in computer vision, due to the large number of potential applications. In particular, tracking the 3D location and orientation of the human face, addressed in this paper, is very important for applications such as multi-modal human-computer interaction, face recognition, analysis of facial expressions and videoconferencing.

There are several commercial products able for accurate and reliable 3D head position and orientation estimation. These are based either on encumbered magnetic sensors or rely on special markers placed on the face, causing discomfort and limiting natural motion. Also, commercial systems based on gaze tracking employ infrared illumination to guarantee reliable detection of eye location, but place restrictions on head position and orientation. Vision-based 3D head tracking provides an attractive alternative, but there are still several challenges to be addressed such as robustness under arbitrary illumination of the scene, coping with cluttered backgrounds and dealing with occlusions.

Detecting the face in the image is the first step in 3D face tracking but is usually disregarded in the literature assuming for example that the face is centered in the image at the beginning of the sequence or manual selection of landmarks. However, face detection can become the bottleneck in applications, especially under real-world conditions (inhomogeneous illumination, occlusions, cluttered background). Also, without a proper face detection technique it is very difficult to recover tracking when lock is lost.

Several face detection techniques have been proposed for grey-scale images [1]. These may be roughly categorized to those based on the detection of facial features possibly exploiting their relative geometric arrangement, and those based on the classification of the brightness pattern inside an image window (obtained by exhaustively sweeping the whole image) as face or non-face. Techniques lying in the second category were recently shown to be more successful in detecting faces in cluttered backgrounds [2], however the correct detection rates reported were below 90%.

Further shortcomings of existing face detection algorithms is their sensitivity to partial occlusion of the face (e.g. glasses, hair), hard illumination and head pose while being computationally demanding.

Color information, when available, is a powerful cue for locating the face [3]. When transformed to the appropriate color space (e.g. HSV), pixel values form tight clusters and thus efficient probabilistic modelling techniques may be applied [4]. However, the parameters of the color distribution were shown to rely on the environmental illumination and the response characteristics of the acquisition device. Furthermore, irrelevant skin-colored image regions will result in erroneous face candidates.

In this paper, a highly robust face detection procedure is proposed based on depth information. By exploiting depth information the human body may be easily separated from the background, while by using a-priori knowledge of its geometric structure efficient segmentation of the head from the body (neck and shoulders) is achieved.

3D face tracking, i.e. dynamic estimation of the 6 degrees of freedom of rigid head motion is subsequently examined. Recovering 3D face pose from a single video camera (up to a scaling factor) is a difficult problem that is usually addressed by exploiting a-priori face geometry models. Proposed tracking techniques may be roughly classified to those based on optical flow and those based on tracking of salient image features such as the eyes and mouth. In the first approach constraints are posed to the optical flow field by incorporating explicitly [5] or implicitly [6] head geom-
etry models. This approach, relies on the assumption of constant pixel brightness across frames, and therefore suffers from illumination variations, shadows, and occlusions. Moreover such techniques are computationally demanding. With the second approach the effect of illumination conditions is relaxed by exploiting facial features and a parametric 3D face model maybe reconstructed directly from them [7, 8]. This approach can not deal well with large rotations of the head since some of the features may be occluded or seriously distorted. To cope with the above difficulties several researchers have proposed using more than one camera. Stereo systems for 3D face pose estimation have been proposed (e.g. [9]) relying on facial feature tracking. By establishing correspondence of these features in the stereo frames, 3D coordinates of these features can be estimated. Although, a two camera approach limits the ambiguity in 3D face pose recovery, tracking is still based on the brightness function and is therefore sensitive to illumination conditions and background clutter.

In this paper a novel 3D sensor capable of real-time dense depth image acquisition is employed. We are not aware of any other technique using 3D images for head tracking. The proposed approach does not rely on brightness information, and thus guarantees robust and accurate 3D head tracking without any constraints on the environment. An appearance based 3D pose detection technique coupled with a Bayesian tracking framework is proposed. Apart from demonstrating very satisfactory results the system achieves real-time performance on conventional hardware.

2. 3D DATA ACQUISITION

A 3D & colour camera acquiring 3D as well as color images is used. This is based on an active triangulation principle, making use of an improved and extended version of the well-known Coded Light Approach (CLA) for 3D data acquisition. The CLA is extended to a Color Coded Light Approach (CCLA). The basic principle lying behind this device is the projection of color-encoded light pattern on the scene and measuring its deformation on the object surfaces. The 3D camera achieves real-time image acquisition of range images and fast image acquisition of both colour and depth images (12 image pairs per second). It is based on low cost devices, an off-the-shelf CCTV-color camera and a standard slide projector [10]. The average depth accuracy achieved, for object located about one meter from the camera, is less than 1mm. For real-time head tracking applications a fast frame rate is required. Therefore, the range-only acquisition mode is preferred. In this mode, the annoying flickering of the projected light pattern is also avoided, since the slide projector is continually flashing. The acquired range images contain artifacts and missing points mainly over areas that cannot be reached by the projected light. Instead of filtering or interpolating 3D data, a process that may lead to further artifacts, we prefer making subsequent processing stages robust to the above artifacts.

3. FACE DETECTION

Separation of the body from the background is efficiently achieved by computing the histogram of depth values and estimating the threshold separating the two distinct modes. Segmentation of the head from the body relies on statistical modelling of the head - torso points in 3D space. The probability distribution of a 3D point \( x \) is modelled as a mixture of two Gaussians:

\[
P(x) = P(\text{head})P(x|\text{head}) + P(\text{torso})P(x|\text{torso})
\]

where \( \pi_1, \pi_2 \) are prior probabilities of the head and torso respectively, and

\[
N(x; \mu, \Sigma) = \frac{1}{(2\pi)^{3/2}|\Sigma|^{1/2}} \exp \left[ -\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu) \right].
\]

Maximum-likelihood estimation of the unknown parameters \( \pi, \mu, \Sigma \), \( k = 1, 2 \) from the 3D data is obtained by means of the Expectation-Maximisation algorithm:

\[
p_{kn} = \frac{\pi_k N(x_n; \mu_k, \Sigma_k)}{\sum_i N(x_n; \mu_i, \Sigma_i)},
\]

\[
\mu_k = \frac{\sum_n x_n p_{kn}}{\sum_n p_{kn}}
\]

\[
\Sigma_k = \frac{\sum_n (x_n - \mu_k)(x_n - \mu_k)^T p_{kn}}{\sum_n p_{kn}}
\]

\[
\pi_k = \frac{\sum_n p_{kn}}{\sum_n \sum_k p_{kn}}
\]

where \( p_{kn} \) are the posterior probabilities of the state \( k \) given the data and the model parameters. The convergence of the above iterative procedure relies on good initial parameter values. During 3D head tracking initialization of the model parameters is obtained by a prediction from the previous instance provided by the tracking algorithm in section 4. In the beginning of the sequence or when the tracker requires re-initialisation initial 3D blob parameters may be obtained by exploiting prior knowledge of the body geometry.

Let \( \mathbf{m} \) be the center of mass and \( u_i, \ i = 1, \ldots, 3 \) be the eigen-vectors of the scatter matrix \( \mathbf{S} = \sum_i (x_i - \mathbf{m})(x_i - \mathbf{m})^T \), computed from the data points \( x_i \), ordered according to the magnitude of the corresponding eigenvalues. Initial estimates of the unknown parameters were selected by:

\[
\mu_1 = \mathbf{m} + \rho_1 s_{\min} \mathbf{u}_1, \quad \mu_2 = \mathbf{m} + \rho_2 s_{\max} \mathbf{u}_1
\]
Fig. 1. Illustration of knowledge-based initialization of 3D blob distribution parameters. Ellipses represent iso-probability contours of posterior distributions. The axes length of the ellipses are selected relative to the iso-probability contours of posterior distributions. The axes 3D blob distribution parameters. Ellipses represent iso-

\[
\Sigma_k = \mathbf{U} \Lambda_k \mathbf{U}^T, \quad \Lambda_k = \text{diag}(\rho_k^2 \lambda_1, \sigma_k^2 \lambda_2, \lambda_3),
\]

\[
\pi_k = \rho_k
\]

where \( \mathbf{U} \) is the orthogonal eigen-vector matrix of \( \mathbf{S}_T \) and \( \lambda_i, i = 1, \ldots, 3 \) the corresponding eigenvalues, while \( \rho_1, \rho_2, \sigma_1, \sigma_2 \) are constants related to the relative size of the head with respect to the torso (in the experiments \( \rho_1 = 1/2 \), and \( \rho_2 = 1/3, \sigma_1 = 1/2 \) and \( \sigma_2 = 1 \) were used). This is illustrated in figure 1.

Classification of a 3D point \( \mathbf{x}_i \) to the class \( k \) is performed by the maximum likelihood criterion i.e. by selecting the class that maximizes \( p_{kn} \). Experimental results demonstrate robustness of the algorithm under various orientations of the head, leading to correct classification of face pixels in almost 100% of the images.

4. 3D POSE ESTIMATION

We have investigated several techniques for the estimation of the 3D pose of the face from 3D data. A feature-based approach has been examined, based on facial feature detection (eye cavities and nose ridge) by analyzing the 3D surface curvature function. Although accurate results may be obtained with this approach it is prone to noise and missing image pixels while being computationally expensive. Also, fitting a 3D ellipsoid to the cloud of 3D face points has been examined [11]. Since less than half of the facial surface is visible the pose estimate is biased especially for large head rotations. The best results were obtained by means of an appearance-based approach described below.

A set of example depth images covering the 3D pose space has been captured. A magnetic sensor was used to acquire the actual orientation and 3D location of the head corresponding to each of the images. Using the sensor measurements it was possible to define a bounding box around the face and thus automatically generate cropped and aligned face pose images \( \{X_i, i = 1, \ldots, N\} \). For every example image a small set of synthetic images is also generated by translation of the original 3D points in three dimensions. In this way, small misalignments may be accommodated and compensated. Then, the 3D space of pose variations was sufficiently quantized (0.5 degree resolution has been used in the experiments) and example images were assigned a corresponding 3D pose quantized parameter triplet \( r_i = \{\theta_i, \phi_i, \omega_i\} \) according to the recorded pose parameters. The pose eigen-space is subsequently computed by applying PCA to the set of \( N \) images. Projection of each frame to the most important eigen-vectors yields a low dimensional face pattern representation \( \hat{X}_i \).

The segmentation algorithm described in section 3 provides as with an approximate estimate of the position of the head in the image. This estimate is subsequently used to obtain the approximate position of the nose by exploiting a-priori knowledge of the face geometry. Then, a local search in the neighborhood of this point is applied on the depth image to locate the tip of the nose that is the point closer to the camera. The 3D coordinates of this point accurately define the 3D location \( \mathbf{p} \) of the face. This is subsequently used to crop the part of the image containing the face and appropriately normalize the depth values thus generating a test image \( \hat{X} \).

By projecting the test image in the pose eigen-space a lower-dimensional representation of the test image \( \hat{X} \) is obtained. The likelihood function of the image as a function of the 3D pose parameters may be approximated by [12]:

\[
P(X | \mathbf{r}) = Z \exp\left( -\frac{1}{2} \sum_{l=1}^{3} (X - \hat{X}_l)_{l}^2 \right)
\]

where \( \hat{r} \) is the index of the face pose bin obtained by quantizing \( \mathbf{r} \) and \( \| \cdot \|_\Lambda \) is the euclidian distance normalized by the eigen-values corresponding to the principal components.

In order to exploit the fact that the pose parameter vector \( \mathbf{r} \) changes slowly, a state transition model is introduced:

\[
r_t = r_{t-1} + n_t, \quad t > 1
\]

where \( P(n_t) \) or equivalently \( P(\mathbf{r}_t | \mathbf{r}_{t-1}) \) is assumed time-
invariant Gaussian with manually obtained covariance matrix.

The set of unknown parameters $r_t$ that maximizes the posterior probability $P(r_t|X_t, X_{t-1}, \ldots, X_1)$ is obtained from the above models using the CONDENSATION algorithm [13]. The tracker is re-initialized when the estimated posterior probability falls below a predefined threshold.

5. EXPERIMENTS

<table>
<thead>
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<th>Rx</th>
<th>Ry</th>
<th>Rz</th>
<th>Tx (mm)</th>
<th>Ty</th>
<th>Tz</th>
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<tr>
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<td>2.17</td>
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<td>0.43</td>
<td>0.78</td>
<td>0.13</td>
<td>0.21</td>
<td>0.19</td>
</tr>
</tbody>
</table>

Table 1. Mean value and standard deviation for 3D pose estimation errors.

The current implementation of the proposed 3D face tracking system runs on a PC platform (Pentium 1GHz) in real-time (15-20 frames/sec). In order to evaluate the performance of the system several sequences depicting natural head movement have been captured. Ground-truth measurements of head pose angles and 3D location have been also recorded using a magnetic tracker. The face pose angles and translation parameters estimated and tracked over time by the tracker are compared to the measurements obtained by the sensor. Due to lack of space we present in table 1 only the mean value and the standard deviation of the errors for each of the estimated parameters.

6. CONCLUSIONS

We have presented a robust method for real-time 3D face tracking using a real-time 3D sensor. The use of 3D information allows robust and accurate 3D head pose estimation under real-world illumination conditions and in the presence of occlusions and background clutter. Future research shall focus in interactively building a 3D face model by integrating a sequence of views.

7. ACKNOWLEDGEMENT

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8. REFERENCES


