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Improving Face Detection with TOF Cameras

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Abstract—A face detection method based on a boosted classifier using images from a time-of-flight sensor is presented. We show that the performance of face detection can be improved when using both depth and gray scale images and that the common use of integration of hypotheses for verification can be relaxed. Based on the detected face we employ an active contour method on depth images for full head segmentation.

I. INTRODUCTION

For object detection and recognition to be useful in real-world applications such as robotics, surveillance, or video indexing, recognizers must have the ability to localize objects of interest in images under viewpoint changes (e.g. changes in object size or position) and must be robust to complex background clutter and preferably fast. The physical size of the objects is often restricted, but appears on multiple scales due to the relative position of camera and the object. Face detection is a particular example of such an object class. Although it has been studied for more than 30 years, developing a fast and robust face detection system that can handle the variations found in different faces, such as facial expressions, pose changes, illumination changes, complex backgrounds, and low resolutions, is still a challenging research topic. The size of the face does not vary much between subjects, but depending on the distance from the camera the apparent face size changes. This is complicated further by features emerging and disappearing with distance. Knowing the distance to the object may thus provide an important cue for face size normalization.

In this paper, we explore the use of cascade classifiers for face detection using both gray level and depth information obtained from a time-of-flight (TOF) camera. We introduce an additional stage to the classifier which uses depth information for size verification. We further employ an active contour model initialized by the face detection for segmenting the human head.

A. Previous Work

Advances in machine learning research have greatly influenced the developments in robust face detection. Neural networks [13], support vector machine (SVM) [11], and boosting [15], [14], [7] are typical current choices of learning-based methods.

Current research is focused on feature extraction and appropriate structures for combining classifiers. Many types of features that have been used, ranging from simple ones such as intensity values [13], [11] and eigenspace [9] to complex ones such as wavelets [14] have been used. Face detectors based on single classifiers such as SVM [11], [12] and neural network [13] are usually slow because they process non-face and face regions equally in the input image. To deal with the problem of processing a large number of patterns, a combination of simple-to-complex classifiers has been proposed [12], [14], [5]. Viola and Jones introduce a fast object detection based on a boosted cascade of Haar-like features [14] and catalyzed a range of related papers. Lienhart extended the haar-like features to an efficient set of 45 rotated features and used discrete AdaBoost, real AdaBoost and gentle AdaBoost for face detection. More complete reviews of face detection methods can be found elsewhere [18], [16].

Several researchers have used depth cues for face tracking. Yang and Zhang [17] have applied head tracking using stereo vision. The method depends on the brightness information due to the nature of stereo imaging and, thus, it is sensitive to cluttered backgrounds or illumination conditions. Malassiotis and Strintzis [8] proposed a head tracking algorithm based on range images obtained using color coded structured light. Their work models the images using a Gaussian mixture of head and torso. A limitation of structured light is that it may be disturbing. Gokturk and Tomasi [4] propose a 3D head tracking method using correlation on large feature vectors of point-wise means and variances obtained from a time-of-flight sensor. Initial investigations of the use of time-of-flight sensors for people tracking is proposed by Bevilacqua et al. [1].

B. Time of flight technology

Time of flight sensors are a relatively new and novel development in imaging devices providing real-time gray scale and depth information from a single sensor. In this paper we use the SwissRanger (SR3000) from Mesa (www.swissranger.ch). The SwissRanger (see Fig. 1) emits sinusoidal modulated IR light with frequency $f_m$. Through the reflected wavefront the camera can obtain distance measurements for each pixel position by measuring the light travelling time between emission and reception. In fact, if $s(t) = \sin(2\pi f_m t)$ is the
emitted light, the reflected and received light measured by
the sensor with a phase shift \( \phi \) is:

\[
\tau(t) = \sin(2\pi f_{\text{sc}} t - \phi) = A \sin(2\pi f_{\text{sc}} (t - \frac{c}{2d}))
\]

where \( A \) is the amplitude of the reflected light, \( d \) the distance between the target and the sensor and \( c \) is
the constant of the speed of light \((3 \times 10^8 \text{ m/s})\). The distance
can thus be calculated by \( d = \frac{ct}{2f_{\text{sc}}} \) for each measuring point
in the image (pixel). The brightness of a pixel is measured
through the amplitude \( A \).

Compared to standard stereo vision, time-of-flight sensors
offer several advantages as only a single sensor is required.
No calibration between the cameras or additional image
processing is needed for obtaining the depth measurement.
Time of flight sensors do not require textured objects. Compared
to structured light methods the time-of-flight cameras emit
much less light, thus neither the image nor a person facing
the camera are disturbed. The major limitations of current
time-of-flight sensors are the reduced resolution \((176 \times 144 \text{ for the}
SwissRanger) and that depth measurements may be influenced
by the reflection angle, object material and color.

Fig. 1. Modulated light is emitted from IR LEDS on the sensor. Light is
reflected on the object and captured by the sensor. The time between emission
and reception and the measured amplitude is used to generate depth and
intensity images.

II. METHOD OVERVIEW

In this paper we propose a face detection and head segmen-
tation method based on depth and gray scale images obtained
from a time-of-flight camera. Initially a set of hypothetical
face regions are extracted through a boosted classifier similar
to the one proposed by Viola and Jones [14], [7]. To reduce the
number of false positives and to generally improve robustness,
face detectors may group (integration of multiple detections)
regions if they are located close. If sufficiently many hyp-
otheses supporting a region are found the region is assumed
to be correct. This approach may reject valid regions if the
support is insufficient. We propose to use depth information
to resolve the ambiguities without defining a support. However,
if several hypothesized regions are sufficiently close, they
are combined into one. Based on a detected face region, the
head is segmented through an active contour model [3]. Since
the depth variations within the face region are limited, we
employ an active contour model that uses the depth variations
in the interior and exterior of the contour to perform the
segmentation.

Section III describes the extended boosted face classifier and
section IV the active contour model. In section V the results
of the classification and head segmentation are presented. The
paper is concluded in section VI.

III. CASCADED CLASSIFIER

Informative and discriminative features usually increase
the detection rate and may reduce the complexity of the
training methods. In a face detector that is scale and location
normalized, the number of analyzed patterns is usually large
(approximately 160,000 patterns for a 320 x 240 pixel image)
because the face classifier needs to scan over the input image
at every location and every scale. However, the vast majority
of the analyzed patterns are non-faces. The number of regions
containing faces is usually low and it thus becomes obvious
that it is important to reject the majority of regions as fast as
possible, while avoiding carelessly rejecting face regions.

As popularized by Viola and Jones [14], the rarity of positive
examples in object detection tasks can be exploited for
computational efficiency via the cascade architecture (Fig. 2).
Each stage of the cascade either rejects an input region
immediately as a non-object, or passes it on to the next stage
for further analysis. Inputs which pass through all classifier
stages are accepted as object instances. The cascade is efficient
because most instances are non-objects and can be rejected by
the first few stages with a minimal amount of computation. In
this approach, the running time of the detector is no longer
simply a function of the size of the image but also reflects
the image’s complexity. Blanchard and Geman [2] present a
general theoretical analysis of such classifier systems.

AdaBoost is used to select discriminative and significant
features from a large number of features and construct the
classifier. Haar-wavelet-like classifiers are used at each stage.
Each simple classifier is efficiently calculated through integral
images. In this paper we add a final step to the cascaded
classifier where the information from the depth image and
a prior model of the face sizes are used to remove invalid
hypothetical regions. The prior model uses anthropomorphic
averages of head sizes of a training set and compares them
with the average depth within the region. The training set
consists of 10 annotated images of faces captured with the
SR3000.

Using similar triangles the apparent area of a fronto-parallel
planar surface is \( A = \frac{Z f}{Z^2} \), where \( f \) is the focal length, \( A \) is the
true area and \( Z \) is the distance from the camera to the surface
(Fig. 3). The depth variations within a face are relatively small
compared to the head size and, at some given scale, the face
is approximately planar.

Therefore, measuring the average depth, \( \bar{Z} \), within a hy-
pothesized region and multiplying this with the apparent size

Fig. 2. A cascade of simple classifiers. Each stage either rejects a region or
passes it on to the subsequent stage for further verification.
provides a measure which is proportional to the true size of the
face. The focal length of the SR3000 is fixed and can thus
be disregarded for classification.

The last stage of the classifier therefore classifies a face
region \( \Omega \) as face when

\[
|a \cdot \bar{Z}|_M \leq \tau
\]

where, \(|\cdot|_M\) is the Mahalanobis distance to the training set (i.e.
using the mean and variance), \( \bar{Z} \) is the average depth within
\( \Omega \).

IV. ACTIVE CONTOUR

Active contours are used for automatic object segmentation.
The basic idea is the evolution of a curve, or curves subject to
constraints from the input data. The curve should evolve until
its boundary segments the object of interest. This framework has
been used successfully by Kass et al. [6] to extract boundaries and
groups. One potential problem with this approach is that the
topology of the region to be segmented must be known in advance.
An algorithm to overcome these difficulties was first introduced
by Osher and Sethian [10].

They model the propagating curve as a specific level set of
a higher dimensional surface. It is common practice to model
this surface as a function of time. So as time progresses, the
surface can change to take on the desired shape.

Several methods, such as snakes, use edge information to
determine when to stop the evolution. For depth images of
faces the contour boundaries give some indication of the
boundary of the head, but there may be other depth discontinu-
ities in the background as well as parts of the boundary in
which the discontinuities are weak. Since the depth variations
within the region are relatively limited, we examine an edge-
free contour model. Rather than basing the model on an edge-
storage function, the curve evolution is determined through
an energy minimization approach [3].

Let \( \Omega \) be a bounded open subset of \( \mathbb{R}^2 \), with \( \partial \Omega \) as
its boundary. The image \( u_0 \) is defined by \( u_0 : \Omega \to \mathbb{R} \). Consider
the evolving curve \( C \) in \( \Omega \), as the boundary of an open subset
\( \omega \subseteq \Omega \) with \( C \equiv \partial \omega \). The main idea is to embed the
propagating curve as the zero level set of a higher dimensional
function \( \phi \) defined by: \( \phi(x, y, t = 0) = \pm d \) where \( d \) is the
distance from \((x, y)\) to \( \partial \omega \) at \( t = 0 \), and the sign is chosen
to indicate inner and outer regions. Evolving the curve in
the direction of its normal amounts to solving the partial
differential equation [10]:

\[
\frac{\partial \phi}{\partial t} = F|\nabla \phi|, \phi(x, y, 0) = \phi_0(x, y)
\]

where the set \( \{ (x, y), \phi_0(x, y) = 0 \} \) defines the initial contour,
and \( F \) is the propagation speed. For certain forms of the
speed function \( F \), this reduces to a standard Hamilton-Jacobi
equation. In this case the normal vector, \( n \), for any point on
the curve \( C \) is given by:

\[
n = \nabla \phi
\]

and the curvature \( K \) is obtained from the divergence of the
gradient of the unit normal vector to the front:

\[
K = \text{div}(\frac{\nabla \phi}{|\nabla \phi|}) = \frac{\phi_x x \phi_y^2 - 2 \phi_x \phi_y \phi_x y + \phi_y y + \phi_y^2}{(\phi_x^2 + \phi_y^2)^{3/2}}
\]

Introducing the minimizing energy function

\[
E(C, c_1, c_2) = \lambda_1 \int_{\Omega} \delta(\phi(x, y))|\nabla \phi(x, y)|dxdy
+ \lambda_2 \int_{\Omega} H(\phi(x, y))dxdy
+ \lambda_3 \int_{\Omega} |u_0(x, y) - c_1|H(\phi(x, y))dxdy
+ \lambda_4 \int_{\Omega} |u_0(x, y) - c_2|(1 - H(\phi(x, y)))dxdy
\]

where \( H \) is the Heaviside function, \( \delta \) the Dirac delta
function, \( c_i \) mean values in the interior and exterior of the
curve, \( \lambda_i \) weighing parameters. The first two terms control
the curve length and area, respectively. The latter two terms
measures the deviation of intensities in the interior and exterior
regions. The Euler-Lagrange partial differential equation of
\( \phi(x, y, t) \) is given by [3]:

\[
\frac{\partial \phi}{\partial t} = \delta(\phi)[\lambda_1 \text{div}(\frac{\nabla \phi}{|\nabla \phi|})
- \lambda_2 - \lambda_3(u_0 - c_1)^2 + \lambda_4(u_0 - c_2)^2] = 0
\]

The solution to this can be found using the Jacobi method
for solving partial differential equations [3]. However, using the
curvature \( K \) leads to a simple system that can be solved
without using the Jacobi method:

\[
\frac{\phi^n_{i,j} - \phi^0_{i,j}}{\Delta t} = \delta(\phi^n_{i,j})[\lambda_1 K
- \lambda_3(u_0 - c_1(\phi^n)^2)
- \lambda_4(u_0 - c_2(\phi^n)^2)]
\]

V. EXPERIMENTS AND RESULTS

In this section we describe the setup and show the results of
the methods. The first part of the test evaluates the perfor-
mance of the face detection the latter part shows the results
of using the active contour for head segmentation.

A set of 5 sequences have been tested totalling 1089 gray
scale and depth image pairs. At most one face in the range of
30 - 80 cm from the camera is present in each frame. Each
face is assumed to be near frontal.
Only the last stage differs in the two methods and thus the classifier using depth (extended classifier) is able to reduce the number of false positives, but cannot perform better on the classification rate than the standard classifier. In fact both methods have a detection rate of 88.3%, but where the extended classifier only has 6 false positive, the standard algorithm has 62. This classification rate is slightly lower than the one reported by Viola and Jones [14]. One reason for this is that the image data is not the same. In fact, when setting the properties of the SwissRanger to automatically adapting the emitted light, the face may become overexposed when rapidly moving towards the camera. It takes about a second for the light to be adapted correctly. When over exposed, the features of the face vanish and consequently insufficient information is available for detection.

![Image of detection results under apparent scale and head pose changes.](image)

Fig. 4. Detection results under apparent scale and head pose changes. The blue rectangles show the result of the boosted classifier which are accepted by the extended classifier using depth information and the red rectangles indicate hypothetical regions suggested by the standard boosted classifier, which are rejected in the depth validation stage of the extended classifier.

Fig. 5 show the results when using the depth for face segmentation using the parameters $\lambda_{1}, \lambda_{2}, \lambda_{3}, \lambda_{4} = [0.5, 0.1, 1, 0.1]$. For these parameters, the depth changes are noticeable within the different areas of the image.

![Image of results from the head segmentation.](image)

Fig. 5. The results from the head segmentation. The depth image is shown to the right of each gray scale image. The detected face is shown in green and the head segmentation is shown by the blue curve.

VI. DISCUSSION

The time-of-flight sensor is a relatively new development in sensors for computer vision. The sensor provides both depth and intensity images in real-time without the need for tedious stereo calibration and image analysis for dense depth estimation. Even though the images are obtained in low resolution, being able to obtain both gray scale and depth images in real-time is particularly useful for many vision applications. Clearly, the combination of intensity and depth images is useful. We have presented a face detection method based on boosting and Haar features using both gray scale and depth images. Face detection on gray scale images can be done efficiently with relatively high accuracy. We show that depth information provides a reliable additional cue to face detection. When obtained from a time-of-flight sensor this added robustness is given with only negligible extra computation. We additionally suggest to use an active contour method for head segmentation using the depth image.

REFERENCES


