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應用基於消失點之影像校正於強健式人臉偵測

Vanishing Point-Based Image Rectification for Robust Face Detection

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我們提出一種新的基於消失點影像校正方法以提高一般監控式系統性能,雖然大多 數現有的人臉資料庫和偵測技術都是基於相機和人臉在同個高度上的假設,但在實際狀 況下,相機很有可能會被安裝在不同的高度上,因此這種差異通常會降低基於正面人臉 影像學習演算法的效能。在這篇論文當中,我們提出影像轉換來校正人臉影像,因此在 訓練過程中可以不必蒐集不同的人臉方向。此外為了達到更佳的偵測效果,我們還提出 基於膚色分析來降低錯誤偵測的方法。在實驗結果中表明我們所提出的方法在人臉偵測 中可以得到顯著的改善。

Vanishing Point-Based Image Rectification for Robust Face Detection

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Abstract

We proposed a novel face detection method based on the vanishing point of vertical lines image rectification to improve system performance in a common surveillance application. While most existing face datasets and detection techniques are based on the assumption that the camera has a similar height as the target faces, in practical situations the camera may be installed at different heights. Such discrepancy often degrades the detection performance of algorithms based on learning with frontal face orientation. In this thesis we propose a transformation to rectify face images such that it is not necessary to collect training data of different face orientations. Furthermore, a method for reducing false alarms by skin analysis is proposed for better performance. The experiments show prominent improvements in face detection performance can be obtained with the proposed methods.

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Chapter 1 Introduction

1.1 Motivation

In recent years, computer vision techniques are widely used in the world, such as surveillance systems [1], access control systems [2] and computer login systems [3]. Most face detection approaches are based on supervised machine learning and highly depend on the training data used in the learning stage. To achieve good performance in the detection, training data under various environmental factors are often needed. However, since it is hard to always collect sufficient training data for so many factors, many researchers try to lessen the effects of these factors. While some researchers focus on developing more robust features or representations [4], others try to recover the underlying properties of the entire image [5] or the target of interest [6].

In this thesis, alleviation of the effect of perspective distortion introduced by a security camera mounted at a higher position, which is usually encountered in common surveillance applications, is considered for face detection. Although most face datasets do include variations such as different lightings, occlusions, and poses, we focus on such an application since most researches on face detection are devoted to the special case that all faces are assumed to have about the same height as the camera. Specifically, we aim to improve face detection performance under this practical condition wherein the camera is installed at a position higher than the human head to avoid any tampering. For example, the camera may be installed above an entrance through which people are entering from different directions with the ordinary forward-looking face orientation, as shown in Figure 1.1. With such setting, the inconstancy between the captured faces and those faces in a training set is illustrated in Figure 1.2. In Figure 1.2 a board with square patterns is also used to more clearly demonstrate this

inconstancy. Moreover, the camera is assumed to be mounted casually, only adjusted for proper viewing angle for surveillance purpose, while its exact location and orientation are actually unmeasured. The only required information for the proposed face detection approach is the vanishing point of vertical lines (VPVL), which can be obtained easily. Under such conditions, we propose three image transformations based on VPVL to partially correct the perspective distortion to improve the performance of face detection for common surveillance camera configuration.

Figure 1.1: Example of a person walking toward a camera with ordinary forward-looking face in different direction. (a) A person walks toward the camera in a straight path. (b) A person walks toward the camera in a different path in (a).

Figure 1.2: (a) Original frontal face. (b) A billboard with patterns representing (a). (c) Image captured by surveillance camera at a higher-up location. (d) A billboard with patterns representing (c).

1.2 Related Work

Image rectification and face detection have both been studied for a long period of time and numerous techniques have been developed. In the following two subsections we briefly introduce some most related work.

1.2.1 Image Rectification

Image rectification is a widely investigated topic. Much of the prior work use different calibration methods to estimate camera parameters and the geometric relation between the 2D image and the 3D scene. In fact, research on this problem is rather mature if sufficient auxiliary tools and manually given marks are used. Often, special objects with specific shapes or patterns are needed for developing the transformation for image rectification. From a different point of view, other methods exploit the structure presented in the image to ease the calibration process. The most straightforward approaches for image rectification are to detect multiple vanishing points (two for each planar patch) [7-12], by edge detection and voting, texture analysis, etc. One major assumption of these approaches is that the content in the image is sufficient enough so that the aforementioned vanishing points can be estimated correctly. For example, Figure 1.3 shows three vertical chessboards with different orientations that four vanishing points can be obtained from their black/white edges. Different from all the existing approaches, three image rectification methods based on a single vanishing point are proposed for enhancement of face detection in this thesis and will be detailed in chapter 2.

Figure 1.3: An image with three chessboards with different positions captured by a higher-up position camera.

1.2.2 Face Detection Techniques

Face detection is also a popular topic with plentiful literatures. Among them the remarkable work proposed by Viola and Jones [13] attracts vast attention in recent years. There are three main contributions in [13] first, the integral image is used to efficiently compute a rich set of image features; second, the learning algorithm, Adaboost, is used to enhance the result of face detection; third, a cascade of several weak classifiers is proposed to reduce computation time and improve detection accuracy.

Figure 1.4: Different structure of MVFD. (a) Parallel Cascades. (b) WFS Tree.

The efficiency and effectiveness of [13] make it a basis of the other two related multi-view face detection (MVFD) works [14, 15]. While in [13] the system is intended for detecting frontal faces only, in [14] and [15] faces with rotations up to \pm 90-degree rotation-out-of-plane and 360-degree rotation-in-plane are also detected. In most MVFD literatures, human faces are divided into different categories according to the variant appearances from different view points. The authors in [14] configure weak classifiers as confidence-rated look-up table of Haar feature for each view category and use Real Adaboost algorithm to boost them. Furthermore, they also use a nesting-structured detector with a corresponding pose estimation method to improve overall performance. In [14] as well as

most MVFD methods, the cascades are trained individually for each view, as shown in Figure 1.4(a). Therefore the complexity of computation makes it hard to reach real-time performance. In [15], a real-time MVFD method with a carefully designed cascade structure, named Width-First-Search (WFS) tree structure, is proposed. WFS adopts the coarse-to-fine strategy which divides entire face space into smaller subspaces, as shown in Figure 1.4(b). Although it improves computational efficiency and accuracy, it is still hard to get satisfied detection performance when it comes to the application we discussed in this thesis, i.e., face detection with a surveillance camera mounted at a higher-up location.

1.3 Organization of thesis

In this thesis we propose a novel image transform based on the vanishing point of vertical lines in the scene to improve the performance of face detection for a surveillance camera with a common higher up mounting position. The flowchart of the proposed face detection approach in this thesis is shown in Figure 1.5. For each video frame, we first solve the image distortion problem with one of the proposed image transformations and then use the face detectors to get face candidates in the transformed image. To further reduce false alarms, we also propose to use skin color analysis to remove some candidates reported by the face detectors.

The rest of this thesis is organized as follows. In Chapter 2, we detail the image transform approach. In Chapter 3, we use skin color percentage in the detection window to reduce false alarms. The experimental results are shown in Chapter 4 and one can see the proposed methods can significantly enhance the detection performance. Finally, we give conclusions and discuss future works in Chapter 5.

Figure 1.5: Flowchart of the propose face detection approach.

Chapter 2 Vanishing Point-based Image Rectification

In this chapter we present three different yet related transformations to rectify images having the perspective distortion caused in common surveillance applications. In Section 2.1, an intuitive transformation regarded as a base-line approach is proposed. A rectification result of Figure 1.2(c) and (d) can be seen in Figure 2.1(a) and (b). In Section 2.2, a transformation significantly improves the result from previous transformation that the aspect ratio of some objects is recovered as shown in Figure 2.1(c) and (d). Finally, a modification of the transformation in Section 2.2 for better performance according to our observation on practical applications is shown in Section 2.3.

Figure 2.1: Rectification results of Figures 1.2(c) and (d). (a)-(b) Obtained from transformation 1 discussed in Section 2.1. (c)-(d) Obtained from transformation 2 discussed in Section 2.2.

For better understanding of the basic idea of the proposed method, we first describe how an object is captured by a surveillance camera. As shown in Figure 2.2, assume the camera is located relatively higher than the object and its optical axis is not horizontal. Suppose there is a square billboard standing vertically in front of the camera, with the pattern on the billboard shown in Figure 1.2(b), the image of the billboard will have perspective distortion, as shown in Figure 1.2(d). Furthermore, the extension of vertical lines on the billboard will meet at a single point in the image plane.

For simplicity, in the following discussion we assume that the image center is the origin of the image plane, and the VPVL, $V = (V_x, V_y)$, can be derived from images of vertical lines via simple camera calibration. Additionally, each image is assumed to be rotated in advance such that $V_x = 0$.

Figure 2.2: The relation between the camera, a standing billboard, and the ground plane, with the camera represented by its lens for simplicity. The billboard is assumed to be facing the vertical line containing the camera center.

2.1 Transformation 1

For the surveillance system described in Figure 2.2, we find that all square patterns on the billboard, *B*, are transformed to trapezoids in the image plane, *P*, as shown in Figure 1.2(d). An intuitive way of image rectification is to make all lines pointing to VPVL vertically parallel. To this end, we propose our first transformation and explain it as follows. Consider Figure 2.3, where we would like to make an image, Figure 2.3(b) from the original image, Figure 2.3(a). In particular, we would like to transform two horizontal line segments, $\overline{OX_1}$ and $\overline{Y_2X_2}$, in Figure 2.3(a) into $\overline{ox_1}$ and $\overline{y_2x_2}$ in Figure 2.3(b), respectively such that $\overline{ox_1}$ and $\overline{y_2x_2}$ are still horizontal and have the same length where O and o are the image center of Figure 2.3(a) and (b). According to triangle geometry and simple calculation, we have

$$
\overline{ov} : \overline{ox_1} = \overline{Y_2 V} : \overline{Y_2 X_2} \quad (2.1)
$$
\n
$$
\overline{Y_2 X_2} = \overline{OX_1} * \overline{Y_2 V} / \overline{OV}
$$
\n
$$
(2.2)
$$

In general we can define a transformation such that for each pixel (x, y) in Figure 2.3(b), its content can be obtained at position (X, Y) in Figure 2.3(a) such that

$$
X = x * \frac{V_y - y}{V_y}
$$

$$
Y = y
$$
 (2.3)

In Figure 2.1(b) we can see that each trapezoid can be recovered as a rectangle, but not a square. Moreover, a white block near the top is much larger than that near the bottom, resulting in rectangles of different heights. At last Figure 2.4 shows an example of image rectification obtained with transformation 1.

Figure 2.3: An illustration diagram for transform 1. (a) Image before rectified. (b) Image after rectified.

Figure 2.4: (a) Origin image. (b) Rectified result of transformation 1.

2.2 Transformation 2

In order to further recover the aspect ratio of an object, a novel image transformation is presented in this section. To simplify the presentation, we first rotate the camera model shown in Figure 2.2 to make the optical axis horizontal as illustrated in Figure 2.5, where θ is the tilt angle, *f* is the focal length of the camera, *l* is a vertical line connect the optical center (*O*) and the ground, and Z_0 is distance from the optical center to the pixel which is the intersection of the optical axis and the billboard (*B*). Furthermore, we set the origin of the 3D coordinate system to be the optical center, with the *z*-axis to the right, the *y*-axis pointing downward, and *x*-axis pointing out of the paper.

Figure 2.5: A rotation of Figure 2.2, to make the optical axis of the camera horizontal.

As shown in Figure 2.6, the value of the unknown parameter *f* can be found as

$$
f = \frac{F}{L} * \sqrt{I_w^2 + I_h^2}
$$
 (2.4)

where F is the focal length in standard metric units, L is the size of the image sensor, and (I_w, I_h) is the size of image width and height.

Figure 2.6: An illustration showing the relationship between the image sensor and the image.

To investigate the relation between the billboard (*B*) and the image plane (*P*), let

where (x', y', z') represents the 3D coordinates and (x_b, y_b) represents 2D coordinates of a 39 G pixel on *B*.

Moreover, let (x_p, y_p, z_p) denote the 3D coordinates of a pixel on the image plane (*P*), we have

$$
x_p = \frac{x_b}{Z_0 + y_b \sin \theta} f
$$

\n
$$
y_p = \frac{y_b \cos \theta}{Z_0 + y_b \sin \theta} f
$$

\n
$$
z_p = f
$$
 (2.6)

Because *P* is parallel to the *XY*-plane of the 3D coordinate, (x_p, y_p) is also the 2D coordinates of this corresponding pixel on *P*. Thus we can define an image transformation from *P* to a recovered image *R* as:

$$
x_p = \frac{x_r}{Z_0 + y_r \sin \theta} f
$$

$$
y_p = \frac{y_r \cos \theta}{Z_0 + y_r \sin \theta} f
$$
 (2.7)

where (x_r, y_r) with being the coordinates of the transformed pixel. Finally, an example of image rectification of transformation 2 is shown in Figure 2.7.

In this transformation, Z_0 affects only the scale of transferred image and can be assigned with an arbitrary value per user's requirement. On the other hand, for the remaining unknown θ in equation (2.7), we can derive $\cos \theta$ and $\sin \theta$ as:

Figure 2.7: (a) Origin image. (b) Rectified result of transformation 2.

2.3 Transformation 3

One characteristic of transformation 2 is that it is only valid for billboards parallel to the *XY*-plane in the 3D coordinate. However, in most applications we are interested in all people facing to *l* in Figure 2.2. For example, if a camera is installed above an entrance, we are more interested in people walking toward the entrance. Besides, people facing *l* also provide more frontal face information and are thus more valuable. To make the proposed method more suitable for any billboard facing *l*, we further propose a modified version, namely transformation 3, of transformation 2 such that after the transformation, all pixels on image plane (*P*) with the same distance to VPVL will be mapped to the same horizontal line in the recovered image. The difference between results of transformation 2 and 3 is also illustrated in Figure 2.8. In Figure 2.8 an image containing a person facing to *l* but not to the *XY*-plane is rectified by transformation 2 and 3 respectively. For better illustrations, we draw a green line on the person's eyes. It is obvious that the green line in the result of transformation 2 (Figure 2.8(a)) is not horizontal while in Figure 2.8(b) the green line is nearly horizontal and thus the face in Figure 2.8(b) is more close to a normal face.

 (a) (b)

Figure 2.8: Rectified image of Figure 1.1(b) by transformation 2 and 3. (a) Result of transformation 2. (b) Result of transformation 3.

Figure 2.9 explains how the corresponding pixels in the original image can be found according to the above description of transformation 3. In Figure 2.9 several corresponding lines and pixels in transformation 3 (Figure 2.9(b)) and in the original image (Figure 2.9(a)) are illustrated. Specifically, the l_1 and l_3 represent the lines with $x = 0$ in the original image and transformation 3, respectively. Now we show that for the pixel p'_2 in Figure 2.9(b), how to find its corresponding pixel p_2 in Figure 2.9(a). Given the pixel p'_2 , we first find the pixel p'_1 which is located at the central vertical line and has the same *y*-coordinate as p'_2 . According to transformation 2 we know that p'_1 comes from the pixel p_1 in the original image. Then we rotate p_1 around the VP by θ which is proportional to the distance, x_t , between l_1 and l_2 as:

Figure 2.9: Relation between original image and rectified image by transformation 3. (a) Original image. (b) Rectified image by transformation 3.

Notice that x_{p1} and V_x are both 0 and hence can be ignored. After combining Equation (2.9) as well as equation (2.7) of the transformation 2, we derive the formulation of transformation 3:

$$
x_p = -\sin\left(\frac{x_t}{V_y}\right) \left(\frac{y_t \cos \theta}{Z_0 + y_t \sin \theta} f - V_y\right)
$$

$$
y_p = \cos\left(\frac{x_t}{V_y}\right) \left(\frac{y_t \cos \theta}{Z_0 + y_t \sin \theta} f - V_y\right) + V_y
$$
 (2.10)

where (x_t, y_t) represents a pixel on rectified image and (x_n, y_n) represents a pixels on plane *P*. An example of the transformation result is shown in Figure 2.10, where in Figure 2.10(a) the red curve with all pixels on it is equidistant to the VPVL is mapped to a straight line in Figure 2.10(b).

Figure 2.10: (a) Origin image. (b) Rectified result of transformation 3.

Chapter 3 Method for Reducing False Alarms

In this chapter we try to reduce false alarms for better detection performance. We propose to use skin detection for its efficiency. The skin detection is carried only on regions of candidates found by face detectors to further reduce the computation demand. In Section 3.1, the skin detection adopted in our system in introduced. The complete process and the final results are present in Section 3.2.

In the work proposed by Garcia et al. [16], a skin color sub-space in YCbCr space is figured out for detection of skin regions in MEPG streams and JPEG images. A data set containing 950 skin colors samples is used in order to approximate the color sub-space. These samples are extracted from various still images and video frames, covering a large range of skin color appearance caused by different races and different lighting conditions. Different from prior work, Garcia et al. propose to use varying intensity (Y) values to deal with strong lighting variations as they notice that the skin color distribution turns out to be different when Y changes extremely. More specifically, for the purpose to approximate the

distribution borders in the extreme light and dark cases, the authors actually propose two groups of planes equations depending on two areas of the color space, separated by the horizontal plane $Y = 128$. Their proposed planes equations are present in equation (3.1) while two skin color sub-spaces defined by equation (3.1) according to two different Y values are shown in Figure 3.1.

Figure 3.1: Skin color region define by [16] at $Y = 110$ and $Y = 140$. (a) YCbCr plane at different *Y* value. (b) Skin region define by equation 3.1. (c) Skin colors at different *Y* value.

3.2 Skin Color Percentage in Candidate Regions

Figure 3.2: (a) A picture with five candidate regions. (b) 0% skin color percentage in region 1. (c) 33% skin color percentage in region 2. (d) 0% skin color percentage in region 3. (e) 79% skin color percentage in region 4. (f) 0% skin color percentage in region 5.

 In this section, we demonstrate how to reduce false alarms with skin detection and get a better detection performance. For each image frame, we first find several candidates by the face detector. Then we exploit the skin detection method mentioned in section 3.1 to find skin pixels among regions of these candidates. Finally a candidate is taken out if the percentage of skin pixels in the region under it is less than a threshold. Take Figure 3.2 for example, in Figure 3.2(a) five candidates are detected and marked with red squares. For each candidate the skin pixels are detected and the percentage of them is recorded in the caption of Figure

3.2(b)-(f). Therefore, we may take out some bad candidates if we can find a suitable threshold for skin pixel percentage. In order to determine such a threshold that can separate true faces and false alarms properly, two videos are tested, i.e., S10 for indoor environment and O5 for outdoor environment, as shown in Figure 3.3. Table 3.1 and Table 3.2 show face detection results for different threshold values for the two videos. One can see that when the threshold is set between 10% and 40% for indoor environment (between 15% and 35% for outdoor environment) best detection results can be achieved. With such thresholds, we keep almost as many true positives as the origin while reduce most false positives.

And we set the threshold to 40% and show the comparison of face detection results on another video with and without the false alarm detection in Figure 3.4. One can see that with false alarm detection most false positives have been removed while the true faces are still preserved.

(b)

Figure 3.3: Videos used to find the threshold of skin pixel percentage. (a) Video S10. (b) Video O5.

	${\rm TP}$	${\rm FP}$	${\rm FN}$
origin	$80\,$	31	$\boldsymbol{0}$
$P > 0\%$	$80\,$	$\mathbf{9}$	$\boldsymbol{0}$
$P > 5\%$	$80\,$	$\overline{2}$	$\boldsymbol{0}$
P > 10%	$80\,$	$\boldsymbol{0}$	$\boldsymbol{0}$
P > 15%	$80\,$	$\boldsymbol{0}$	$\boldsymbol{0}$
P > 20%	$80\,$	$\boldsymbol{0}$	$\boldsymbol{0}$
P>25%	$80\,$	$\boldsymbol{0}$	$\boldsymbol{0}$
P>30%	80	\mathbf{u}_0	$\boldsymbol{0}$
P>35%	80	$\overline{0}$	$\boldsymbol{0}$
P>40%	80	$\overline{0}$	$\boldsymbol{0}$
P>45%	$78\,$	0 ¹	$\overline{2}$
$P > 50\%$	63	896 $\overline{0}$	17
P>55%	41	$\mathbf{0}$	39
$P > 60\%$	19	$\boldsymbol{0}$	61
P>65%	$\boldsymbol{0}$	$\boldsymbol{0}$	80
P > 70%	$\boldsymbol{0}$	$\boldsymbol{0}$	$80\,$
P>75%	$\boldsymbol{0}$	$\boldsymbol{0}$	$80\,$
$P > 80\%$	$\boldsymbol{0}$	$\boldsymbol{0}$	$80\,$
P>85%	$\boldsymbol{0}$	$\boldsymbol{0}$	80
P>90%	$\boldsymbol{0}$	$\boldsymbol{0}$	80
P>95%	$\boldsymbol{0}$	$\boldsymbol{0}$	$80\,$
$P = 100%$	$\boldsymbol{0}$	$\boldsymbol{0}$	80

Table 3.1: The detection results for S10 with different thresholds of skin pixel percentage.

	${\rm TP}$	${\rm FP}$	${\rm FN}$
origin	115	184	$\boldsymbol{0}$
$P > 0\%$	115	$80\,$	$\boldsymbol{0}$
$P > 5\%$	115	56	$\boldsymbol{0}$
P > 10%	$115\,$	$\sqrt{6}$	$\boldsymbol{0}$
P > 15%	115	$\boldsymbol{0}$	$\boldsymbol{0}$
P > 20%	115	$\boldsymbol{0}$	$\boldsymbol{0}$
P > 25%	115	$\boldsymbol{0}$	$\boldsymbol{0}$
P>30%	115	\mathcal{U}_0	$\boldsymbol{0}$
P>35%	115	$\overline{0}$	$\boldsymbol{0}$
P>40%	112	$\overline{0}$	$\overline{3}$
P>45%	107	0 ¹	$8\,$
P>50%	102	896 $\overline{0}$	13
P>55%	96	$\mathbf{0}$	19
P>60%	85	$\boldsymbol{0}$	30
$P > 65\%$	$78\,$	$\overline{0}$	37
P > 70%	$70\,$	$\boldsymbol{0}$	45
P>75%	39	$\boldsymbol{0}$	$76\,$
P>80%	14	$\boldsymbol{0}$	$101\,$
P>85%	$\boldsymbol{6}$	$\boldsymbol{0}$	109
P>90%	$\boldsymbol{0}$	$\boldsymbol{0}$	115
P>95%	$\boldsymbol{0}$	$\boldsymbol{0}$	115
$P = 100%$	$\boldsymbol{0}$	$\boldsymbol{0}$	115

Table 3.2: The detection results for O5 with different thresholds of skin pixel percentage.

Figure 3.4: Reducing false alarms with 40% skin color in candidate regions method in different path images.

Chapter 4 Experimental Results

In this chapter, we give four experiments to show how face detection can be improved with the proposed method. We have tested our method on videos under three real environments as well as on some synthesized images. In Section 4.1, the specifications of cameras used in our experiments and the installation parameters are detailed. In Section 4.2, we show some image samples from our testing videos. An experiment for comparison is present in Section 4.3. In this experiment, the videos are simply rotated such that the new position of the VPVL is at the horizontal center. The face detection results of our method with or without reducing false alarms method on videos under real environments are reported in Section 4.4 and in Section 4.5, respectively. Finally, in Section 4.6 we show the experiments on synthesized images with multiple camera installation settings.

4.1 Environment Settings

 Through our experiments two cameras, named as AXIS 207MW and VIVOTEK FD8161 according to their model names, are used. In the indoor experiments, the AXIS 207MW is attached at the ceiling without any calibration and is located about 2.7 meters above the ground plane, as shown in Figure 4.1. In the outdoor experiments, we install the VIVOTEK FD8161 above an entrance also without any calibration. The height of the camera is about 2.5 meters, as shown in Figure 4.2.

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Figure 4.2: Camera VIVOTEK FD8161 settings. (a) Experimental environment. (b) Close-up view of camera.

4.2 Video Demonstration

We have captured 25 videos and use them in our experiments. As mentioned previously, our experiments contain videos both on an indoor environment and on an outdoor environment. These videos have different resolutions according to the camera models and thus have different resolutions on the two environments. In our experiments the resolutions of the indoor and outdoor videos are 640x480 and 800x600, respectively. In all videos one or multiple people walking and roughly toward the camera are captured. Furthermore, these people start walking from different positions so that we can see faces with different sizes, rotations, and distortions, in these videos.

Figure 4.3: Frame examples of a single person walking in the laboratory. (a) Video S1. (b) Video S2. (c) Video S3. (d) Video S4. (e) Video S5. (f) Video S6. (g) Video S7. (h) Video S8. (i) Video S9. (j) Video S10.

Figure 4.4: Frame examples of multi people walking in the laboratory. (a) Video M1. (b) Video M2. (c) Video M3. (d) Video M4. (e) Video M5. (f) Video M6. (g) Video M7.

Figure 4.5: Frame examples of a single person walking in the outdoor environment. (a) Video O1. (b) Video O2. (c) Video O3. (d) Video O4. (e) Video O5. (f) Video O6. (g) Video O7. (h) Video O8.

4.3 Experiment 1 – Face Detection using Image Rotation

In this section, we present a simple method using only image rotation to improve face detection with a surveillance camera. Based on the observation that faces in directions other than the front of the camera seem like faces with in-plane rotations, to treat them just like in-plane rotated faces like [14, 15] is an intuitive way. In [14, 15], faces with rotations in different degrees are detected by rotated detectors. Unlike them, for easier implementation, we instead rotate the image and repeat the detection procedure several times.

To decide the amount of the angular shift in each face detection procedure, we first investigate the limitation of the frontal face detector, which is proposed in [17] and provided in OpenCV, on in-plane rotations. A subset of the MUCT face database [18] is used in this testing. More specifically, we use images captured by the camera "e" as shown in Figure 4.6. There are total 751 images in the database and each subject is captured under 2 to 3 different lightings as shown in Figure 4.7. In our testing each image is rotated 360 times with the step of one degree and then the face detection results are carried out on all rotated versions. The detection result of an image with all its rotated versions is shown in Figure 4.8 where the maximum continuous region in which the face detection succeeds is of 48 degree. With the same procedure on all images, we have the result that the smallest maximum continuous region is of 28 degree and the average maximum continuous region is of 47.47 degree.

Figure 4.6: The relationship between five cameras and human face in MUCT.

Figure 4.7: Three different lighting for a person in MUCT face database captured by camera e.

Figure 4.8: The testing result of Figure 4.7(a). 1=face was detected; 0=no face was detected. 22-(-25)+1=48, 48 is the maximum rotation in plane degree result for Figure 4.7(a).

Although the face detector is proved effective for faces rotated up to ± 23.7 degree (half of the average result 47.47), we take a relatively conservative rotation step of 15 degree in our experiments. The maximum in-plane rotation of faces in our videos is about +24.8 degree, thus it should be enough to rotate the images by ± 15 degrees to deal with all in-plane rotations occurred here. However, we also rotate images by ± 30 degree and merge the results for more robustness. An example of face detection on an image in rotations of different degrees is shown in Figure 4.9. In Figure 4.9 the face detector can detect only one face in the original image. In the meantime, the remaining two faces are detected in the -15 and -30 degree rotated versions separately. It is obvious that more faces can be found if we provide more rotated versions of an image.

(d) \blacksquare (e)

Figure 4.9: Example of rotating image. (a) Origin image. (b) Rotate -15 degree. (c) Rotate 15 degree. (d) Rotate -30 degree. (e) Rotate 30 degree.

By combining results in different rotations, we have the result shown in Figure 4.10. One can see that although more faces are detected, the number of false positives is also increased.

Figure 4.10: Combine the detection results of Figure 4.9 into one image. (a) Combine Figure 4.9(a)-(c) and 2 TP/FP in the image. (b) Combine Figure 4.9(a)-(e) and 3 TP/FP in the image.

Finally we show the detection results in Table 4.1 \sim Table 4.3. Where O represents the origin method without any preprocessing on images; R1 represents combining the results on the origin images and on the 15-degree rotated version; and R2 represents combining results on the origin images, 15-degree rotated version and 30-degree rotated version. In the table, we give precision and recall to show the detection performance. One can see that the more rotated images are added, the higher recall and lower precision will be. In Table 4.4 we give the average results across all videos. It is obviously to see that R2 has the best recall but the lowest precision in most groups.

		S ₁		S2 11 177		S ₃	S4	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
\overline{O}	100% (126/126)	61.1% (126/206)	30.5% (37/121)	40.6% (37/91)	38.8% (33/85)	27.5% (33/120)	8.8% (8/90)	7.7% (8/95)
R1	100% (126/126)	49.6% (126/254)	99.1% (120/121)	55.8% (120/125)	96.4% (82/85)	34.4% (82/238)	97.7% (88/90)	35.3% (88/249)
R ₂	100% (126/126)	47.0% (126/268)	99.1% (120/121)	50.0% (120/120)	96.4% (82/85)	32.2% (82/254)	100% (90/90)	33.4% (90/269)
		S ₅		S ₆		S7		S ₈
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
\overline{O}	1.8% (1/55)	2.4% (1/41)	22.8% (13/57)	22.0% (13/59)	1.1% (1/85)	1.4% (1/71)	100% (79/79)	63.7% (79/124)
R1	98.1% (54/55)	38.8% (54/139)	98.2% (56/57)	33.5% (56/167)	97.6% (83/85)	36.2% (83/229)	100% (79/79)	51.9% (79/152)
R ₂	98.1% (54/55)	35.0% (54/154)	100% (57/57)	32.3% (57/176)	97.6% (83/85)	34.2% (83/242)	100% (79/79)	45.6% (79/173)
		S9		S ₁₀				
	Recall	Precision	Recall	Precision				
\mathbf{O}	95.5% (86/90)	61.4% (86/140)	100% (80/80)	72.0% (80/111)				
R1	100% (90/90)	39.1% (90/230)	100% (80/80)	42.1% (80/190)				
R ₂	100% (90/90)	35.1% (90/256)	100% (80/80)	34.0% (80/245)				

Table 4.1: Face detection results of $S1 \sim S10$ videos by image rotation.

		M1	M ₂			M ₃		M ₄	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	
O	42.2% (76/180)	69.0% (76/110)	50.4% (58/115)	71.6% (58/81)	50.0% (62/124)	65.2% (62/95)	51.9% (109/210)	74.6% (109/146)	
R1	66.6% (120/180)	60.3% (120/199)	62.6% (72/115)	56.6% (72/127)	76.6% (95/124)	59.3% (95/160)	77.6% (163/210)	73.7% (163/221)	
R2	75.0% (135/180)	48.9% (134/276)	79.1% (91/115)	45.5% (91/200)	89.5% (111/124)	44.4% (111/250)	83.3% (175/210)	55.2% (175/317)	
	M5		M ₆			M ₇			
	Recall	Precision	Recall	Precision	Recall	Precision			
O	46.9% (123/262)	75.9% (123/162)	62.2% (79/127)	60.7% (79/130)	61.4% (129/210)	61.1% (129/211)			
R1	69.4% (182/262)	67.1% (182/271)	69.2% (88/127)	48.3% (88/182)	69.5% (146/210)	51.2% (146/285)			
R2	77.1% (202/262)	51.5% (202/392)	77.9% (99/127)	44.7% (99/221)	75.2% (158/210)	48.0% (158/329)			

Table 4.2: Face detection results of M1 ~ M7 videos by image rotation.

Table 4.3: Face detection results of O1 ~ O8 videos by image rotation.

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	$S1 \sim S10$ videos		$M1 \sim M7$ videos		$Q1 \sim Q8$ videos		All 25 videos	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
Ω	49.9%	35.9%	52.1%	68.3%	82.5%	49.3%	61.5%	51.2%
R1	98.7%	41.6%	70.2%	59.5%	92.1%	38.1%	87.0%	46.4%
R ₂	99.1%	37.8%	79.5%	48.3%	92.8%	33.4%	90.4%	39.8%

Table 4.4: Average detection results of image rotation method.

4.4 Experiment 2 – Face Detection based on Image Rectification

In this section, we show the detection performance by the proposed image rectification methods. The results are reported in Table 4.5 \sim Table 4.8. Where O means the origin method without any preprocessing on images; T1 means transformation 1; T2 means transformation 2; and T3 means transformation 3. Again, we give precision and recall to show the detection performance. Some images with different rectifications and face detection result are present in Figure 4.11~4.13.

Figure 4.11: Results of S3 video. (a) Results of O. (b) Results of T1. (c) Results of T2. (d) Result of T3.

In Table 4.8 we find that the face detection performances are generally improved by the proposed methods. With the proposed three transformations the overall recall are improved from 0.615 to 0.781, 0.837, and 0.905 separately. As the results show, transformation 3 has the best recall. We also find that transformation 3 is very stable through all directions.

		S1		S ₂		S ₃		S ₄
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
\mathbf{O}	100% (126/126)	61.1% (126/206)	30.5% (37/121)	40.6% (37/91)	38.8% (33/85)	27.5% (33/120)	8.8% (8/90)	7.7% (8/95)
T1	100% (126/126)	78.2% (126/161)	81.8% (99/121)	66.4% (99/149)	83.5% (71/85)	59.1% (71/120)	77.7% (70/90)	56.0% (70/125)
T ₂	100% (126/126)	62.3% (126/202)	98.3% (119/121)	59.8% (119/199)	90.5% (77/85)	30.9% (77/249)	94.4% (86/90)	34.2% (86/90)
T ₃	100% (126/126)	43.9% (126/287)	96.6% (117/121)	42.7% (117/274)	97.6% (83/85)	52.2% (83/159)	98.8% (89/90)	47.5% (89/187)
	S ₅			S ₆		S7		S8
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
\overline{O}	1.8% (1/55)	2.4% (1/41)	22.8% (13/57)	22.0% (13/59)	1.1% (1/85)	1.4% (1/71)	100% (79/79)	63.7% (79/124)
T1	98.1% (54/55)	65.0% (54/83)	98.2% (56/57)	63.6% (56/98)	81.1% (69/85)	56.1% (69/123)	100% (79/79)	57.2% (79/138)
T ₂	94.5% (52/55)	33.7% (52/154)	98.2% (56/57)	33.9% (56/165)	91.7% (78/85)	32.2% (78/242)	100% (79/79)	34.2% (79/231)
T ₃	100% (55/55)	49.1% (55/112)	100% (57/57)	50.4% (57/113)	98.8% (84/85)	48.5% (84/173)	100% (79/79)	46.7% (79/169)
		S ₉		S10				
	Recall	Precision	Recall	Precision				
\overline{O}	95.5% (86/90)	61.4% (86/140)	100% (80/80)	72.0% (80/111)				
T ₁	78.8% (71/90)	65.7% (71/108)	100% (80/80)	62.9% (80/127)				
T ₂	92.2% (83/90)	33.2% (83/250)	100% (80/80)	36.7% (80/218)				
T ₃	100% (90/90)	49.1% (90/183)	100% (80/80)	54.7% (80/146)				

Table 4.5: Face detection results of $S1 \sim S10$ videos by image rectification.

	M1		M ₂		M ₃			M4	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	
Ω	42.2%	69.0%	50.4%	71.6%	50.0%	65.2%	51.9%	74.6%	
T1	(76/180) 55.5%	(76/110) 67.1%	(58/115) 60.0%	(58/81) 51.8%	(62/124) 65.3%	(62/95) 60.0%	(109/210) 70.9%	(109/146) 60.8%	
T ₂	(100/180) 61.1%	(100/149) 55.2%	(69/115) 69.5%	(69/133) 44.6%	(81/124) 66.9%	(81/135) 44.6%	(149/210) 80.0%	(149/245) 54.9%	
T ₃	(110/180) 74.4% (134/180)	(110/199) 62.3% (134/215)	(80/115) 74.7% (86/115)	(80/179) 51.8% (86/166)	(83/124) 89.5% (111/124)	(83/186) 57.2% (111/196)	(168/210) 84.2% (177/210)	(165/306) 51.6% (177/343)	
	M ₅		M ₆			M7			
	Recall	Precision	Recall	Precision	Recall	Precision			
O	46.9% (123/262)	75.9% (123/162)	62.2% (79/127)	60.7% (79/130)	61.4% (129/210)	61.1% (129/211)			
T ₁	59.1% (155/262)	58.4% (155/265)	66.1% (84/127)	70.0% (84/120)	54.7% (115/210)	61.5% (115/187)			
T ₂	64.1% (168/262)	47.0% (168/357)	74.0% (94/127)	64.3% (94/146)	59.0% (124/210)	48.2% (124/256)			
T ₃	77.4% (203/262)	49.5% (203/410)	79.5% (101/127)	59.7% (101/169)	74.2% (156/210)	48.3% (156/323)			

Table 4.6: Face detection results of M1 ~ M7 videos by image rectification.

Figure 4.12: Results of M7 video. (a) Results of O. (b) Results of T1. (c) Results of T2. (d) Result of T3.

		O ₁	O ₂		O ₃			O4
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
O	1.1%	1.1%	91.1%	53.5%	100%	56.2%	91.2%	49.3%
	(1/86)	(1/91)	(82/90)	(82/153)	(90/90)	(90/160)	(73/80)	(73/148)
T ₁	32.5%	16.7%	85.5%	48.4%	100%	52.9%	86.2%	53.9%
	(28/86)	(28/167)	(77/90)	(77/159)	(90/90)	(90/170)	(69/80)	(69/128)
T ₂	50.0%	19.2%	91.1%	37.1%	97.7%	41.7%	92.5%	46.8%
	(43/86)	(43/224)	(82/90)	(82/221)	(88/90)	(88/211)	(74/80)	(74/158)
T ₃	69.7%	26.3%	91.1%	34.0%	100%	38.4%	98.7%	40.9%
	(60/86)	(60/228)	(82/90)	(82/241)	(90/90)	(90/234)	(79/80)	(79/193)
		O ₅		O ₆		O ₇	O ₈	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
$\mathbf O$	93.0%	58.4%	98.9%	48.9%	98.2%	70.1%	86.8%	57.2%
	(107/115)	(107/183)	(94/95)	(94/192)	(113/115)	(113/161)	(139/160)	(139/243)
T ₁	93.0%	58.7%	83.1%	40.1%	95.6%	71.9%	88.1%	53.0%
	(107/115)	(107/182)	(79/95)	(79/197)	(110/115)	(110/153)	(141/160)	(141/266)
T ₂	94.7%	49.3%	87.3%	29.9%	98.2%	58.8%	88.7%	42.0%
	(109/115)	(109/221)	(83/95)	(83/277)	(113/115)	(113/192)	(142/160)	(142/338)
T ₃	95.6%	37.4%	98.9%	28.9%	100%	66.8%	93.7%	53.9%
	(110/115)	(110/294)	(94/95)	(94/325)	(115/155)	(115/172)	(150/160)	(150/278)

Table 4.7: Face detection results of O1 \sim O8 videos by image rectification.

Figure 4.13: Results of O8 video. (a) Results of O. (b) Results of T1. (c) Results of T2. (d) Result of T3.

	$S1 \sim S10$ videos		$M1 \sim M7$ videos		$Q1 \sim Q8$ videos		All 25 videos	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
Ω	49.9%	35.9%	52.1%	68.3%	82.5%	49.3%	61.5%	51.2%
T ₁	89.9%	63.0%	61.6%	61.3%	83.0%	49.4%	78.1%	57.9%
T ₂	95.9%	39.1%	67.8%	51.2%	87.5%	40.6%	83.7%	43.6%
T ₃	99.1%	48.4%	79.1%	54.3%	93.4%	40.8%	90.5%	47.8%

Table 4.8: Average detection results of image rectification method.

 Now we compare the proposed methods with the image rotation method mentioned in the previous subsection. Comparing Table 4.4 and Table 4.8, we can see that T3 has better recall and precision than R1 and R2. The computation times of different methods on three different videos are shown in Table 4.9. Where T1 is 1.3 times slower than O; T2 and T3 are almost 1.5 times slower than O. When compared with the image rotation method, we see that T1, T2, and T3 on the contrary are over 1.8 and 3.3 times faster R1 and R2. This leads to the conclusion that although image rotation can improve the detection performance, it also results more false positives and computation times than our proposed methods.

	Frame Number	Ω	T1	T ₂	T ₃	R ₁	R ₂
S ₁	126	70.14	92.00	112.72	105.14	189.47	327.47
M1	90	47.44	69.57	77.19	71.48	132.91	217.20
O ₁	115	96.77	131.14	156.56	153.11	295.93	496.16

Table 4.9: The computation time(s) of each face detection methods.

4.5 Experiment 3 – Face Detection based on Image Rectification with Reducing False Alarms Method

 In this section, we show the face detection results by combining the false alarms reducing method proposed in Chapter 3 with the transformation 3. As suggested in Section 3.2, we test two thresholds, 40 and 45, on percentage of skin region in this experiment. The results are reported in Table 4.10 \sim 4.12. Where T3 denotes transformation 3; P0 means reducing false alarms in T3 with the threshold 35%; P1 means reducing false alarms in T3 with the threshold 40%; and P2 means reducing false alarms in T3 with the threshold 45%. As used in previous sections, we give precision and recall to show the detection performance.

		S1		S ₂		S ₃		S ₄
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
T ₃	100% (126/126)	43.9% (126/287)	96.6% (117/121)	42.7% (117/274)	97.6% (83/85)	52.2% (83159)	98.8% (89/90)	47.5% (89/187)
P ₁	100% (126/126)	100% (126/126)	96.6% (117/121)	100% (117/117)	97.6% (83/85)	98.8% (83/84)	98.8% (89/90)	100% (89/89)
P2	100% (126/126)	100% (126/126)	96.6% (117/121)	100% (117/117)	97.6% (83/85)	100% (83/83)	98.8% (89/90)	100% (89/89)
	S ₅			S ₆		S7		S ₈
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
T ₃	100%	49.1%	100%	50.4%	98.8%	48.5%	100%	46.7%
	(55/55)	(55/121)	(57/57)	(57/113)	(84/85)	(84/173)	(79/79)	(79/169)
P ₁	100%	98.2%	100%	100%	98.8%	100%	100%	100%
	(55/55)	(55/56)	(57/57)	(57/57)	(84/85)	(84/84)	(79/79)	(79/79)
P ₂	100%	100%	100%	100%	98.8%	100%	100%	100%
	(55/55)	(55/55)	(57/57)	(57/57)	(84/85)	(84/84)	(79/79)	(79/79)
		S ₉		S ₁₀				
	Recall	Precision	Recall	Precision				
T ₃	100%	49.1%	100%	54.7%				
	(90/90)	(90/183)	(80/80)	(80/146)				
P ₁	88.8%	100%	100%	100%				
	(80/90)	(80/80)	(80/80)	(80/80)				
	80.0%	100%	95.0%	100%				
P ₂	(72/90)	(72/72)	(76/80)	(76/76)				

Table 4.10: Face detection results of $S1 \sim S10$ videos by image rectification with reducing false alarms.

		M1	M ₂		M ₃			M4
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
T ₃	74.4% (134/180)	62.3% (134/215)	74.7% (86/115)	51.8% (86/166)	89.5% (111/124)	57.2% (111/196)	84.2% (177/210)	51.6% (177/343)
P ₁	74.4% (134/180)	100% (134/134)	74.7% (86/115)	100% (86/86)	89.5% (111/124)	100% (111/111)	84.2% (177/210)	97.2% (177/185)
P ₂	74.4% (134/180)	100% (134/134)	74.7% (86/115)	100% (86/86)	89.5% (111/124)	100% (111/111)	84.2% (177/210)	100% (177/177)
	M ₅		M ₆		M7			
	Recall	Precision	Recall	Precision	Recall	Precision		
T ₃	77.4% (203/262)	49.5% (203/410)	79.5% (101/127)	59.7% (101/169)	74.2% (156/210)	48.3% (156/323)		
P ₁	77.4% (203/262)	97.6% (203/208)	79.5% (101/127)	99.0% (101/102)	73.8% (155/210)	98.7% (155/157)		
P ₂	77.4% (203/262)	100% (203/203)	79.5% (101/127)	100% (101/101)	73.8% (155/210)	99.3% (155/156)		

Table 4.11: Face detection results of M1 ~ M7 videos by image rectification with reducing false alarms.

Table 4.12: Face detection results of O1 ~ O8 videos by image rectification with reducing false alarms.

	O ₁		O ₂		1896 O3		O4	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
T ₃	69.7%	26.3%	91.1%	34.0%	100%	38.4%	98.7%	40.9%
	(60/86)	(60/228)	(82/90)	(82/241)	(90/90)	(90/234)	(79/80)	(79/193)
P ₀	69.7%	100%	90.0%	100%	100%	100%	98.7%	100%
	(60/86)	(60/60)	(81/90)	(81/81)	(90/90)	(90/90)	(79/80)	(79/79)
P ₁	69. %	100%	83.3%	100%	100%	100%	98.7%	100%
	(60/86)	(60/60)	(75/90)	(75/75)	(90/90)	(90/90)	(79/80)	(79/79)
	O ₅		O ₆		O ₇		O ₈	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
T ₃	95.6%	37.4%	98.9%	28.9%	100%	66.8%	93.7%	53.9%
	(110/115)	(110/294)	(94/95)	(94/325)	(115/115)	(115/172)	(150/160)	(150/278)
P ₀	100%	100%	98.9%	100%	99.1%	99.1%	93.7%	100%
	(115/115)	(115/115)	(94/95)	(94/94)	(114/115)	(114/115)	(150/160)	(150/150)
P ₁	97.3%	100%	98.9%	100%	93.0%	99.0%	93.7%	100%
	(112/115)	(112/112)	(94/95)	(94/94)	(107/115)	(107/108)	(150/160)	(150/150)

	$S1 \sim S10$ videos		$M1 \sim M7$ videos		$Q1 \sim Q8$ videos		All 25 videos	
	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
T ₃	99.1%	48.4%	79.1%	54.3%	93.4%	40.8%	90.5%	47.8%
P ₀					93.7%	99.8%	93.7%	99.8%
P ₁	98.0%	99.7%	79.0%	98.9%	91.8%	99.8%	89.6%	99.5%
P ₂	96.6%	100%	79.0%	99.9%			87.8%	99.9%

Table 4.13: Average detection results of image rectification with reducing false alarms.

 After the false alarm reducing process, one can see in Table 4.13 that the precision in all videos has been improved to 0.9 and 1. In the meanwhile, the precision is enhanced by nearly 0.5 while the detection rate is only decreased less than 0.03. The computation times are reported in Table 4.14, where P combining the false alarm reducing method with transformation 3. As shown in Table 4.14, with the proposed false alarms reducing method the computation time are only be increased by 1 second through the three videos, which is about 0.01 second per frame.

Table 4.14. The computation third s/ or 15 and reducing raise alarm include.						
Video	Frame Number	T ₃				
S ₁	126	105.14	106.94			
M1	90	71.48	72.57			
	115	153.11	154.15			

Table 4.14: The computation time(s) of T3 and reducing false alarm method.

4.6 Experiment 4 – Face Detection in Synthetic Scene

 In order to show how the proposed methods can work under different situations in an efficient way, we build a synthetic scene by Autodesk MAYA for our experiments. With MAYA we construct a scene containing 21 people and a camera. These virtual people are positioned in three rows and spaced equally by one meter. Besides, we set the distance between the camera and the person in the middle of the first row to 2.5 meters. An example of these settings is shown in Figure 4.14 and some images captured by the camera are shown in Figure 4.15.

Figure 4.14: The environment of synthetic scene. (a) An aerial image of the synthetic scene. (b) A side view of the synthetic scene with camera at 3 meters height and 40 degree angle of depression.

Figure 4.15: Examples of synthetized images capture by camera. (a) $2m$, 0^{\degree} . (b) $4m$, 40^{\degree} .

(b)

Figure 4.16: The detection rates of different transformations by different camera settings. (a) The detection rates from different transformations according to varying camera heights. (b) The detection rates from different transformations according to varying camera angles.

(b)

Figure 4.17: The detection rates of different face detection methods by different camera settings. (a) The detection rates from different face detection methods according to varying camera heights. (b) The detection rates from different face detection methods according to varying camera angles.

 Because of the clean background with which no false alarm occurs in our experiment, we only focus on the detection rate (recall) in the following. In this experiment we have five heights, from 2m to 6m, and nine tilt angles, from 0^{\degree} to 80^{\degree} , in the camera settings. The detection rates are plotted in Figure 4.16. In Figure 4.16(a), we show the detection rates with different camera heights across all camera angles. In Figure 4.16 (b), conversely we show the detection rates with different camera angles across all heights. Throughout the experiments we see that best face detection result is obtained with transformation 3; the second is with transformation 2; the third is with transformation 1; and with the original images we have the worse result. We also add the detection result with the image rotation method introduced in Section 4.3 for comparison which is shown in Figure 4.17. From it we can conclude that transformation 3 is more suitable than all the rest methods in the common surveillance applications.

Chapter 5 Conclusions and Future Works

 In this chapter we give our conclusions of this thesis in Section 5.1 and some future works in Section 5.2.

5.1 Conclusions

 In this thesis we propose a novel method to improve face detection in a practical condition with vanishing point-based image rectification. Our approach requires only the position of the vanishing point of vertical lines or two vertical lines marked by the user. Compare with the simple image rotation method, our method gives better results and requires much less computational resource. For better detection performance, we further propose a method for reducing false alarms by skin analysis. This method significantly decreases false alarms and only causes negligible additional computation time. Through the proposed framework, the face detection performance is significantly improved for common surveillance camera installation.

5.2 Future Works

 In our future works, a detection scheme which is more suitable for image rectified by the proposed method is considered. For example, since the lower part of the rectified image is generally enlarged, the minimal detection window could be set larger around there for better efficiency. On the other hand, how to properly adopt a multi-view face model for face detection is also considered. By these works, the integrity of the detection method can be enhance and support.

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