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Adaptive Kalman filter with GLBP feature for low resolution face tracking

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Abstract-

Face tracking is useful for many applications, such as video conferencing, gaming, surveillance, facial expression analysis, and animated avatars for web communication. A good face tracker should work stably and accurately for different illuminations and environments, persons, head motions and face expressions. To perform tracking in an illumination-insensitive feature space, called the gradient logarithm field (GLF) feature space and Gabor local binary pattern (GLBP). The GLF feature mainly depends on the intrinsic characteristics of a face and is only marginally affected by the lighting source. In addition, the GLF with GLBP feature is a global feature and does not depend on a specific face model, and thus is effective in tracking low-resolution faces. Fast accurate face tracking by using adaptive kalman filter, it's reduce the abrupt error and detection time. The proposed method work well significant illumination changes and outperforms many state-of- the-art tracking algorithms.

Index Terms—Face tracking, GLF, GLBP, adaptive kalman filter Illumination variations, low-resolution faces.

I. INTRODUCTION

Object tracking is important in many computer visions and pattern recognition large numbers of surveillance cameras have been installed in cities all over the world. The videos captured by these networked cameras contain a lot of useful information, but the sheer volume of video data makes it very difficult to extract useful intelligence information within a reasonable timeframe. While camera designs are well-developed, the software supporting these applications lags behind. With increasing demands placed on video-based surveillance applications, low resolution face tracking under illumination changes is a challenging problem as the amount of information a tracker can use is limited. One effective method to deal with variations in the appearance of a tracked object is to automatically update the tracking model using an online learning approach. For example, the online adaptive appearance model frequently updates the object template, while the online boosting model automatically adjusts the boosting classifier. These online trackers have been highly successful in handling small variations in pose and the occlusion, but do not work well for tracking a face when major illumination changes occurs.

Another possible approach to this problem is to perform illumination normalization before tracking existing illumination normalization algorithms can be roughly classified into two categories: model-based approaches and model-free approaches. Methods based on the 3D morphable model (3DMM) [4] and the face reflectance model are typical examples of model-based approaches. Model-based methods require a high resolution face image to perform image analysis and to fit the model, and so may not be effective for tracking low resolution faces. Under a model-free approach, the underlying rationale is to find illumination invariant features [3] [7]. Model-free methods have been used principally for object recognition, and have not been extensively applied to resolve the low resolution face tracking problem.

B. Contributions

A novel GLF is proposed and the GLBP tracker to resolve the low resolution face tracking problem under illumination changes. In the GLF tracker, the face to be tracked is converted from the intensity space to the GLF feature space. Fast accurate face tracking by using adaptive kalman filter, it's reduce the abrupt error and detection time.

II. RELATED STUDIES

A. Face Tracking Algorithms

Adaptive appearance models are also known as online appearance models. OAM using a particle filter which provides more robust and computationally effective performance [8]. The boosting algorithm uses the face image generated by the tracking algorithm is also known as a wrapped face image to update all the weak classifiers and the voting weights in the boosting algorithm to deal with variations in the appearance of the object.

B.Relative Image Gradient Features

To develop a face recognition system that is robust against lighting variations based on the relative image gradient features. The Fast K-Nearest Neighbour algorithm is used for location of the face and also used to find me candidate pose of the face in the image.

C. Face illumination Normalization Features

In face illumination normalization the large scale and small scale features can be used first single face image is decomposed in to large and small scale features using logarithmic total variation model. Illumination normalization is performed on large scale features while the small scale features are smoothed. Finally a normalized large scale image and smoothed small scale feature image are combined to generate a normalized face image.

D. Limitations of Existing Methods

Face images from videos are usually small, and are of low visual quality due to random noise, blurring, occlusion, etc. In addition, variations in illumination cause rapid changes in the appearance of the face and further complicate the tracking problem. One theoretically possible solution is to apply an illumination normalization method to reduce the effect of the illumination variations before tracking. However, this is not an effective solution because the illumination normalization algorithms do not work well in low resolution face images.

Under model-based approaches, they often require a good degree of face alignment which is not feasible since the face region is really small in the video. By using only GLF they cannot track the low resolution face.

III. PROPOSED METHOD

The proposed method, to mitigate the effects of illumination changes, face images are converted to an illumination insensitive feature space called the Gradient Logarithm Field (GLF) feature space, and Gabor local binary pattern (GLBP). GLF-tracker is developed to resolve the tracking problem.

In addition, the GLF with GLBP feature is a global feature and does not depend on a specific face model, and thus is effective in tracking low-resolution faces. Fast accurate face tracking by using adaptive kalman filter, it's reduce the abrupt error and detection time. The face detector locates faces from the candidates separated from the background using real time updated skin color information.

A.Illumination Insensitive Feature for Low Resolution Face Tracking

Three criteria are suggested for extracting illumination insensitive features which will be effective for low resolution visual tracking.

1) Features should be insensitive to illumination variation. Considering the Lambertian model

$$(I = \alpha < n, l >),$$

This criterion implies that the feature should mainly depend on its intrinsic structure - the albedo α and the surface normal n of a face rather than the illumination component l .

2) Features should be global rather than block or point based. Because the face region in a video is often small, the face image consists of only a small number of pixels, such as 16 × 16. In such a case, block or point-based features are not adequate to characterize the face, and global features are more powerful and flexible.

3) Features should not depend on any face model. A face model often provides extra information that may assist the tracker in dealing with illumination variations, it is not effective for tracking low resolution faces in videos.

This is because most of the model-based algorithms require a high degree of alignment between the face image and the face model, which is challenging for low resolution face images. Moreover, most model based algorithms are computationally expensive, making them not useful for practical real-time face tracking applications.

B.Gradient Logarithm Field

Let I (x, y) be the intensity of a video frame at position (x, y). We assume that the face surface has a Lambertian reflectance with the albedo α(x, y).In the logarithm feature space, the contribution of the albedo is independent of the illumination component. In addition when the gradient is applied, the resulting GLF feature is insensitive to illumination changes during tracking The GLF feature designed in accordance with these criteria describes the intrinsic characteristics of a face. The GLF feature depends mainly on the intrinsic features of the face and is weakly dependent on the lighting source l. By utilizing the visual and motion features present in a video, the GLF feature is suitable for tracking a face in the presence of illumination changes.

C. Gabor local binary pattern

A face image is modeled as a histogram sequence by the following procedure:

(1) An input face image is normalized and transformed to obtain multiple Gabor Magnitude Pictures (GMPs) in frequency domain by applying multi-scale and multi-orientation Gabor filters.
(2) Each GMP is converted to Local Gabor Binary Pattern (LGBP) map.
(3) Each LGBP Map is further divided into non-overlapping rectangle regions with specific size, and histogram is computed for each region.
(4) The LGBP histograms of all the LGBP Maps are concatenated to form the final histogram sequence as the model of the face.

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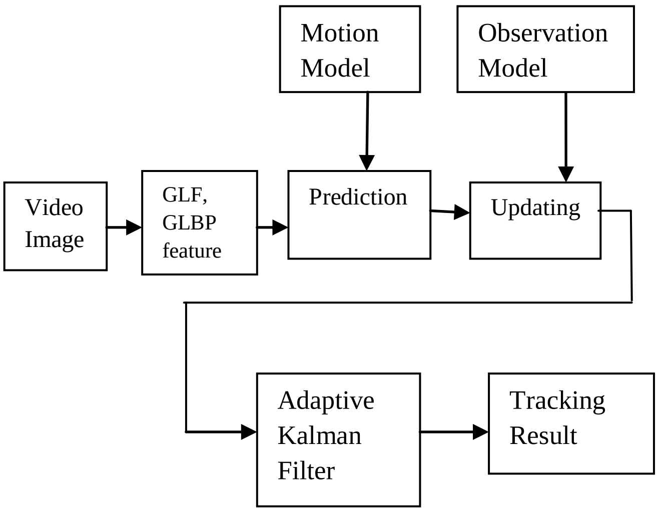

Fig.1.1 Overview of the GLF, GLBP tracker

D. Implementation of the VideoTracker

1) Pre-processing

In pre-processing, first the original input image is read from the database. Next, converts the input image RGB to the grayscale intensity image by eliminating the hue and saturation information while retaining the luminance. After conversion, resize the image by using bicubic interpolation.

2) Feature extraction

The features are extracted by Gabor local binary pattern; and GLF, the operator takes a local neighbourhood around each pixel, thresholds the pixels of the neighbourhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3×3 neighbourhoods, giving 8 bit codes based on the 8 pixels around the central one. In GLF, Let I (x,y) be the intensity of a video frame at position (x,y). The GLF feature F is obtained after two steps. First, the face image is converted into the logarithm space as follows:

$$\log(I) = \log \alpha + \log < n, l > \quad (1)$$

In the logarithm feature space, the contribution of the albedo is independent of the illumination component. In addition when the gradient is applied, the resulting GLF feature is insensitive to illumination changes during tracking.

3) Motion model

A modified version of the adaptive motion model for motion prediction. If the motion of the object between consecutive frames is small, the current motion state can be adequately covered by the particles from the previous state. The model uses a first-order linear predictor that forecasts the velocity of the moving object. This method facilitates the tracking of linear motion. However, it may not work well for more complex motions, such as when the moving object changes direction during tracking, which requires more computations when a large dimensional feature vector is used. The motion model is used to find the difference between the current frame and the next frame. In the motion model used to predict the face and get the motion vector.

4) Observation model

To calculate the likelihood of the observation model, an appearance model is employed. A face is represented using three components: The W component, also known as the wandering model, characterizes two-frame variations which allow both rapid temporal variations and shorter temporal histories. In particular, it is modeled by a Gaussian distribution in which the mean is set as the previous tracked face image. The S component depicts the stable structure in past observations. That is the S component is intended to capture the behavior of the stable face appearance with time. In particular, a Gaussian density distribution is used to model this component. The F component is the fixed template describing the most likely appearance of the face.

5) Adaptive Kalman filter

The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing noise and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system rate. The Kalman filter has numerous applications in technology.

The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. It is a common misconception that the Kalman filter assumes that all error terms and measurements are Gaussian distributed. Kalman original derived the filter using orthogonal projection theory to show that the covariance is minimized. The Kalman filtering estimation at epoch k can be considered as weighted adjustment between the new measurements and the predicted state vector. If too much weight were put to the dynamic model, the estimation would ignore the information from measurements and causes the divergence of the filtering process. By applying a factor S>1 to the predicted covariance matrix to deliberately increase the variance of the predicted state vector, more weight will be given to the measurements.

Adaptive estimation of the measurement noise covariance matrix R with Q fixed. The covariance matrixR represents the accuracy of the measurement instrument measured data means that we trust this measured data less and more on the prediction. Assuming that the noise covariance matrix Q is completely known, an algorithm to estimate the measurement noise covariance matrix R can be derived. Here an IAE algorithm to adapt the matrixR has been derived. The technique known as covariance-matching is used to adapt the covariance matrix R. The basic idea behind this technique is to make the residuals consistent with their theoretical covariance. The innovation sequence has a theoretical covariance factors can be obtained from the Kalman filter algorithm.

$$S_k = H_k P_k H_k^T + R_k \qquad (2)$$

To monitor the discrepancy of S and its actual value a new variable is defined. H_k is filter coefficient, P_k predicated value, R_k is the covariance matrix. This variable is called Degree of Matching (DoM),

$$DoM_k = S_k - C_{rk} \qquad (3)$$

The covariance matrix Q represents the uncertainty in the process model. S_k is the predicated output and C_{rk} is the original output. An increase in the covariance matrix Q means that trust less the process model and more on the measurement. Assuming that the noise covariance matrix R is completely known an algorithm to estimate matrix Q can be derived.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed GLF and GLBP feature. The results of experiments at both feature level and system level. For feature level evaluation, compare the GLF and GLBP feature with existing illumination insensitive features by performing tracking in different feature spaces. For system level evaluation, compare the GLF and GLBP tracker with the incremental visual tracking (IVT) algorithm [5] and the L-1 tracker [4]. Both qualitative and quantitative comparisons show that the proposed GLF and GLBP feature is insensitive to illumination changes and outperforms many state-of-the-art algorithms.

A. Tracking on GLF Feature Versus Tracking on Existing Features

In this experiment, the GLF and GLBP feature with the modified OAM model in the particle filter framework and evaluate it using videos captured outdoors. Each video shows a person is moving towards the camera. The severe illumination changes make tracking challenging. The face region in the video is small, and the quality of which is not good, showing a blurred face. The contrast of the face region is low, and parts of the face are over-exposed. First, apply the proposed method in conjunction with the modified OAM model to an outdoor video captured on a trail.

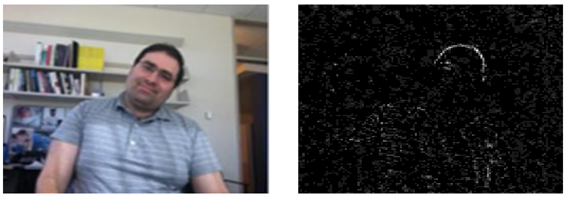

Fig.1. a) Input image b) Difference image

c) Gobar output

TABLE 1: RESULTS OF TRACKING ON DIFFERENT FEATURE SPACES

Video	IVT	L1	GLF	GLBP
You Tube	25	50	80	95
Outdoor Camera	290	170	440	480
Office	420	250	420	450

B. Tracking Low Resolution Faces from Surveillance Videos

To evaluate the performance in tracking faces in low resolution videos, then perform tracking on videos from the CAVIAR database. Given the small size of the face region in the video, the IVT tracker and the L–1 tracker lose the face in frames respectively.

The proposed GLF and GLBP tracker tracks the face properly. Then record the number of frames successfully tracked by the proposed GLF and GLBP tracker, and the IVT tracker, a tracker a Gradient Face feature and a tracker with a Weber Face feature.

TABLE 2: TRACKING RESULT

Number	1	2	3	4	5
GLBP	100	152	173	248	339
GLF	80	148	166	245	248
IVT	75	57	135	240	219
GF	70	53	86	23	57
WF	45	30	55	25	46

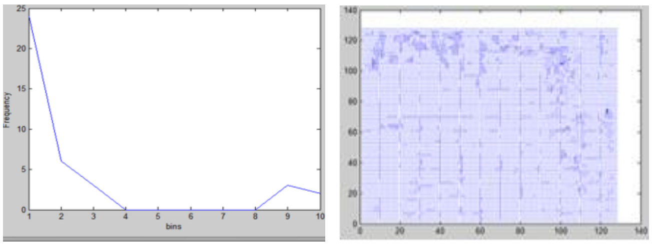

Fig.2. a) GLBP Histogram b) Motion Vector

The proposed tracking framework incorporates an adaptive learning scheme that frequently updates the face template so the change in the GLF and GLBP feature will not affect the tracking results. The proposed tracker works effectively even when illumination changes are occurred.

V. CONCLUSION

GLF and GLBP Feature space tracker is proposed to address the problem of tracking a low resolution face subject to illumination changes. This method transforms image in to the gradient domain first then an illumination insensitive measure is extracted for recognition. This new feature possesses three desirable properties: first, it is a globally dense feature which is effective in low-resolution videos, in contrast with the point based features which may not perform well; second, because the GLF and GLBP feature is easy to implement and does not impose a heavy computational burden, the GLF and GLBP tracker can run in real-time; third, it does not depend on a specific face model.

Gradient face is effective method for illumination problem in face recognition and robust to different lighting and noise. Experiments shows that when implemented using a particle filter, the GLF and GLBP feature space tracker is insensitive to illumination variations and outperforms many state-of-the-art tracking algorithms.

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