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# A Robust Online Method for Face Recognition Under Illumination Invariant Conditions

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A ROBUST ONLINE METHOD FOR FACE RECOGNITION UNDER ILLUMINATION INVARIANT CONDITIONS

*Strictly as per the compliance and regulations of:*

# A Robust Online Method for Face Recognition Under Illumination Invariant Conditions

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## I. Introduction

During the past decade, face recognition has drawn significant attention from the perspective of different applications [1, 2]. A general statement of the face recognition problem can be formulated as follows [2, 3]. Given still or video images of a scene, the problem is to identify or verify one or more persons in the scene using a stored database of faces. Face recognition under varying lighting conditions is challenging, especially for single image based recognition system. Exacting illumination invariant [4] features is an effective approach to solve this problem. However, existing methods are hard to extract both multi-scale and multi-directivity geometrical structures at the same time, which is important for capturing the intrinsic features of a face image. The environment surrounding a face recognition application can cover a wide spectrum – from a well controlled environment to an uncontrolled once, means offline respect to online [5].

In a controlled environment, frontal and profile photographs of human faces are taken complete with a uniform background and identical poses among the participants. In the case of uncontrolled environment, recognition of human faces is to be done at different scales, positions, luminance and orientations; facial hair, makeup and turbans etc. In conditions such as these, invariance to changing lighting is perhaps the most significant practical challenge for face recognition algorithm boosting. The illumination setup in which recognition is performed is in most cases impractical to control, its physics difficult to accurately model and recover, with face appearance differences due to varying illumination often larger in magnitude than those differences between individuals Additionally, the nature of most real-world applications is such that prompt, often real-time system response is needed, demanding appropriately efficient as well as robust matching algorithms [6]. This challenging and interesting problem has attracted researchers from various background i.e., psychology, pattern recognition, neural networks, computer vision and computer graphics [7]. The challenges associated with face recognition can be attributed to the following factors:

- Pose: The images of a face vary due to the relative camera-face pose (frontal, tilted, profile, upside down).
- Presence or absence of structural components: Facial features such as beards, mustaches, and glasses may or may not be present and there is a great deal of variability among these components including shape, color and size.
- Facial expression and emotions: The appearance of faces is directly affected by a person's facial expression and emotions.
- Occlusion: Faces may be partially occluded by other objects. For an example, in an image with a group of people, some faces may partially occlude other faces.
- Image orientation: Face images directly vary for different rotations about the camera's optical axis.
- Imaging conditions: When the image is formed, factors such as lightning and camera characteristics affect the appearance of a face.

In general, face recognition algorithms can be divided into two groups based on the face representation [8], they are:

- Appearance-based which uses holistic texture features and is applied to either whole-face or specific regions in a face image.

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- Feature- based which uses geometric facial features (mouth, eyes, brows, cheeks etc.) and geometric relationships between them.

Holistic based method uses the whole face region as input to the recognition system. Subspace analysis is done by projecting an image into a lower dimensional subspace formed with the help of training face images and after that recognition is performed by measuring the distance between known images and the image to be recognized. The most challenging part of such a system is finding an adequate subspace. Some well known face recognition algorithms for face recognition are Principal Component Analysis (PCA), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA) [9, 10], Incremental LDA allows highly efficient learning to adapt to new data sets. A solution closely agreeing with the batch LDA result can be obtained with far lower complexity in both time and space; there are very few works on incremental learning for sparse LDA. Computational models of faces have been an active area of research since late 1980s, for they can contribute not only to theoretical insights but also to practical applications, such as criminal identification, security systems, image and film processing, and human-computer interaction, etc.

One of the difficulties might be due to the fact that the sparse LDA problem is non-convex and NP-hard. It is not straightforward to design an incremental solution for sparse LDA. Computation cost and memory requirements for training an AdaBoost detector are extremely high. Viola and Jones spent weeks on training a detector with 6060 features (weak learners) on a face training set of 4916, the fast implementation of AdaBoost methods and forward feature selection (FFS) for fast training under online boosting. The illumination based incremental LDA [11,12] algorithm can also be incorporated into a classic semi-supervised learning framework and applied to many other problems in which LDA-like discriminant components are required. However, developing a computational model of face recognition is quite difficult, because faces are complex, multidimensional, and subject to change over time [13, 14].

## II. Illumination Invariant

First, A traditional method for dealing with illumination changes in tracking algorithm has been to use illumination invariant features [1, 11], such as edges. In principle, the entire sets of contour-tracking algorithms are invariant to illumination. However, the computer vision community has recently witnessed the development of several excellent tracking methodologies that are based primarily on tracking photometric, i.e. illumination dependent, variables (such as intensity, color, or texture). Second, Shadow compensation method that compensates for illumination variation in a face image so that the image can be recognized by a face recognition system designed for images under normal illumination condition. Generally, human faces are similar in shape in that they are comprised of two eyes, a nose and a mouth. Each of these components forms a shadow on a face, showing distinctive characteristics depending on the direction of light in a fixed pose. By using such characteristics generated by the shadow, we can compensate for illumination variation on a face image caused by the shadow and obtain a compensated image that is similar to the image taken under frontal illumination. There could be two approaches to illumination invariant face recognition: by a highly nonlinear face matching engine with an illumination variant representation or by an illumination invariant face representation with a less complicated face matching engine. Work in illumination invariant face recognition focused on image representations that are mostly insensitive to changes in illumination the image representations and distance measures are evaluated on a tightly controlled face database which varied face pose, illumination and expression. The image representations include edge maps, 2D Gabor-like filters, first and second derivatives of the gray-level image and the logarithmic transformations of the intensity image along with these representations; under normal illumination condition shown in figure 1.

*Figure 1 :* Common conditions of illumination-invariant

Generally, human faces are similar in shape in that they are comprised of two eyes, a nose and a mouth algorithm for illumination-invariant change detection that combines a simple multiplicative illumination model with decision theoretic approaches to change detection. The core of our algorithm is a new statistical test for linear dependence color of vectors observed in noise. This criterion can be employed for a significance test, but a considerable improvement of reliability for real-world image sequences is achieved if it is integrated into a Bayesian framework that exploits spatial-temporal contiguity and prior knowledge about shape and size of typical change detection masks.

### *a) Extrapolation in Illumination Specifications*

The Recognition in uncontrolled situations is one of the most important bottlenecks for practical face recognition systems. We address this by combining the strengths of robust illumination normalization, local texture based face representations and distance transform based matching metrics [11]. Specifically, here make three main contributions: (i) we present a simple and efficient preprocessing chain that eliminates most of the effects of changing illumination while still preserving the essential appearance details that are needed for recognition; (ii) we introduce Local Ternary Patterns (LTP), a generalization of the Local Binary Pattern (LBP) local texture descriptor that is more discriminant and less sensitive to noise in uniform regions; and (iii) we show that replacing local histogramming with a local distance transform based similarity metric further improves the performance of LBP/LTP based face recognition, which is an illumination invariant signature, to generate face images under arbitrary illumination conditions proposed a method to eliminate the influence due to illumination variation by using a 2D shape model, which separates an input image into a texture model and a shape model for retaining shape information.

An incremental method is tries to alleviate the effect of uneven illumination by using the techniques of local normalization of local binary pattern. In order to handle pose variation, Pentland [2], proposed a view-based Eigen-space method and Huang, used a neural network with a view-specific eigen-faces for face recognition [6, 7].

Ralph Gross, presented the concept of light field to characterize the continuous pose space, and (Liu-2005), are proposed a Gabor-based kernel PCA using Gabor wavelets and a kernel. However, most of 2D image-based methods deal with either illumination or pose variation, and so it is difficult to apply them directly when both illumination and pose variations are present.

*b) Face recognition under low illumination and high Dirt*

It is difficult to exclude impact of human factor upon recognition result. In condition of environment and light factor is fully effective on camera properties and performance and it is defected accuracy of result, although fingerprint identity recognition technology has been mature. However, it is not applicable to a complicated environment under low illumination and high dirt [1, 6, 11]. Low illumination and high dirt identity recognition technology based on facial features has an extensive application prospect since it is needed in many industry sectors. Under low illumination and high dirt environment, compared with other biological features (fingerprint, voice, DNA, etc.), it is the most direct and natural method to use facial features in identity verification technology.

*c) Illumination by Sparse Function representation*

In the statistical signal processing community, the algorithmic problem of computing sparse linear representations with respect to an over complete dictionary of base elements or signal atoms has seen a recent surge of interest. Much of this excitement centers on the discovery that whenever the optimal representation is sufficiently sparse, it can be efficiently computed by convex optimization [9], even though this problem can be extremely difficult in the general case. We exploit sparse representation [1, 2] for robust visual tracking with the intuition that the appearance of a tracked object can be sparsely represented by its appearances in previous frames. One reason often asserted for the superiority of 3D is that it is ''illumination independent'' whereas 2D appearance can be affected by illumination in various ways.

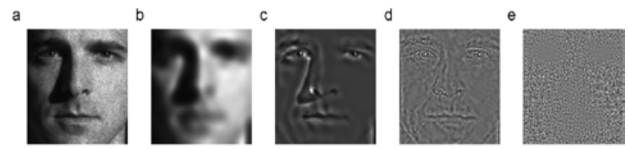


*Figure 2 :* Illumination based image classification (a) Noise-blur-red image, (b) low-pass sub-band, (c) strong edges, (d) weak-edges and (e) noise

The challenges in designing a robust visual tracking algorithm are caused by the presence of noise, occlusion, varying viewpoints, background clutter, and illumination changes [11, 12]. To overcome these challenges, we develop a robust visual tracking framework by casting the tracking problem as finding a sparse approximation in a template subspace. It is true that 3D shape per se is illumination independent, in the sense that a given 3D shape exist the same independent of how it is illuminated. However, the sensing of 3D shape is generally not illumination independent changes in the illumination of a 3D-shape can greatly affect the shape description that is acquired by a 3D sensor. Sparse Bayesian learning is used in; online [2, 5, 10] multiple instance learning is used in to achieve robustness to occlusions and other image corruptions. A new tracker is proposed by bootstrapping binary classifiers with structural constraints, and the tracker is shown to be reliable in long sequence tracking.

## III. Incremental Method Under Face Recognition

In this section we review only the most relevant visual tracking work, focusing on algorithms that operate directly on grayscale images. An incremental method is:

- Sequentially one by one Compute and updates
- Successively updating an earlier model as new observations

Number of incremental versions of LDA have been suggested, which can be applied to on-line learning tasks, an incremental version [5, 10 ] of LDA, which includes a single new data point in each time step. A major limitation is the computational complexity of the method when the number of classes C is large, as the method involves an eigen-decomposition of C × C-sized scatter matrices. Incremental linear discriminant analysis (ILDA) in its two forms: a sequential ILDA and a Chunk, ILDA. In experiments;

*Step (1) updating the within-class scatter matrix; {$S_W$}*
*Step (2) updating the between-class scatter matrix; {$S_B$}*
*Step (3) updating sparse total scatter matrix: {$S_T$}*

Respectively $S_B$, $S_W$, and $S_T$ are well arranged to boosting of each training samples incrementally;

$$\mathbf{S}_W = \sum_{i=1}^{C} \sum_{\mathbf{x} \in C_i} (\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^T \tag{1}$$

$$\mathbf{S}_B = \sum_{i=1}^{C} n_i (\mathbf{m}_i - \boldsymbol{\mu})(\mathbf{m}_i - \boldsymbol{\mu})^T \tag{2}$$

$$\mathbf{S}_T = \sum_{all\ \mathbf{x}} (\mathbf{x} - \boldsymbol{\mu})(\mathbf{x} - \boldsymbol{\mu})^T \tag{3}$$

Here C the total number of classes, $n_i$ the sample number of class i, mi the mean of class i, and $\mu$ the global mean, and total scatter matrix;

$$S_T = S_B + S_W \tag{4}$$

Inspiration for incremental LDA can be drawn from work on incremental PCA. Numerous algorithms have been developed to update eigenbases as more data samples arrive (Table-I). However, most methods assume zero mean in updating the eigenbases except where the update of the mean is handled correctly. In the methods, the size of the matrix to be eigen-decomposed is reduced by using the sufficient spanning set (a reduced set of basis vectors spanning the space of most data variation). As the computation of the Eigen problem is cubic in the size of the respective scatter matrix, this update scheme is highly efficient. Similarly to the proposed tracker is essentially an eigen-tracker, where the eigen-space is adaptively learned and updated online.

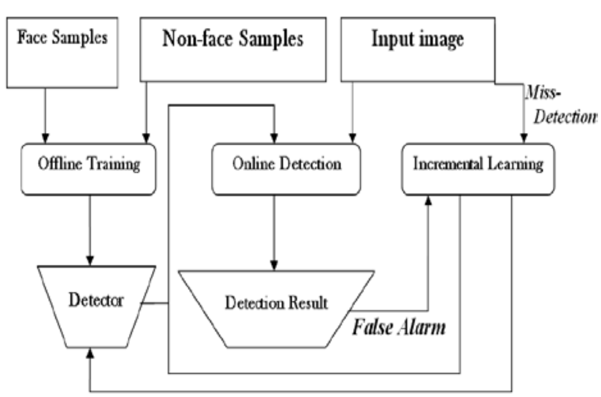


*Figure 3 :* A Framework of incremental learning based Offline and Online Recognition and Detection

The appearance of a target object may change drastically due to intrinsic and extrinsic factors as discussed earlier. The incremental LDA solution of first performs incremental PCA then updates LDA bases. The method similarly takes a single new data point as input and suffers when C is large, introduced a scheme for updating the between-class and within-class scatter matrices. Linearly combines it in an optimal way into a stronger classifier,

$$\mathbf{S(x)} = \boldsymbol{sign} \sum_{i,j=0}^{T} \boldsymbol{Xm_i\ \mu mi} \tag{5}$$

An AdaBoost learning procedure is aimed at deriving Xmi and *μmi*, so that an upper error bound is minimized, therefore, to produce a robust tracker, it is important to adapt the appearance model online, while tracking, to reflect these changes.

## IV. Proposed Framework Working Mechanism

In this Approach we help Sparse approximation is a key technique developed in engineering and the sciences which approximates an input signal, $X_i$, in terms of a "sparse" combination of fixed bases N. Main keys of sparse approximation is;

- High dimension data reduced to Low Samples.
- Matrix based Eigen value Decomposer.
- Comparative with PCA, LDA, etc.

Unlike many existing algorithms which are based upon online boosting, our framework makes use of SLDA based feature selection which aims to maximize the class-separation criterion. It is relies on an optimization algorithm to infer the Maximum A-Posteriori (MAP) weights W that best reconstruct the signal, given the model .The Sparse LDA (SLDA) maximizes a generalized Eigen-value (generalized Rayleigh) quotient) in a cardinality-constrained subspace (variable subset). Sparse LDA methods are preferable over regular LDA methods. In presented a MATLAB technique to compute optimal sparse linear discriminants using branch and bound approaches. Nevertheless, finding the globally optimal solutions for high dimensional data is computationally infeasible. ILDA instead tries to find a nearly optimal solution to this problem in a greedy way. This gives an exact formulation of sparse generalized [1, 2] Eigen Value Decompositions and also suggests a simple post-processing step (variation renormalization) for improving continuous solutions.

**Input**: training data *D* (*person; illumination*),
Filtered data *F* (*person; illumination*),
Sparse function *S*, Filter *F*.
**Output**: estimate S (X, *μ*)

1. **Initialization**
   *p* (X*μ*) = 0
2. **Simulated matching iteration**
   **For all** illuminations *i; j* **and** persons p
3. **Initial separation**

$S_B \geq S_T \leq S_W = \{S, F\}$;

Then *Sparse function equities of Illumination filter*

4. Iteration

For all $p = S_T$

5. Separation given

$\{S, M\} = \{p\ (X, \mu)\}$

6. Update incremental density estimate

$D_{ij} \geq S, F, p\ (X, \mu)$

7. Smooth the output

$S \equiv F \equiv D$

Algorithm 1: Illumination separation with sparse function

Although our algorithms performs well in the most of scenes, it may lose the target if the object experiences a large out-of-plane rotation video is recorded in an indoor environment with large illumination changes from the sunlight, our algorithm is not only suited for planar tracking like experiment but also is effective and efficient compared with ordinary tracking algorithms like Particle Filter and Ensemble Tracking , performance of our proposed object tracking algorithm is more promising to cope with various appearance changes and illumination variance. Some Computational efficiency tested experimentally as;

*Table 1 :* Eigenvalues Computed for Sparse Feuture Extraction.(Input Same)

| Eigenvalues determined using Liu's method | Eigenvalues determined by our experiment |
|---|---|
| 1.00000000e+00 | 3.31404839e+04 |
| 1.00000000e+00 | 2.39240384e+04 |
| 1.00000000e+00 | 1.67198579e+04 |
| 1.00000000e+00 | 1.01370563e+04 |
| 1.00000000e+00 | 6.88308959e+03 |
| 1.00000000e+00 | 7.41289737e+03 |
| 1.00000000e+00 | 2.70253079e+03 |
| 1.00000000e+00 | 5.53323313e+03 |
| 1.00000000e+00 | 3.46817376e+03 |

In experimental purpose, we use Yale B face databases, Sony 16MP camera based image under Intel Quad 64-bit processor with 6GB of RAM, for MATLAB 7.0.1., and generated some critical results as;

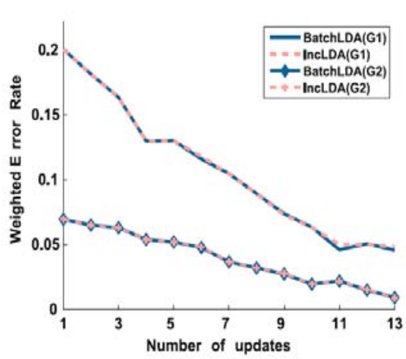


*Figure 5 :* A comparison under online weighted error detection

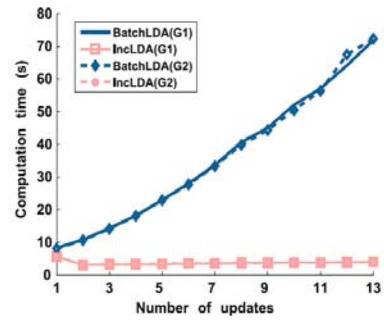


*Figure 6 :* A comparison under online computational complexity

Because the initial training of online ILDA is the same as offline ILDA, here we briefly explain the time complexity of SLDA; Let us assume we choose decision stumps as our weak learners. Let the number of training samples be *N*, finding an optimal threshold of each feature needs *O (N log N)*. Assume that the size of feature sets is *M*. The time complexity for training weak learners is ***O (M N log N)***.

*Table 2 :* Complexity Factor of Figure 6

| Factor | Batch LDA | Incremental LDA |
|---|---|---|
| Time | $O(NM^2+\min(N,M_3)^3)$ | $O(d_{T,1})^3+d_{B,1}+N\ d_{T,3}+3d_{B,3}$ |
| Space | $O(NM_3+NC_3)$ | $O(Nd_{T,3}+Nd_{B,3})$ |

Both time and space complexity of the proposed incremental LDA are independent of the size ($d_T$ and $d_B$); of the total sample set and the total number of classes. During ILDA learning, we need to find mean *O (n)*, variance and correlation *($OT^2$)* for each feature.

## V. Conclusion

In this paper we discuss why the face recognition rate is changed via different illumination invariant case under the optometry of camera or other input source is automatically changed depend the problems of light variant. Major idea is incrementally changed the AdaBoost based object detector can be trained to achieve a high detection performance for online face processing, recognition, detector efficiency, we devise a new edge orientation based features, which is approximately invariant to illumination variance through the theory proof. Besides, to reduce the amount of computation and increase the efficiency of particles, another preprocessed layer is added to cut the particles according to the difference between the average value of edge orientation in the particle region and the original target region. It is obviously seen that our proposed algorithm achieves excellent results even under large illumination variances.

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