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Face Recognition Across Non-Uniform Motion Blur, Illumination and Pose

[1]V.Abirami | [2]V.Jothilakshmi

[1]PG Student, Jayalakshmi Institute of Technology, Dharmapuri,

[2]Asst professor, Jayalakshmi Institute of Technology, Dharmapuri.

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ABSTRACT

Face recognition algorithms perform very unreliably when the pose of the probe face is different from the stored face typical feature vectors vary more with pose than with identity. We propose a generative model that creates a one-to-many mapping from an idealized “identity” space to the observed data space. In this identity space, the representation for each individual does not vary with pose. The measured feature vector is generated by a posecontingent linear transformation of the identity vector in the presence of noise. Existing methods for performing face recognition in the presence of blur are based on the convolution model and cannot handle non-uniform blurring situations that frequently arise from tilts and rotations in hand-held cameras. In this paper, we propose a methodology for face recognition in the presence of space-varying motion blur comprising of arbitrarily-shaped kernels. We model the blurred face as a convex combination of geometrically transformed instances of the focused gallery face, and show that the set of all images obtained by non-uniformly blurring a given image forms a convex set.

1. INTRODUCTION

In face recognition, there is commonly only one example of an individual in the database. Recognition algorithms extract feature vectors from a probe image and search the database for the closest vector. Most previous work has revolved around selecting optimal feature sets. The dominant paradigm is the “appearance based” approach in which weighted sums of pixel values are used as features for the recognition decision.

Turk and Pentland used principal components analysis to model image space as a multidimensional Gaussian and selected the projections onto the largest eigenvectors. Other work has used more optimal linear weighted pixel sums, or analogous non-linear techniques One of the greatest challenges for these methods is to recognize faces across different poses and illuminations. In this paper we address the worst case scenario in which there is only a single instance of each individual in a large database and the probe image is taken from a very different pose than the matching test image. Under these circumstances, most methods fail, since the extracted feature vector varies considerably with the pose. Indeed, variation attributable to pose may dwarf the variation due to differences in identity. Our strategy is to build a generative model that explains this variation.

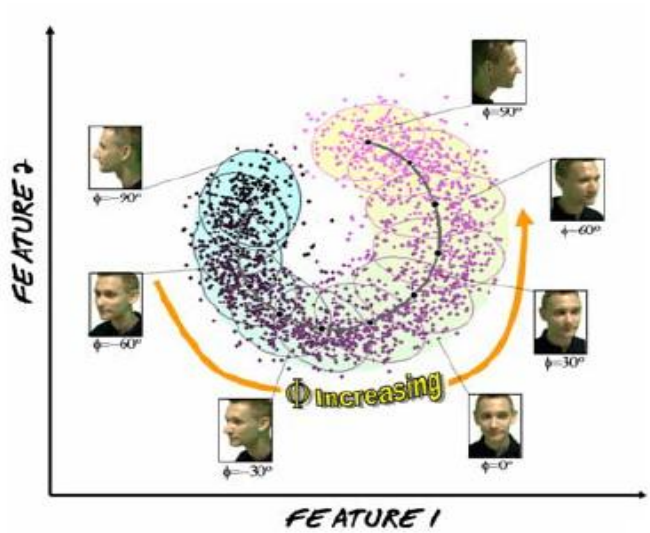

Fig.1. The effect of pose variation in the observation space.

In particular we develop a one-to-many transformation from an idealized "identity" space in which each individual has a unique vector regardless of pose, to the conventional feature space where features vary with pose. A subspace learning approach using image gradient orientations for illumination and occlusion-robust face recognition. Practical face recognition algorithms must also possess the ability to recognize faces across reasonable variations in pose. Methods for face recognition across pose can broadly be classified into 2D and 3D techniques.

2. CONVOLUTION MODEL FOR SPACE-INVARIANT BLUR

As discussed in the introduction, while the convolution model is sufficient for describing blur due to in-plane camera translations, a major limitation is that it cannot describe several other blurring effects (including out-of-plane motion and in-plane rotation) arising from general camera motion.

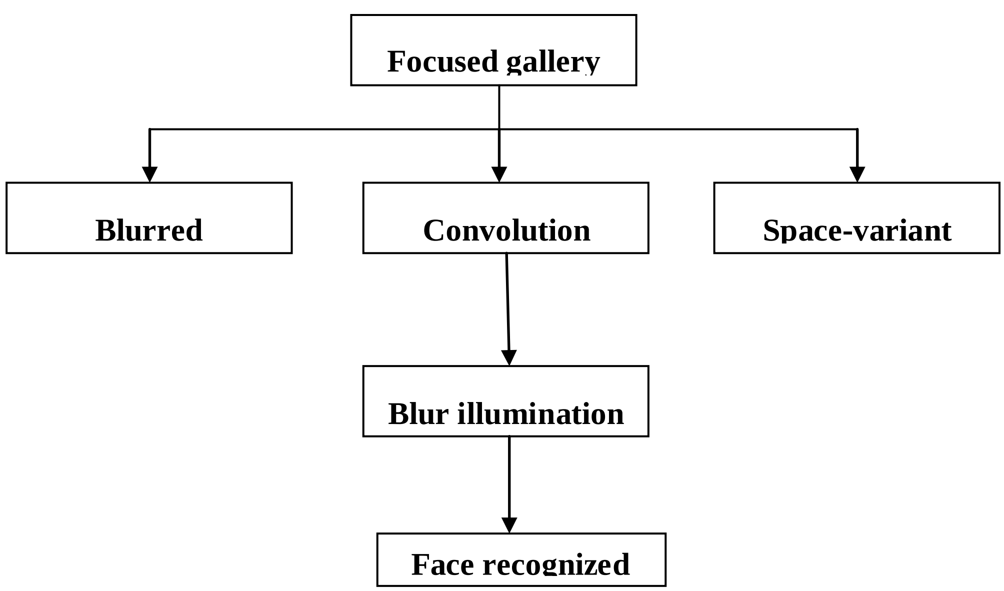

Fig.2. General Block Diagram

In order to demonstrate the weakness of the convolution model in handling images blurred due to camera shake, we synthetically blur the focused gallery image to generate a probe, and provide both the gallery image and the blurred probe image as input to two algorithms- errors between the probe and the gallery reblurred using the camera motion estimated by both the methods.

Observe that except for in-plane translations, where, as expected, the RMS is the same for both the models, in all the other cases, the space-variant motion blur model gives significantly smaller RMS error than the convolution model. Note that the RMS value is smaller than one, except for 6D motion for which it is marginally higher as our algorithm needs to search through a very large set of transformations. Furthermore, we propose extensions to the basic framework to handle variations in illumination as well as pose. We approximate the face to a convex Lambertian surface, and use the 9D subspace model in and the bi-convexity property of a face under blur and illumination variations in the context of the TSF model. Our motion blur and illumination (MOBIL)-robust face recognition algorithm uses an alternating minimization (AM) scheme wherein we solve for the TSF weights in the first step and use the estimated TSF to solve for the nine illumination coefficients in thesecond, and go on iterating till convergence. Face recognition is also useful in human computer interaction, virtual reality, database recovery, multimedia, computer entertainment, information security e.g. operating system, medical records, online banking., Biometric e.g. Personal Identification - Passports, driver licenses , Automated identity verification - border controls , Law enforcement e.g. video surveillances , investigation , Personal Security - driver monitoring system, home video surveillance system.

3. MOTION BLUR MODEL FOR FACES

In many of the access control applications, such as office access or computer logon, the size of the group of people that need to be recognized is relatively small. The face pictures are also caught under natural conditions, such as frontal faces and indoor illumination. The face recognition system of this application can achieve high accuracy without much co-operation from user. When the user leaves for a predetermined time, a screen saver covers up the work and disables the mouse & keyboard. When the user comes back and is recognized, the screen saver clears and the previous session appears as it was left. Any other user who tries to logon without authorization is denied. Security: Today more than ever, security is a primary concern at airports and for airline staff office and passengers. Airport protection systems that use face recognition technology have been implemented at many airports around the world. Since we are fundamentally limited by the resolution of the images, having a very fine discretization of the transformation space **T** leads to redundant computations. Hence, in practice, the discretization is performed in a manner that the difference in the displacements of a point light source due to two different transformations from the discrete set **T** is at least one pixel..

Method	S1	S2	S3	S4	S5
NU-MOB	94.5	90.5	94	97	79
DRBF [19]	81	77	78	71	51
[17]	64.5	59.5	59.5	64.5	37
FADEIN [14]	31.5	23	13.5	25.5	12.5
FADEIN + LPQ [14]	39	17	23	50	6
SRC [27]	31.5	33.5	14.5	47.5	13
[9] + SRC [27]	25.5	25	11.5	40.5	13
DFR [26]	34	31	18.5	34.5	16
[9] + DFR [26]	30	26	16.5	27	13
[9] + LBP [30]	39.5	30	30	44	9.5

Table.1. Recognition Results (%) On The Feret Dataset Using Nu-Mob Along With Comparisons

It should be noted that since the TSF is defined over 6 dimensions, doubling their sampling resolution increases the total number of poses, NT , by a factor of 26. As the number of transformations in the space **T** increases, the optimization process becomes inefficient and time consuming, especially since only a few of these elements have non-zero values. Moreover, the resulting matrix **A** will have too many columns to handle.

4. EXPRIMENTAL RESULTS

We first demonstrate the effectiveness of our MOBIL algorithm in recognizing faces across blur and illumination using two publicly available databases, Note that, as before, we blur the images synthetically to generate the probes as these two databases do not contain motion blur. Therefore, these experiments To perform recognition using MOBIL, we first compute the nine illumination basis images for each gallery image for pose variations in addition to blur and illumination. We once again use the PIE dataset. We begin by selecting four *near-frontal* poses (pitch and yaw angles within $\sim 15°$) and explore the robustness of MOBIL itself to small variations in pose.

Blur Setting	S1		S2		S3		S4		S5	
Illumination	GI	BI	GI	BI	GI	BI	GI	BI	GI	BI
MOBIL	99.75	99.51	99.26	98.04	99.75	99.51	99.75	99.75	93.38	74.51
NU-MOB	93.87	57.60	85.29	47.30	88.24	50.00	97.79	78.19	45.10	12.25
IRBF [19]	93.87	82.11	93.38	79.17	77.45	61.27	97.30	91.67	52.70	40.69
[17]	56.86	24.51	58.58	24.75	50.98	18.87	75.25	37.75	28.92	12.99
FADEIN [14]	18.87	1.96	17.89	1.72	12.01	1.72	17.16	1.72	9.31	1.72
FADEIN + LPQ [14]	71.32	45.59	37.75	19.12	48.04	26.47	67.16	48.04	23.28	12.50
SRC [27]	41.67	35.05	38.97	32.11	25.49	23.28	82.60	67.40	21.32	17.40
[9] + SRC [27]	38.73	31.86	33.33	32.60	21.32	22.79	77.45	58.58	17.89	16.18
DFR [26]	54.66	46.32	50.25	39.71	32.60	30.88	75.25	64.95	22.30	19.85
[9] + DFR [26]	51.23	43.14	46.81	39.46	32.11	27.70	67.40	55.64	21.81	17.65
[9] + LBP [30]	57.60	32.84	43.38	26.72	49.75	28.68	69.36	38.24	24.75	14.71

Fig.2. Recognition Results (%) On The Pie Dataset Using Mobil Along With Comparisons

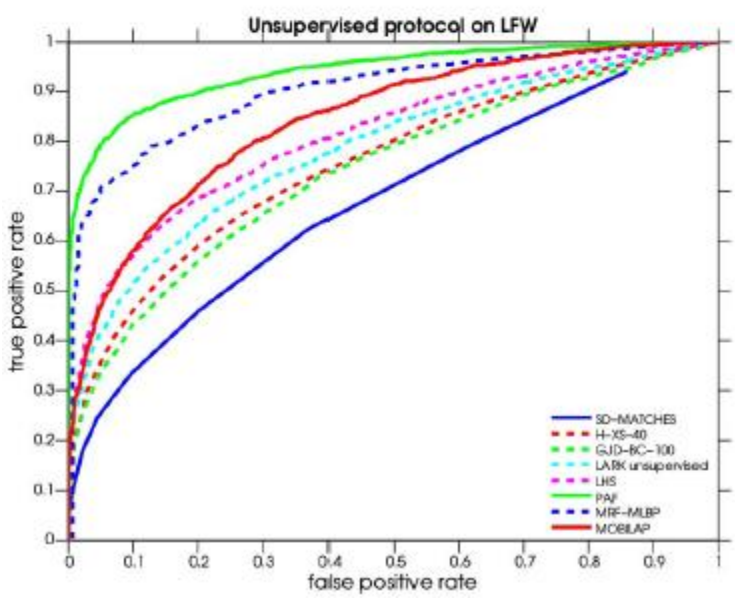

Fig.3. ROC curves of different approaches on the LFW dataset for the Unsupervised protocol.

Finally, we report recognition results on a real dataset that contains face images that we ourselves captured in unconstrained settings. There are 50 subjects in the dataset. The gallery contains one frontal, sharp and well-illuminated image taken outdoor under diffuse lighting. The probe images, 2,200 in number, were captured using a hand-held camera under indoor and outdoor lighting conditions. The probe
images suffer from varying types and amounts of blur, variations in illumination and pose, and even some occlusion and facial expression changes. Although the blur was predominantly due to camera shake, no restriction was imposed on the movement of the subjects during image capture, and, therefore, a subset of these images could possibly have both camera and object motion.

CONCLUSION

We proposed a methodology to perform face recognition under the combined effects of non-uniform blur, illumination, and pose. We showed that the set of all images obtained by non-uniformly blurring a given image using the TSF model is a convex set given by the convex hull of warped versions of the image. Capitalizing on this result, we initially proposed a non-uniform motion blur-robust face recognition algorithm NU-MOB. We then showed that the set of all images obtained from a given image by non-uniform blurring and changes in illumination forms a bi-convex set, and used this result to develop our non-uniform motion blur and illumination-robust algorithm MOBIL. We then extended the capability of MOBIL to handle even non-frontal faces by transforming the gallery to a new pose. We established the superiority of this method called MOBILAP over contemporary techniques. Extensive experiments were given on synthetic as well as real face data. The limitation of our approach is that significant occlusions and large changes in facial expressions cannot be handled.

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