Generalizing Face Quality and Factor Measures to Video

Yooyoung Lee, P. Jonathon Phillips, James J. Filliben, J. Ross Beveridge, Hao Zhang

National Institute of Standards and Technology, Information Technology Laboratory
100 Bureau Drive, Gaithersburg, MD 20899, USA
Colorado State University, the Computer Science Department, Fort Collins, CO 80523, USA
{yooyoung, jonathon, filliben}@nist.gov, {ross, zhangh}@cs.colostate.edu

Abstract

Methods for assessing the impact of factors and image-quality metrics for still face images are well-understood. The extension of these factors and quality measures to faces in video has not, however, been explored. We present a specific methodology for carrying out this extension from still to video. Using the Point-and-Shoot Challenge (PaSC) dataset, our study investigates the effect of nine factors on three face recognition algorithms, and identifies the most important factors for algorithm performance in video. We also evaluate four factor metrics for characterizing a single video as well as two comparative metrics for pairs of videos. For video-based face recognition, the analysis shows that distribution-based metrics are generally more effective in quantifying factor values than algorithm-dependent metrics. For predicting face recognition performance in video, we observe that the face detection confidence and face size factors are potentially useful quality measures. From our data, we also find that males are easier to identify than females, and Asians easier to identify than Caucasians. Finally, for this PaSC video dataset, face recognition algorithm performance is primarily driven by environment and sensor factors.

1. Introduction

Interest in face recognition from video has grown due to the broad range of videos now being taken “anytime and anywhere”; e.g., webcam and mobile devices including cell phone. Recognizing a person’s face from a wide spectrum of video domains presents significant challenges. Unlike static face images, a sequence of video contains multiple frames of the same face and it can display the same object from multiple angles, illuminations, and expressions [1].

There are numerous factors that can affect the performance of video-based face recognition algorithms. Beyond facial characteristics, factors include camera types, location and background, illumination, subject action (e.g., pose), distance, body-visible, algorithmic parameters, etc.

Factor effect analysis (sensitivity analysis) is the study of how the output of an algorithm is affected by the properties of the stimuli (imagery), subjects, and acquisition conditions. A number of studies on factors that affect algorithm performance have been conducted [2][3][4][5]. In face recognition from still images, it is well understood how to assess the impact of factors on algorithm performance; however, generalizing factors from still images to video sequences has not been studied. For example, stating the pose or size of a face in a still image is straightforward; but, what is the pose or size of a face in a video sequence? The sensitivity analysis in the video domain is a relatively new research approach and this paper introduces problems of face recognition in video.

A major contribution of our study is generalizing still-based factor value measures to video sequences. The generalization is based on the distribution of factors estimated from each frame. We conduct a sensitivity analysis based on our new methodology, and demonstrate the methodology with nine factors on three algorithms using the Point-and-Shoot Challenge (PaSC) video dataset [6]. The three algorithms are: the open-source Local Region PCA (LRPCA) [7], the commercial algorithm PittPatt [8], and the Principal Angle (PA) algorithm [9][10] developed by Colorado State University (CSU). Two algorithms (LRPCA and PittPatt) are extensions of still image face recognition (frame-to-frame matching), while the PA algorithm is a method based on matching selected sets of video frames.

Our results demonstrate the effectiveness of our approach on the two classes of video algorithms. This study provides a comparative characterization of the algorithms themselves, and delivers a ranking (and understanding) of key factors that affect algorithm performance.

Specifically, we address the following questions: (i) How do we extend factor measures from still to video imagery? (ii) How do we quantify factors for video? (iii) Are these video factors suitable for sensitivity analysis? What are the important factors that affect the performance of face recognition algorithm in video? (iv) Are these conclusions about factors robustly true over multiple algorithms? (v) Can our analysis methods be used to derive quality measure metrics for predicting general performance of face recognition algorithms?

The impacts/contributions of this paper are as follows: (i) Developing a baseline methodology framework for quantifying/generalizing factor measures for video. (ii) Characterizing current face recognition technology that provides guidance for algorithm improvement. (iii) Leveraging the existing factor studies on stills to the more challenging videos. (iv) Determining the most important factors (and interactions) for face recognition in video.

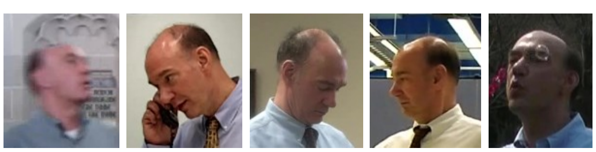
2. Dataset and Algorithm

This section describes the video dataset and the three face recognition algorithms that are used in our evaluation.

2.1. Dataset

The Point-and-Shoot Challenge (PaSC) dataset was recently introduced by Beveridge et al. [6]. The dataset contains both still and video imagery. Since our study focuses on the video sequences, we describe only the video portion of the PaSC dataset. PaSC contains videos that were captured by six different sensors, in six different environmental conditions, with subject movement at a distance. Sensor types can be divided into two classes; handheld and tripod-mounted camera (which we call control). Unfortunately, the five handheld sensors are indistinguishably confounded with the six environments, which means that sensor and environment effects are inextricably mixed. The number of videos is 1,401 for handheld and 1,401 for control.

(a) FVRT2006



(b) Sub-images from the PaSC video dataset

Figure 1 Comparison of (a) traditional face image and (b) challenging face images from PaSC

Figure 1 shows sample images from the (a) FVRT2006 dataset [11] and the (b) PaSC dataset—note the image quality differences between (a) traditional still-based face images and (b) near real-world environment video-based face images. These differences illustrate the challenge of recognizing a face in less-than-optimal environments, while further coping with low video quality.

2.2. Algorithm and Performance

We evaluate three face recognition algorithms; Local Region PCA (LRPCA) [7], Pittsburgh Pattern Recognition (PittPatt) SDK [6], and Principal Angle (PA) [9][10]. LRPCA is an open-source algorithm developed as a baseline for face recognition; PittPatt is a black-box commercial system; PA is a frame-set to frame-set matching algorithm for video-based face recognition. LRPCA and PittPatt are still-based benchmark algorithms used by Beveridge et al. [6].

Algorithm performance is normally assessed by the comparison of video pairs, which we call the query (input) and the target (reference) video. The first step in video-based face recognition is to detect and extract the face region in each frame. The PittPatt SDK was utilized throughout to extract face sub-images within each frame in a video. A face was not detected in every frame; therefore, not every frame in a video contributed a face sub-image. For 62 videos, no faces were detected in any frame, we thus omitted 42 out of 1401 control videos and 20 out of 1401 handheld videos in this study. Our analysis is thus based on the 2740 videos where a face was detected in at least one frame. On average, a face was detected in ~100 frames in each video.

For videos, the first step for the LRPCA and PittPatt algorithms is to compare all extracted face region across two videos (query and target), and compute corresponding similarity scores. After ranking all frame pairs based on the scores, the frame pair with the highest similarity score [6] is then selected. In PA, a random subset of frames from each query and target video is selected and then similarity scores are computed by the principle angle between the two face sub-image sets.

The major difference between the (LRPCA, PittPatt) algorithms and the PA algorithm is that LPPCA and PittPatt ultimately use information from the best frame pair to assess the similarity between two videos, while the PA algorithm uses multiple information extracted across a set of randomly sample frames within a video.

The total number of similarity scores calculated for all possible pairs is approximately 1.87M for both control (1,359) and handheld (1,381) videos. For the control data, the PittPatt algorithm has a 48% verification rate (VR) at a false accept rate (FAR) = 0.01, 23% for PA, and 10% for LRPCA. For the handheld data, the VR at a FAR = 0.01 is 38% for PittPatt, 19% for PA, and 8% for LRPCA. For both control and handheld videos, PittPatt has the highest performance followed by PA and LRPCA.

3. Method

Measuring characteristics of an algorithm assist in the understanding and improvement of already-developed as well as future algorithms [12][13]. We introduce factor measures for quantifying the performance of face recognition algorithms in a video. The goal of the analysis is to provide developers/researchers of face recognition system insight via a ranking of the factors that affect algorithm performance.

3.1. Factors

Out of the many potential factors that can affect algorithm performance, we focus on nine. The factors are based on experience with analyzing the performance of face recognition on still images.

The nine factors are:

1) *Face pose yaw (Yaw)*

The pose yaw is the horizontal face rotational angle in degrees to the left and right. The range of the angles is approximately -40 to 40.

2) *Face pose roll (Roll)*

The pose roll is the angle of rolling/tilting the head to the shoulder. The PaSC video dataset has a range of -30 to 30—outliers exist for this factor (less than 0.001%), which we omitted from our study.

3) *Face size (Size)*

The face size is an approximation of face size as reported by the PittPatt SDK [8]. The raw units for this factor range are 0 to 16 on a logarithmic scale.

4) *Face detection confidence (Confidence)*

The face detection confidence is the PittPatt SDK's self-assessment of correct face detection [8] with a range of 0 to 10.

5) *Environment with Activity (Environment)*

The PaSC video dataset has six different environment settings (namely, ball, phone, paper, easel, canopy, and bubble). This factor is associated with multiple factors. Four key contributing factors are subject activity, back-ground, indoor/outdoor, and lighting condition—in this study, we combine these variables into a single environ-ment factor. For example, in videos taken of the scene ball, a person walks and bounces a ball indoors in front of a complex background.

6) *Sensor*

The PaSC video dataset was collected by six different cameras as shown in Table 1.

Table 1 Sensor (camera) information

Code	Type	Sensor Model	Size	Env. Code
C	Control	Panasonic HD700	1920x1080	All
H1	Handheld	Flip Mino F360B	640x480	canopy
H2	Handheld	Kodak Zi8	1280x720	phone, canopy
H3	Handheld	Samsung M. CAM	1280x720	paper
H4	Handheld	Sanyo Xacti	1280x720	easel, bubble
H5	Handheld	Nexus Phone	720x480	ball

The Panasonic HD HS 700 (coded as C) is only the stationary control camera, while the remaining entries are a handheld camera. The control camera was used in all six environments while the handheld cameras were used in one or two environments. The PaSC dataset has the property that the environment and sensor factors are confounded.

7) *SubjectID (Individual)*

The PaSC data are from 265 individuals. The average number of videos per person is approximately 22.

8) *Gender*

Out of 265 subjects, the gender is fairly balanced between males (55%) and females (45%).

9) *Race*

The PaSC videos contain five different races: Caucasian, Asian-pacific, Black-American, Hispanic, and Unknown. The population is mainly driven by Caucasians (81%) followed by Asian-pacific (12%). The remaining races don't have a sufficient number of subjects for evaluation; we therefore include only Caucasian (White) and Asian-pacific (Asian) in our race study.

The nine factors can be divided by three groups; 1) image/video, 2) environment, and 3) subject. The four factors (yaw, roll, size, and confidence) are the image/video group. The environment group consists of two factors (environment and sensor) and the subject group consists of the three factors (subjectID, gender, and race).

Another grouping of the nine factors is "local" vs. "global". A local factor is a measurable (typically, continuous and ordinal) quantity which describes a feature or characteristic of an image/video that can be predictive of the performance of a recognition algorithm. A global factor is a non-measurable variable (typically, discrete and categorical). For video, local factor values usually change frame-by-frame; whereas global factors normally remain constant over the set of frames or the entire video sequence.

In our case, the image/video factors are local; the remaining five factors from the environment and subject group are global.

We choose these nine factors because most of them have been investigated for still face images, and because they serve as a useful subset to demonstrate our analysis methodology.

3.2. Factor Measures

For the nine factors, we have constructed metrics based on the four factors of the image/video group. We first describe how these factor metrics apply to still images and then discuss their extension to video.

A. Still Image Metrics

Let q (query) and t (target) be two still face images. Given q and t, an algorithm A returns a similarity score

$S_A(q,t)$, where a high score indicates that the subjects from the two face images are likely the same person.

Let X_k denote factor k from a set of factors under consideration. For our study, X_k is yaw, roll, size, and confidence. $X_k(q)$ and $X_k(t)$ are factor k values from images q and t, respectively. A goal of this study is to characterize and predict algorithm performance $S_A(q,t)$ by $X_k(q)$ and $X_k(t)$.

Since a similarity score $S_A(q,t)$ is based on a pair of images, the similarity score not only is related to $X_k(q)$ and $X_k(t)$ individually, but also to $X_k(q)$ and $X_k(t)$ jointly. To measure such behavior of a pair of $X_k(q)$ and $X_k(t)$, we construct a comparative metric. The comparative metric is a function of image factors that produces a quantitative evaluation of the similarity of the two images with respect to that factor. We denote the comparative metric as:

$$M_k(q,t) = g(X_k(q), X_k(t))$$

To return a comparative score $M_k(q,t)$, we use examples of g as follows:

1) Absolute difference (Δ):

$$|X_k(q) - X_k(t)|$$

2) Extremum (max/min):

$$|\,max(X_k(q), X_k(t))\,| \text{ or } min(X_k(q), X_k(t))$$

For absolute difference (Δ), a near-zero comparative score indicates that factor k values are near-identical between images q and t. This absolute difference is used for all four factors. For example, for yaw, a face pose direction from images q and t is near equivalent if Δ is near-zero.

Before discussing the extremum approach, note that two images would be considered "ideal" for comparison if the following four conditions hold 1) both yaw values are near-frontal (near-zero angle), 2) both roll values are near-frontal, 3) both size values are large (higher resolution is better than smaller resolution), and 4) both confidence values are large (higher face detection confidence is better than smaller confidence).

In this light, the extremum (max/min) approach provides the poorer value out of the two images. The choice of max and min depends on the factor; max is used for factors yaw and roll, and min for factors size and confidence. A small max and a large min indicate that factor k between images q and t has the ideal factor characteristics.

B. Extension to Video

This section describes how we extend still-based algorithms to video and encompass X_k from still to video.

Let $q = \{q_1, q_2, \dots, q_Q\}$ frames and $t = \{t_1, t_2, \dots, t_T\}$ frames be sets of face extracted images from the query and target video, respectively. To extend still-based algorithms to video, we first compute similarity scores $S_A(q_i, t_j)$ for all frame-to-frame pairs (q_i, t_j), and then provide a final similarity score $S_A(q,t)$ as follow:

$$S_A(q,t) = f(S_A(q_i, t_i))$$

Usually, f *is* the max, medium, mean, or 90th percentile. Let frame q^* and t^* be the best frame pair such that:

$$S_A(q,t) = S_A(q^*, t^*)$$

For a specific algorithm A, the similarity score $S_A(q,t)$ is thus provided by that particular frame pair (q^*, t^*), where the similarity score was obtained by the f function. For example, LRPCA and PittPatt are still-based face recognition algorithms. To return a similarity score for videos q and t, LRPCA uses the max rule and PittPatt uses the 90th percentile rule [6].

To demonstrate extending X_k from still to video, we look at four single-video metrics; 1) LRPCA best frame pair, 2) PittPatt best frame pair, 3) mean, and 4) sum of mean and standard deviation. The LRPCA and Pittpatt best frame pair are algorithm-dependent metrics, while the other two (mean and sum of mean and standard deviation) are distribution-attribute metrics.

1) Algorithm-dependent

For a single video, the algorithm-dependent metrics provide a factor value from one frame pair out of all frame-to-frame pairs used by a specific algorithm.

To extend X_k from still to video, the factor values $X_k(q)$ and $X_k(t)$ are computed from corresponding frame q^* for the query video and t^* for the target video. The best frame pair method is:

$$X_k(q) = X_{k,A}(q^*) \text{ and } X_k(t) = X_{k,A}(t^*)$$

where A is an algorithm for face recognition, and q^* and t^* are particular frame pairs provided by algorithm A. For example, for the best frame pair for the LRPCA algorithm, we denote the factor yaw values as $Yaw_{lrpca}(q^*)$ and $Yaw_{lrpca}(t^*)$, and for the PittPatt algorithm as $Yaw_{pitt}(q^*)$ and $Yaw_{pitt}(t^*)$.

2) Distribution-attribute

A distribution-attribute metric provides a representative factor value that is derived from the distribution of all frames within a video; thus:

$$X_k(q) = h(q_1, q_2, \dots, q_Q) \text{ and } X_k(t) = h(t_1, t_2, \dots, t_T)$$

Examples of h are the mean (μ) and the sum of mean and standard deviation ($\mu + \sigma$). μ is a location-based metric and $\mu + \sigma$ combines a location-based metric and a spread-sensitive metric.

The comparative metric for videos q and t is:

$$M_k(q,t) = g(h(q_1, q_2, \dots, q_Q), h(t_1, t_2, \dots, t_T))$$

where the g function for videos is the same as the still cases.

For each of these four metrics, we shall consider two functions g (Δ and max/min)—this thus leads to a total of eight metrics for each factor (See Table 2 for further details).

4. Analyses and Results

This section discusses the analysis methods and results for the nine factors for each of the three algorithms (PittPatt, PA, and LRPCA). We first examine the eight factor metrics (four single-video metrics times two comparative metrics) for each of yaw, roll, size, and confidence within the image/video group. Second, we investigate the cross-domain analysis for the environment group factors (environment and sensor). Third, we present results for the subject group factors (subjectID, gender, and race). Finally, for the nine factors, we carry out a sensitivity analysis and provide a ranked list of factors based on their relative importance to the performance of face recognition algorithms in video.

4.1. Yaw, Roll, Size, and Confidence Analysis

The factor metrics introduced in Section 3.2 can be applied to only the local (image/video) factors since these factor values are measurable and change frame-by-frame basis. We choose the four single-video metrics ($lrpca_{best}$, $pittpatt_{best}$, μ, and $\mu+\sigma$) and the two comparative metrics (Δ and min/max) for our experiment. For each of the four factors, Table 2 summarizes the 8 (4 x 2) metrics.

Table 2 Factor metric designations for each of the four factors

Factors	$M_k(q,t)$	Algorithm-dependent		Distribution-attribute	
		LRPCA Best Frame Pair ($lrpca_{best}$)	PittPatt Best Frame Pair ($pittpatt_{best}$)	Mean (μ)	Mean+SD ($\mu+\sigma$)
Yaw	ΔY	ΔY_{lrpca}	ΔY_{pitt}	ΔY_{μ}	$\Delta Y_{\mu+\sigma}$
	$maxY$	$maxY_{lrpca}$	$maxY_{pitt}$	$maxY_{\mu}$	$maxY_{\mu+\sigma}$
Roll	ΔR	ΔR_{lrpca}	ΔR_{pitt}	ΔR_{μ}	$\Delta R_{\mu+\sigma}$
	$maxR$	$maxR_{lrpca}$	$maxR_{pitt}$	$maxR_{\mu}$	$maxR_{\mu+\sigma}$
Size	ΔS	ΔS_{lrpca}	ΔS_{pitt}	ΔS_{μ}	$\Delta S_{\mu+\sigma}$
	$minS$	$minS_{lrpca}$	$minS_{pitt}$	$minS_{\mu}$	$minS_{\mu+\sigma}$
Conf.	ΔC	ΔC_{lrpca}	ΔC_{pitt}	ΔC_{μ}	$\Delta C_{\mu+\sigma}$
	$minC$	$minC_{lrpca}$	$minC_{pitt}$	$minC_{\mu}$	$minC_{\mu+\sigma}$

To assess the relative importance of the 32 (factor, metric) combinations of Table 2, we sort and plot them based on the |correlation coefficients| (%) with the matching scores. Higher correlations indicate greater predictability of algorithm performance.

Figure 2 illustrates the 32 (factor, metric) combinations for each of the three algorithms. The x-axis is the (factor, metric) combinations (1 to 32) ordered by the PittPatt results; the y-axis is |correlation| (%). The red dotted line is the ranking for PittPatt, green for PA, and blue for LRPCA.

Figure 2 indicates that the two metrics ($minC_{\mu}$ and $minC_{\mu+\sigma}$) are the best for all three algorithms—note that both $minC_{\mu}$ and $minC_{\mu+\sigma}$ emanate from the distribution-attribute group. With obvious exceptions, the general trend of all three algorithms is similarly decreasing.

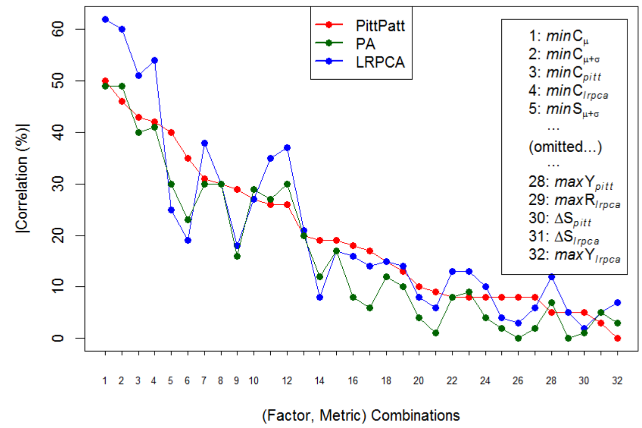


Figure 2 Ranking of the 32 (factor, metric) combinations for three algorithms and for all data (control+handheld)—ordered by the PittPatt results

Based on the ranking of the 32 (factor, metric) combinations, a detailed analysis (not shown) indicates that for the comparative metrics, Δ is the best for yaw and roll, while the extreme (min) is the best for size and confidence. We thus extracted the best comparative metric for each of the four factors and reordered the factors for the PittPatt case as shown in Table 3.

Table 3 Ranking (1=best) of the chosen comparative metrics with the four single-video metrics for PittPatt (control+handheld)

Factors	M_k	μ	$\mu+\sigma$	$lrpca_{best}$	$pitt_{best}$	Ave.
Confi.	$minC$	1	2	4	3	2.5
Size	$minS$	6	5	9	14	8.5
Yaw	ΔY	11	11	7	20	12.3
Roll	ΔR	18	19	22	22	20.3
Average		9.0	9.3	10.5	14.8	

For PittPatt, Table 3 indicates that confidence/$minC$ has the highest correlation with algorithm performance (with an average rank of 2.5) followed by size/$minS$ (8.5), yaw/ΔY (12.3), and roll/ΔR (20.3). For single-video metrics, the distribution based metric μ has the highest rank (9.0) and $\mu+\sigma$ the second highest (9.3). On the other hand, the algorithm-dependent metric $PittPatt_{best}$ has the lowest average rank (14.8).

We now compare the algorithm-dependent ($lrpca_{best}$, and $pittpatt_{best}$) approach with the distribution-attribute (μ and $\mu+\sigma$) approach. For this analysis, we use the block plot shown in Figure 3. The four items within each block are the four metrics, with blue indicating algorithm-dependent and red indicating distribution-attribute; the plot is based on the handheld data ordered by confidence ($minC$), size ($minS$), yaw (ΔY), and roll (ΔR).

In Figure 3, the x-axis consists of the four factors for each of the three algorithms. The y-axis is the |correlation| (%) of the four metrics with the matching scores.

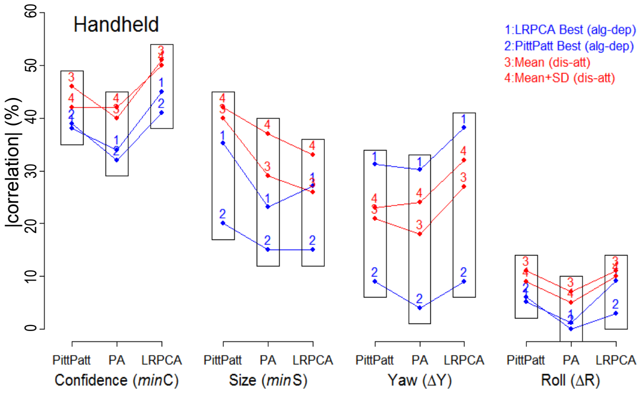


Figure 3 Comparison of the algorithm-dependent (alg-dep) and distribution-attribute (dis-att) approach for handheld

For this handheld data and across all three algorithms, the distribution-attribute metrics (μ and $\mu + \sigma$) perform better than the algorithm-dependent metrics—with exception of yaw (ΔY). This conclusion also holds for control data.

In summary, for video-based face recognition, the distribution-attribute approach can be more effective than the algorithm-dependent approach for measuring factor values. We also observe that the face detection confidence followed by face size may serve as a quality measure metric for predicting video-based face recognition performance.

4.2. Cross-Domain Analysis for Environment and Sensor

The cross-domain analysis here examines the effects of the environment or sensor factors on the algorithm performance. Since the environment factor is confounded by the sensor factor (especially for handheld), we examine a cross-domain environment effect for control and handheld separately. Figure 4 shows the results for handheld-only.

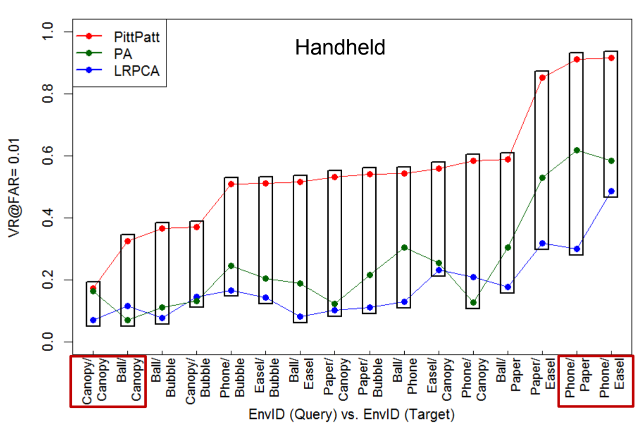


Figure 4 Performance ranking by environment combinations (16 pairs) for three algorithms (handheld-only)—ordered by the PittPatt results

Considering query and target pairs, the PaSC video dataset yielded a total of 16 (out of 36 possible) environment combinations.

The x-axis illustrates all 16 combinations, and the y-axis is the VR at FAR=0.01. In general, for both control and handheld cases, the ranking follows a similar pattern for all three algorithms. For the handheld results in Figure 4, the pair {canopy, canopy} has the lowest VR for PittPatt and LRPCA, and {ball, canopy} for PA, while the pair {phone, easel} is the highest for PittPatt and LRPCA, and {phone, paper} for PA. The plot (not shown) from the control camera has near-identical results.

We also observe that all canopy or bubble pairs have a lower performance, while ball, phone, paper, and easel have a higher performance. This observation is robustly true for all three algorithms for both control and handheld data. Interestingly, both the canopy and the bubble scenes were taken outdoors while the others were taken indoors.

The performance-ranking for sensor pairs has a relatively similar pattern for all three algorithms. The results show that pair {H4, H4} has the lowest performance for both PittPatt (16%) and LRPCA (0%), and {H2, H2} for PA (2%). On the other hand, {H2, H3} has the highest for both PittPatt (69%) and PA (38%), and {H2, H4} for LRPCA (25%). Note that the environment and sensor factors may have an interaction effect (due to environment and sensor confounding in the PaSC dataset).

4.3. SubjectID, Gender and Race Analysis

For subjectID, we observe that effect of subject on algorithm performance is markedly different among the three algorithms—the best subjects for PittPatt may not be the best subjects for PA and LRPCA. For gender, males have a higher verification rate than females. For race, Asians have a higher verification rate than Caucasians. For the PaSC dataset, the gender and race conclusions are robustly consistent across all three algorithms.

4.4. Sensitivity Analysis

This section discusses the relative importance of the nine factors on algorithm performance. We estimate each factor's effect and compare its relative effect on the performance of the three algorithms. Figure 5 shows PittPatt main effects plots for the nine factors for both control and handheld data; the results from control-only and handheld-only data are relatively similar to the results from all data for three algorithms, we thus illustrate the main effect plot for all data (control+handheld) and for PittPatt.

The x-axis lists the factor name and its (selected) discretized settings, and the y-axis is the response (VR at FAR=0.01).

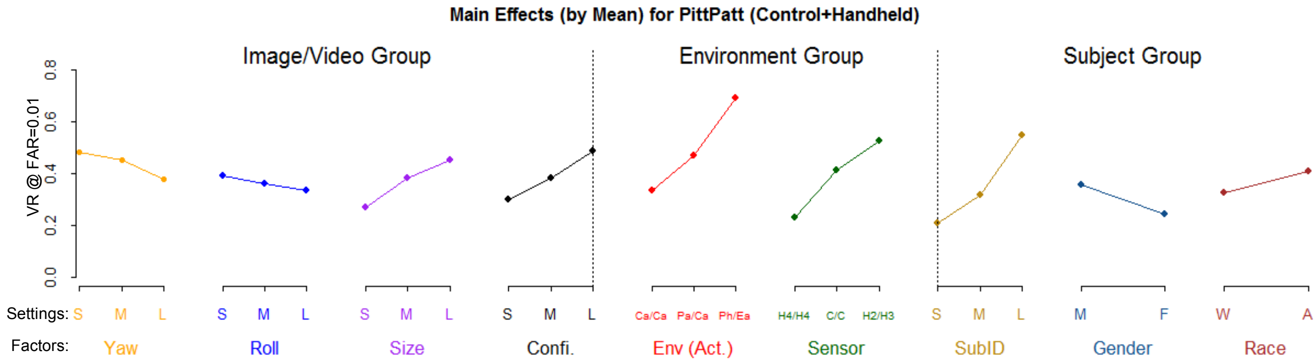


Figure 5 Summary of the nine factors effect for PittPatt (control+handheld)

A steeper line (large magnitude) indicates that a factor has a greater effect on the performance while a flatter line indicates that the factor has a lesser effect.

Based on the results in Section 4.1, the four factors within the image/video group are computed from the single-video factor metric "mean", with the comparative metric Δ for yaw and roll, and min for size and confidence.

The choice of the settings was done as follows: For each of the four factors from the image/video group, we marginally divided the settings into three levels: S (small), M (middle), L (large). For the environment group factors, we select combinations of the lowest, medium, and highest VR. In the PittPatt case, for environment, the lowest pair is {canopy, canopy}, the medium {paper, canopy}, and the highest {phone, easel}. For sensor, the lowest of the pair is {H4, H4}, the median {C, C}, and the highest {H2, H3}. For the subject group factors, the subjectID settings were divided into the three levels (S, M, L) based on the ordered individual performance. The gender factor has two levels (M: male, F: female), and the race with the two levels (W: White/Caucasian, A: Asian).

Within the image/video group, for PittPatt, confidence and size have the highest effect on performance followed by yaw. For PA, these four factors have less effect on performance and the most important factor is confidence and size. For LRPCA, these four factors have little effect on algorithm performance. Within the environment group, the environment with activity factor has slightly higher effect than sensor. For the subject group, subjectID has the highest impact on performance for PittPatt but a lesser effect for PA and LRPCA. For each of the three groups, the environment group has the highest effect on performance across all three algorithms. Our methodology is also applied in [14] with similar conclusions. The conclusions of the factors such as environment, gender, and race agreed with a previous still-image based study conducted by Givens et al [2] and Lui et al [3].

Though independence issues are a consideration, the pair (query and target) sample sizes are markedly large, which yield negligibly small confidence limits and corresponding statistical significance.

For all (control+handheld) videos and for PittPatt, the ranked list of the relative importance (with due caution to environment and sensor confounding) of the nine factors is as follows; 1) environment with Activity, 2) subjectID, 3) sensor, 4) confidence, size, yaw, and 5) gender, race, roll.

In summary, the ranked lists are relatively similar across all three algorithms. Out of the nine factors, environment with activity is the most important and {gender, race, and roll} are the least important factors—this conclusion is robustly true across all three algorithms for both control and handheld.

5. Discussions and Conclusions

We presented an analysis method to examine factor effects on face recognition algorithms in a video. Using the PaSC video dataset, nine factors from three groups (image/video, environment, and subject) were investigated to examine their impacts on the performance of three algorithms (PittPatt, PA, and LRPCA). We also introduced and studied four single-video and two comparative factor metrics for characterizing face recognition algorithms in a video.

For the comparative metrics, and for the four factors (yaw, roll, size, and confidence), we found that the "extremum (min)" approach performed better for confidence and size, while the "difference (Δ)" approach performed better for yaw and roll. For single-video metrics, the distribution-attribute metrics (μ and $\mu + \sigma$) performed better than the algorithm-dependent metric. Thus, the distributional approach is generally more effective to quantify factor values for video-based face recognition. These conclusions were robustly valid for all three algorithms and for each of control and handheld videos. We also observed that the local factors (e.g., face detection confidence and face size) could potentially serve as quality measures for predicting face recognition performance in video.

We next conducted a cross-domain analysis for factors environment and sensor within the environment group. For environment, we reaffirmed that videos taken outdoors are indeed more challenging than indoors for recognizing a person using the face—this conclusion agreed with a previous study on the FRVT2006 dataset done by Beveridge et al. [4]. We observed that the environment and sensor factors have an interaction effect due to these two factors being confounded in our PaSC dataset.

For subject group, the effect of subjectID on algorithm performance is markedly different among the three algorithms. For gender, males had a higher verification rate than females, and for race, Asians had a higher verification rate than Caucasians. These gender and race conclusions were robustly consistent across all three algorithms, and for both control and handheld data.

In summary, over the nine factors, environment with person's activity had the largest effect on algorithm performance in a video, followed by subjectID and sensor (confounded)—these conclusions were valid for each of the three algorithms, and for both control and handheld. We thus conclude that scene/action matters significantly for face (human) recognition—this implies reinforcing the importance of isolating a subject from the background, or characterizing a subject's action.

The examination of the effects of factors on the performance of biometric algorithms in the video domain is a relatively new research approach, and it extends the important existing factor studies on stills. We believe that the methodology demonstrated herein can be applied to other video-based biometric systems (e.g., gait, body, iris). The methods could also be utilized in related law-enforcement applications, for example, in providing a means to assess the relative importance of facial features, which would be an invaluable tool for security and forensics.

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References

[1] S. K. Zhou and R. Chellappa, "Beyond one still image: Face recognition from multiple still images or a video sequence," *Face Processing: Advanced Modeling and Methods*, pp. 547–567, 2005.

[2] G. Givens, J. R. Beveridge, B. A. Draper, P. Grother, and P. J. Phillips, "How features of the human face affect recognition: a statistical comparison of three face recognition algorithms," in *Computer Vision and Pattern Recognition (CVPR2004)*, 2004, vol. 2, pp. II–381.

[3] Y. M. Lui, D. Bolme, B. A. Draper, J. R. Beveridge, G. Givens, and P. J. Phillips, "A meta-analysis of face recognition covariates," in *Biometrics: Theory, Applications, and Systems (BTAS)*, 2009.

[4] J. R. Beveridge, G. H. Givens, P. J. Phillips, B. A. Draper, and Y. M. Lui, "Focus on quality, predicting FRVT 2006 performance," in *Automatic Face & Gesture Recognition (FG)*, 2009.

[5] P. J. Phillips, J. R. Beveridge, D. S. Bolme, B. A. Draper, G. H. Given, Y. M. Lui, S. Cheng, M. N. Teli, and H. Zhang, "On the existence of face quality measures," in *Biometrics: Theory, Applications and Systems (BTAS)*, 2013.

[6] J. R. Beveridge, P. J. Phillips, D. Bolme, B. A. Draper, G. H. Givens, Y. M. Lui, M. N. Teli, H. Zhang, W. T. Scruggs, and K. W. Bowyer, "The Challenge of Face Recognition from Digital Point-and-Shoot Cameras," *Biometrics: Theory, Applications, and Systems (BTAS)*, 2013.

[7] P. J. Phillips, J. R. Beveridge, B. A. Draper, G. Givens, A. J. O'Toole, D. S. Bolme, J. Dunlop, Y. M. Lui, H. Sahibzada, and S. Weimer, "An introduction to the good, the bad, & the ugly face recognition challenge problem," in *Automatic Face & Gesture Recognition and Workshops (FG)*, pp. 346–353, 2011.

[8] Pittsburgh Pattern Recognition, "PittPatt SDK v5.2.2 Documentation: Detection User's Guide." .

[9] O. Yamaguchi, K. Fukui, and K. Maeda, "Face recognition using temporal image sequence," in *Automatic Face & Gesture Recognition (FG),* pp. 318–323, 1998.

[10] J. R. Beveridge, B. A. Draper, J. M. Chang, M. Kirby, H. Kley, and C. Peterson, "Principal angles separate subject illumination spaces in YDB and CMU-PIE," in *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 31, no. 2, pp. 351–363, 2009.

[11] P. J. Phillips, W. T. Scruggs, A. J. O'Toole, P. J. Flynn, K. W. Bowyer, C. L. Schott, and M. Sharpe, "FRVT 2006 and ICE 2006 Large-Scale Experimental Results," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 32, no. 5, pp. 831–846, May 2010.

[12] R. B. Vaughn Jr, R. Henning, and A. Siraj, "Information assurance measures and metrics-state of practice and proposed taxonomy," in *Proceedings of the 36th Annual Hawaii International Conference on System Sciences,* 2003.

[13] Y. Lee, J. J. Filliben, R. J. Micheals, and P. J. Phillips, "Sensitivity analysis for biometric systems: A methodology based on orthogonal experiment designs," *Computer Vision and Image Understanding*, vol.117, pp. 532–550, Jan. 2013.

[14] J. R. Beveridge, H. Zhang, P. J. Flynn, Y. Lee, V. E. Liong, J. Lu, M. A. Angeloni, T. F. Pereira, H. Li, G. Hua, V. Struc, J. Krizaj, and P. J. Phillips, "The IJCB 2014 PaSC Video Face and Person Recognition Competition," in *Proceedings of the International Joint Conference on Biometrics (IJCB)*, 2014.