Illumination-invariant Face Recognition by Kalman Filtering

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Abstract – *We propose a novel algorithm for the identification of faces from image samples. The algorithm uses the Kalman filter to identify significant facial traits. Kalmanfaces are compact visual models that represent the invariant proportions of face classes. We employ the Kalmanfaces approach on the Physics-based Face Database (provided by the University of Oulu), a collection of face images that were recorded under varying illumination conditions. Kalmanfaces show robustness against luminance changes and outperform the classic Eigenfaces approach in terms of identification performance and algorithm speed. The paper discusses Kalmanfaces extraction, application, tunable parameters, experimental results and related work on Kalman filter application in face recognition.*

Keywords – *Face Recognition, Kalman Filtering, Eigenfaces, Statistical Mean, Face Databases*

1. INTRODUCTION

Face recognition is one of the classic areas of pattern recognition [1]. Applications are manifold ranging from video surveillance to content-based retrieval. Research focuses on two problem areas: detection of faces in visual media streams and identification of detected faces. Face identification comprises of holistic approaches (e.g. Eigenfaces [2]), classification approaches (Linear Discriminant Analysis, etc.) and regression approaches (e.g. Neural Networks).

We propose a novel holistic approach for face identification from image samples that uses a simplified Kalman filter [3]-[4] to detect *luminance-invariant* face features. The Kalman filter is frequently employed in face recognition for face detection in videos. However, the author is not aware of proposals to use the powerful linear data processing capabilities of the Kalman filter for the extraction of face features.

We employ the Kalman filter on a dataset of face images that were recorded under varying illumination conditions. These data are distinguished by high variations of the *luminances* of characteristic face elements (nose tip, eyes, etc.) and partial invisibility of the typically considered face features (eyes, mouth, etc.). The results for classic Eigenfaces confirm that face recognition under varying illumination is a hard to solve problem. The Kalman filter considers variances in the data analysis process. Hence, it should be an advantageous element of a model for robust face identification under such circumstances. The paper explains the extraction of Kalmanfaces in Section 2 and discusses experimental results in Section 3.

2. KALMANFACES APPROACH

2.1. Kalmanfaces Extraction

The Kalmanfaces approach identifies the most likely face class for an image by feature similarity. It expects every face class (person) to be represented by a sequence of image samples. The number of inputs should not be smaller than 3-5 for reasonable application of the Kalman filter. Each face class is represented by a single feature vector that is extracted as follows:

1. *Image normalization*. All face images are transformed to luminance matrices of the same size (for example, just three by three pixels). Every pixel represents one face *region*.
2. *Averaging*. An average face is computed from the normalized images by a Kalman filter ("Kalmanface").
3. *Feature extraction*. Only those regions of the Kalmanface are considered as features that are sufficiently invariant. The luminance variance of a region must not exceed a certain threshold.

The Kalman filter is applied in the second step to compute a class average that represents the facial traits adequately. Fig. 1 shows an example. The face class consists of about ten images (*a*). Element *b* shows the mean image, element *c* shows the Kalman-averaged image. As can be seen, the Kalman-averaged image contains a large amount of the high-frequency information present in the examples. It is *almost invariant* against the varying lighting in the samples. The average image *b* is not able to capture relevant facial traits properly. It consists of very dark self-similar pixel neighbourhoods.

Kalmanface averaging is performed as follows. We assume the class samples to be a temporal sequence and compute the Kalman estimate *for each pixel*:

$$x_t = x_{t-1} + k_t\left(x_{t-1} - l_t\right) \qquad (1)$$

x_t is the estimate of the pixel average at time t (the tth example image), l_t is the luminance value and k_t is the Kalman weight given in equation (2) (depending on the luminance variances at times t and $t-1$).

Fig. 1. Kalmanface example. Kalmanface *c* is constructed from face class *a* (*b* is the mean image).

$$k_t = \frac{\sigma_{t-1}}{\sigma_{t-1} + \sigma_t} \qquad (2)$$

Weight k_t is the crucial factor in this simplified version of the Kalman filter that does not consider complex noise models and weights for the measurements l_t. k_t approaches zero if the variance increases, i.e. if the luminance of a pixel changes from sample to sample. In this case, the Kalman filter trusts on the earlier estimate and disregards l_t. k_t approaches *1* if the variance decreases. In this case, the Kalman filter trusts on the luminance. The short time behaviour of the Kalman filter is to eliminate variances. In the long term Kalman filtering results in an average that preserves the properties of the input sequence (see Fig. 1). It processes all information that is provided [3].

In the third step, features are extracted from the Kalman-averaged face. We select those pixels as face features that have a luminance variance σ_t below a certain threshold. Hence, the face feature vector consists only of those traits that are relatively invariant over the samples.

2.2. Similarity Measurement

Kalmanfaces querying is a straightforward application of the vector space model. We assume an Euclidean feature space. The query example is normalized to the same number of pixels as the face classes and compared to each of the Kalmanfaces. That is, one distance measurement operation per individual in the database has to be performed. We suggest a first order Minkowski distance for dissimilarity measurement.

$$d(f,c) = \frac{\sum_{i}^{n_c} |f_i - c_i|}{n_c} \qquad (3)$$

The dissimilarity of a face f to a face class c (represented by a Kalmanface) depends on the first order distance normalized by the feature vector size n_c of the face class. Only those pixels are considered for distance measurement that satisfy the variance condition stated above. This feature selection may (and usually will) change from face class to face class.

2.3. Discussion

We propose the Kalmanfaces approach as a solution for face detection in environments with high variance (e.g. varying camera angles, varying lighting). In particular, Kalmanfaces have the following advantages:

1. Face class information is easily extensible. One further iteration of the Kalman filtering process is sufficient to add a new face image of an already registered person.
2. The application of the variance condition leads to short feature vectors. Distance measurement of short vectors by a linear function allows for fast querying.
3. The length of the feature vectors is generally independent of the number of individuals in the database. Effective discrimination will require longer feature vectors for larger databases. However, database size and feature vector length are not as closely linked as, for example, in the Eigenfaces approach. In classic Eigenfaces the number of weights equals the number of face classes [2].

The proposed Kalmanfaces approach does not try to influence the order of the images that are employed in the filtering process. If k_t is assumed constant, then the Kalman filter tends to lay a higher weight on the last samples than on the first. However, we found that in practical application k_t alone determines the extent to which samples are represented in Kalmanfaces. A technical report that describes these findings will be made available on the author's website by the time of the workshop.

The Kalman filter weight (equation 2) and the variance threshold cause – to a certain extent – opposite effects. The application of k_t leads to a maximum of entropy in the Kalmanfaces. However, only those pixels are picked by the variance condition that are sufficiently invariant ("trustworthy"). Hence, Kalmanfaces feature vectors represent face classes by a maximum of information at a controllable level of trust.

3. EXPERIMENTS AND RESULTS

Below, we compare the performance of Kalmanfaces to the Eigenfaces approach [2] on the Physics-based

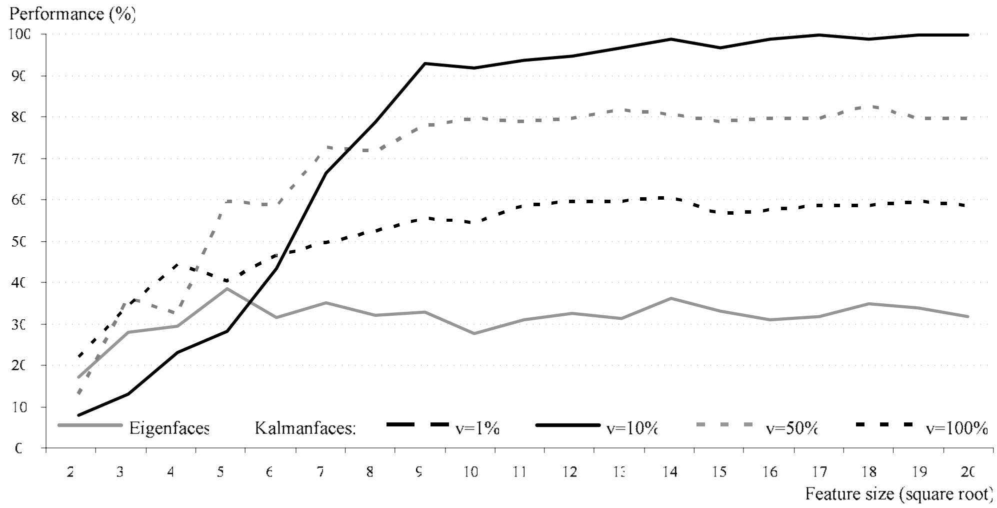

Fig. 2. Performance of Eigenfaces and Kalmanfaces at different variance threshold levels (not smoothed). "v=50%" means that the Kalmanfaces variance threshold is set to 50%.

Face Dataset provided by the University of Oulu [5]. Every Eigenfaces class Ω_i is averaged over *all* class members (highest quality). The Oulu dataset comprises of photographs showing individuals that were recorded with the same expression from slightly varying camera angles under highly variant lighting conditions. Kalmanface averaging is employed with the following approximation for all pixels of the first two faces (otherwise, k_1 would always be zero):

$$x_1 = \frac{l_0 + l_1}{2} \qquad (4)$$

3.1. Face Retrieval Performance

Fig. 2 summarizes the face identification performance depending on the feature size, i.e. the frame length in pixels of the quadratic face images. Kalmanfaces that use all feature elements (variance threshold of 100%, depicted as "v=100%") perform comparable to Eigenfaces. Interestingly, Eigenfaces and Kalmanfaces with a variance threshold of 50% or more (all features with at most 50% of the maximum variance are used) fail in reaching 100% face identification performance independently of feature size. Obviously, these parameterizations lead to feature vectors that contain partially misleading elements (those with high variance). Kalmanfaces with a variance threshold of 50% perform already significantly better than Kalmanfaces with a threshold of 100% (a gap of about 20% face identification performance).

However, the best performance can be observed for Kalmanfaces with a variance threshold of 20%. At this level the relationship of entropy and invariance in the feature data leads to optimal results. The parameterization reaches a face classification performance of 100% for features of 14 by 14 pixels. Even for very short feature vectors it is already superior over Eigenfaces. A Kalmanface of 6 by 6 pixels and a variance threshold of 20% lead to a feature vector of approximately 23 (6^2*0,65; see Subsection 3.2) elements. At a feature size of about 127 elements (14^2*0,65) the face identification performance reaches the ceiling. For more accurate Kalmanfaces performance remains almost constant at the optimal recognition level.

The results reflect the seriousness of the investigated recognition problem in the relatively weak performance of the Eigenfaces. We have decided to compare Kalmanfaces to this approach, because they are structurally similar. Firstly, both are holistic approaches. That is, they derive face similarity from the entire image data and do not try to extract particular facial features. Secondly, both methods neglect semantic knowledge. In fact, both methods could be applied to arbitrary object recognition problems. Eventually, neither Kalmanfaces nor Eigenfaces require a training process for sample-based classification. Without doubt, a feature-based approach that makes use of kernel-based learning (e.g. a Support Vector Machine) would be able to outperform Eigenfaces (especially, on a small but well-defined scientific database). However, it would be difficult to find a relation of such results to the performance gain achieved by Kalmanfaces with increasing feature size.

Clearly, the variance threshold is the decisive parameter in the application of Kalmanfaces. At a threshold of 50% Kalmanfaces outperform Eigenfaces clearly, at 20% retrieval performance is soon optimal. At very small values (1% and lower) performance decreases. Precise judgement of the variance threshold is crucial for retrieval performance.

3.2. Relevance of the Variance Condition

The variance threshold determines which features are used for Kalmanfaces similarity measurement. Only

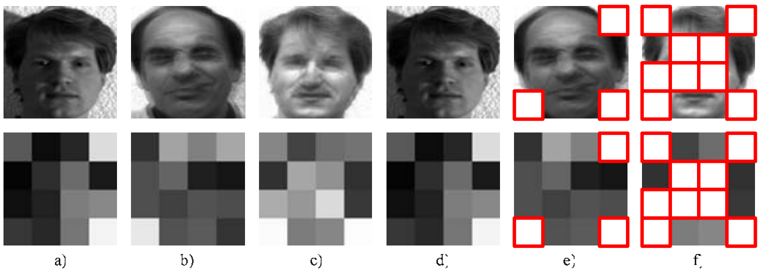

Fig. 3. Misclassification example (images from [6]). If all features (bottom line, *a*-*c*) are considered, then face *a* is misclassified as element of *b* instead of *c*. If only features with a variance of at most 50% of the maximum are considered (colored rectangles in elements *d*-*f*), then the face is classified correctly.

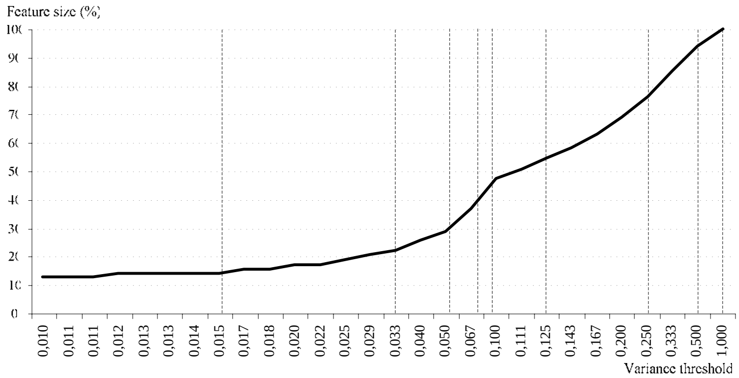

Fig. 4. Variance and feature size. Feature size depends on the threshold. The graph uses two log scale at the intervals [0, 0.1] and [0.1, 1].

those features of a face class are selected that have a variance σ_t below the threshold (given in percent of the maximum variance in the face class). That is, only sufficiently invariant features are considered. The application of variance thresholds causes no computational overhead, since the variances have to be calculated for Kalmanface averaging anyway.

Fig. 3 shows a typical misclassification example (feature vector edge lengths of four pixels, face images from the Yale dataset [6]). If a threshold of 100% is used, face *a* is misclassified as member of face class *b* instead of *c*. If a threshold of 50% is employed, fewer regions are considered (depending on the face classes). Then, face *d* is correctly classified as a member of Kalmanface class *f*.

However, it has to be mentioned that the reduction of the feature vector to just eleven elements in Fig. 3f is not typical. Fig. 4 gives the average relationship of variance threshold value and feature vector size (in percent to the Kalmanface class sizes). In average, a variance threshold of 50% leads to the elimination of just 3-5% of the features with highest variance.

4. CONCLUSION

We propose a novel approach for face identification that uses the Kalman filter for face class averaging. Experimental evaluation shows that Kalmanfaces perform excellently on face images that were recorded under varying lighting conditions. Classic Eigenfaces are outperformed by up to 65%. The Kalmanfaces approach scales well with increasing numbers of individuals and face examples. In future work, we will investigate its sensitivity to more/less-variant face classes and its performance on other face identification problems (e.g. aging) and databases (e.g. FERET).

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