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Effectively Lossless Subspace Appearance Model Compression Using Prior Information

Yang Li, Xiaoming Tao*, and Jianhua Lu

Abstract: Subspace appearance models are widely used in computer vision and image processing tasks to compactly represent the appearance variations of target objects. In order to ensure algorithm performance, they are typically stored in high-precision formats; this results in a large storage footprint, rendering redistribution costly and difficult. Since for most image and vision applications, pixel values are quantized to 8 bits by the acquisition apparatuses, we show that it is possible to construct a fixed-width, effectively lossless representation of the bases vectors, in the sense that reconstructions from the original bases and from the quantized bases never deviate by more than half of the quantization step-size. In addition to directly applying this result to losslessly compress individual models, we also propose an algorithm to compress appearance models by utilizing prior information on the modeled objects in the form of prior appearance subspaces. Experiments conducted on the compression of person-specific face appearance models demonstrate the effectiveness of the proposed algorithms.

Key words: data compression; principal component analysis; appearance modeling

1 Introduction

In computer vision and image processing, subspace appearance models have been used in a variety of tasks including visual tracking\cite{1}, animation\cite{2}, and object detection/recognition\cite{3}. For a given class of objects, its subspace appearance model is constructed by identifying a subspace within the high-dimensional object appearance space of pixel intensities, such that the appearances of new object instances can be approximated closely by linear combinations of several or all of its basis vectors. They are typically trained using Principal Component Analysis\cite{4} or its robust variations\cite{5}. Often, once a model is trained on data gathered from an application scenario, it can be used in other similar scenarios without retraining. Due to the high computational complexity of most model-training algorithms, training is often carried out in a centralized server on data gathered from terminal devices. Therefore, the cost of model storage and redistribution is largely dependent on the model’s size, which mainly consists of the storage of the basis vectors of the appearance subspace.

Applications that make use of subspace appearance models typically store the basis vectors in high-precision floating-point formats, such as 64-bit floating-point numbers, in order to maintain good orthogonality between the basis vectors. Such formats have large storage footprints and are difficult to compress. While orthogonality is important in theoretical analysis and many numerical (especially iterative) algorithms, a significant number of practical applications only require the representation of an object instance by a set of model parameters (in the form of a weight vector in the linear combination of the model basis), or the reconstruction of an object instance from a set of model parameters. These are one-shot operations, thus not subject to error propagation. Since both operations involve operands which are pixel intensities typically represented by 8-bit positive integers, the
high-precision of the basis vectors are often wasted.

In addition, when Object-Specific Models (OSM) are used (such as in the case of expression analysis[6] and model-based video coding[7], where a separate model is constructed for each object, instead of constructing an overall model for all objects within the same class), a large number of models need to be stored and transmitted between the server and terminal devices. An important observation is that since such OSMs describe objects within a common class, they tend to exhibit strong similarities. Specifically, if samples from a large number of objects in the given class can be collected, a large overall subspace model can be built that encompasses both intra-object and inter-object variations. Using this overall subspace model as prior knowledge, more succinct representations of the subspace basis vectors of OSMs can be made possible.

In this paper, we attempt to find a more efficient representation of the basis vectors of subspace appearance models by exploring two approaches: (1) identifying the amount of precision needed to maintain the precision of the results of typical one-shot operations as mentioned above, and (2) for OSMs, making use of prior knowledge on the class to which the modeled objects belong in order to further compress the models. We found that, for typical pixel-intensity appearance models, their basis vectors can be quantized into fixed-point representations; with sufficient bit-width, they can be represented losslessly in the sense that given the same weight vector, the results of the weighted linear combinations of both the original basis vectors and the quantized basis vectors, after proper scaling and rounding, are identical. Furthermore, in the case of OSMs, by introducing a General Class Model (GCM) built on all available samples from the same class, the basis vectors of OSMs can be well-approximated by weighted linear combinations of the basis vectors of the GCM with small-entropy residuals, which can be effectively compressed with lossless entropy-coding. Our experiments confirm the effectiveness of our approach, which exhibits lossless quantization precision required to maintain the lossless property.

2 Quantization of Subspace Basis Vectors

For most image-based applications where subspace appearance models are used, the input signals are pixel intensity values quantized to 8-bit integer representations. Therefore the precision of the resulting calculations is already limited, regardless to the precision with which the subspace basis vectors are stored. Intuitively, if the input values have 8 significant binary digits, and more than 8 significant digits are preserved in all intermediate calculations, then the output values also have 8 significant binary digits. Since the concept of significant digits is not mathematically rigorous, in this section we develop a definition for effectively lossless quantization of subspace basis vectors, and proceed to derive the necessary quantization precision required to maintain the lossless property.

2.1 Definition of effectively lossless quantization

Let \( S = [s_1, \ldots, s_D] \) be a matrix whose columns form the orthonormal basis of an object’s appearance subspace. For simplicity, in our discussion we will ignore the limit of precision of floating-point formats, and regard the floating-point representation of \( S \) as lossless. By some quantization scheme \( Q(\cdot) \), an approximate basis \( \hat{S} \) can be obtained such that:

\[
\forall (\hat{s}_{ij}, s_{ij}) \in (\hat{S}, S), \quad s_{ij} \in \left[ \hat{s}_{ij} - \frac{\delta_{ij}}{2}, \hat{s}_{ij} + \frac{\delta_{ij}}{2} \right] \quad (1)
\]

where \( \delta_{ij} \) is the quantization step size for the \((i, j)\)-th entry. By definition of the object appearance subspace, any instance of the object’s appearance can be approximated by a linear combination of the appearance basis vectors; in other words, an appearance instance \( \mathbf{g} \) with uniform quantization step size \( \delta_g \) can be encoded by a set of subspace coefficients \( \mathbf{c}_\mathbf{g} \) via projection onto the appearance subspace \( S \), i.e., \( \mathbf{c}_\mathbf{g} = \mathbf{S}^T \mathbf{g} \), such that \( \mathbf{g} \) can be approximately reconstructed by \( \tilde{\mathbf{g}} = \mathbf{S} \mathbf{c}_\mathbf{g} \). Then, in order to obtain a reconstruction image \( \tilde{\mathbf{g}} \), \( \tilde{\mathbf{g}} \) is subjected to the same quantization \( Q_g(\cdot) \) as experienced by \( \mathbf{g} \), such that:

\[
\forall (\tilde{\mathbf{g}}_i, \mathbf{g}_i) \in (\tilde{\mathbf{g}}, \mathbf{g}), \quad \tilde{\mathbf{g}}_i \in \left[ \mathbf{g}_i - \frac{\delta_g}{2}, \mathbf{g}_i + \frac{\delta_g}{2} \right] \quad (2)
\]

Therefore, we define Effective Lossless Quantization (ELQ) of \( S \) as \( \hat{S} \) that satisfies the following:

\[
\max(|Q_g(S\mathbf{c}_\mathbf{g}) - Q_g(S\tilde{\mathbf{c}}_\mathbf{g})|) \leq \delta_g \quad (3)
\]

In other words, the quantization can be considered effectively lossless if, in the task of reconstructing input appearance images given subspace coefficients \( \mathbf{c}_\mathbf{g} \), the intensity levels of the reconstruction image produced by \( \tilde{\mathbf{S}} \) do not deviate from those produced by \( S \) by more than the quantization step size. For our following discussion on subspace basis compression, we use the word lossless thus defined, and go on to consider the
problem of finding a sufficient upper bound on $\delta_{ij}$ for this condition to be satisfied.

### 2.2 Quantizing subspace bases losslessly

It is clear that for Formula (3) to be false, it is necessary that:

$$\max(|S \epsilon_g - \hat{S} \epsilon_g|) > \delta_g$$

(4) since otherwise the maximum deviation after quantization will be less than or equal to one step size. Therefore, as long as the error introduced into the computation of the non-quantized reconstruction image $\tilde{g}$ via our usage of $\hat{S}$ instead of $S$ does not exceed $\delta_g$, Formula (3) will hold. We can ensure this condition by specifying the following:

$$\forall j \in \{1, \cdots, K\}, \ |\bar{s}_j^T \epsilon_g - \tilde{s}_j^T \epsilon_g| \leq \delta_g$$

(5)

where $K$ is the number of elements in the appearance vector, while $s_j^T$ and $\tilde{s}_j^T$ indicate the $j$-th row of $S$ and $\hat{S}$, respectively. Equation (5) expresses the view that each element in the reconstructed appearance vector is a weighted linear combination of the same respective element from all basis vectors, the weights being $\epsilon_g$. Most objects have bounded variability in their appearances; the amount of variation along each subspace axis can be evaluated during the model-training stage by projecting all appearance samples onto each axis and computing the standard deviation of the magnitudes of the projections (in the case of PCA, they are obtained directly as the square root of the eigenvalues of the sample autocorrelation matrix). Let such a vector of standard deviations along all subspace axes be denoted as $\lambda$. In most practical applications, the elements of $\epsilon_g$ are constrained to lie within $\pm 3\lambda$. Therefore, let $\Xi = \hat{S} - S$ denote the error caused by the quantization of the subspace bases, and $\xi_{ij}^*$ denote its $j$-th row, it can be seen that Formula (5) holds if the following is true:

$$\forall j \in \{1, \cdots, K\}, |\xi_{ij}^* \lambda_j| \leq \frac{\delta_g}{3}$$

(6)

while it is clear that $\Xi$ cannot be known a priori due to its dependence on the actual values of the subspace bases, given any quantization scheme, we can find the worst case quantization error $\Xi^*$ whose elements $\xi_{ij}^*$ are equal to half of their respective quantization step sizes $\delta_{ij}$. Therefore, let $\Delta = \{\delta_{ij}\}$ denote the quantization step size matrix for the subspace bases, then $\Xi^* = \Delta/2$. Hence, we can guarantee ELQ by finding $\Delta$ such that Formula (6) is satisfied with worst case quantization errors. For fixed-point representations, the number of bits required to represent a number shares a linear relationship with the negative logarithm of the quantization step size; therefore, in order to minimize the total length of the representation of $\hat{S}$, the following problem needs to be solved:

$$\min_{\Delta} \sum_{i,j} \frac{D \cdot K}{\Delta} - \log(\delta_{ij})$$

(7)

subject to $\sum_{i} \delta_{ij} \lambda_i \leq \frac{2\delta_g}{3}, \forall j \in \{1, \cdots, K\}$, where $D$ is the dimensionality of the subspace bases, and $\lambda_i$ denotes the $i$-th element of $\lambda$. The inequality constraint of Formula (7) comes from Formula (6), dropping the absolute value since both $\delta_{ij}$ and $\lambda_i$ are non-negative by definition. It can be seen that the $K$ constraints of Formula (7) are independent, whereas the objective function is in the form of a summation; therefore we can decompose Formula (7) into $K$ subproblems, each only concerned with one row of $\Delta$, such that $\forall j \in \{1, \cdots, K\}$, we solve the following problem:

$$\min_{\delta_{ij}} \sum_{i} \frac{D}{\Delta} - \log(\delta_{ij})$$

(8)

subject to $\sum_{i} \delta_{ij} \lambda_i \leq \frac{2\delta_g}{3}$, where $\delta_{ij}^T$ denotes the $j$-th row of $\Delta$. As all $K$ subproblems share the same form, they have the same solution. Using the method of the Lagrange Multipliers, a close-form solution can be found. For the sake of brevity we omit detailed derivations, and present the solution directly:

$$\forall (i, j) \in \{(1, \cdots, D), \{1, \cdots, K\}\}, \delta_{ij}^* = \frac{2\delta_g}{3K\lambda_i}$$

(9)

where $\sum_{i,j} \frac{D \cdot K}{\Delta} - \log(\delta_{ij}^*) = \min \sum_{i,j} - \log(\delta_{ij})$.

We note that in the above solution, for a given $i$, $\delta_{ij}^*$ is a constant for all $j$. This means that all columns of $\Delta$ are the same, and we can rewrite $\Delta$ into a row vector $\delta^T$, whereas its $i$-th element $\delta_i$ is the optimal quantization step for the $i$-th subspace basis vector, $i \in \{1, \cdots, D\}$. As our derivation shows, this scheme guarantees ELQ when the magnitude of $\epsilon_g$ is constrained to lie within $\pm 3\lambda$, as is often true in practice. In the case where no additional prior knowledge is available, the quantized subspace vectors are entropy-coded via algorithms such as that proposed in Ref. [9] to achieve maximum compression.
3 Compression of Object-Specific Models Using Prior Knowledge

While the entropy gives the lower bound for the average code length required to losslessly store data where each sample is an independent and identically distributed random variable \( \text{Shannon1948} \), shorter code lengths are possible if the variables are not independent, and prior knowledge on their joint distribution can be obtained. For example, motion compensation is an essential part of modern video coding algorithms where the temporal correlation of successive video frames is exploited by using the previous frame to generate a prediction of the current frame \( \text{frames is exploited by using the previous frame to} \). As long as the prediction is sufficiently accurate, the residual errors are mostly small, possessing a narrow probability distribution with lower entropy than the original image. Thus motivated, we propose in this section a method to use prior knowledge on the appearance of a class of objects to further reduce the code lengths of the quantized subspace bases of object-specific models.

For many applications, all target objects of interest belong to a common class of objects denoted by \( C \) (e.g., facial action unit detection, model-based video coding, etc.). Let a specific object belonging to \( C \) be denoted by \( I \). These applications require the construction of OSMs, where an appearance subspace basis is identified based on data gathered from each \( I \) independently. It is often the case that the individual objects share many common characteristics in their appearances; independent compression of their models overlook this correlation, resulting in inefficiency.

In this section, we show how our prior knowledge on the common appearance characteristics of objects within the same class can be used to further improve the compression ratio. Firstly, a general subspace appearance model is built on all available samples belonging to the same class, regardless of the identities of the objects depicted by the samples; we call this model the GCM. Since each OSM is trained from a subset of the samples used to train the GCM, it can be seen that the appearance subspace of any given OSM is mostly contained within that of the GCM. Therefore, the subspace axes of the OSM can be encoded by GCM parameters via projections onto the GCM subspace; any residuals can then be quantized using the ELQ scheme derived above and coded with a small average code length due to their low entropy.

3.1 Compressing OSMs

Assume that a dataset \( D_C = D_{Z1} \cup D_{Z2} \cup \cdots \cup D_{ZM} \) consists of samples drawn from \( M \) objects all belonging to the same class \( C \), with cardinalities \( |D_C| = N \) and \( |D_{Zi}| = N_i \), respectively. For each object \( I \), a subspace appearance model is trained on \( D_{Zi} \) to produce a subspace basis \( S_{Zi} \) and a mean appearance vector \( \mu_{Zi} \). In addition to the OSMs, a GCM is trained on \( D_C \) to produce an overall subspace basis \( S_C \) and mean appearance vector \( \mu_C \), which represents the common appearance characteristics of the entire class.

The compression of the appearance subspace basis of each OSM \( S_{Zi} \) is realized by projecting each of its columns \( s_{Zi}^{(i)} \) onto the overall basis \( S_C \) to obtain a set of coefficients \( c_{Si}^{(i)} \). Since in general not all energy of each OSM subspace basis vector is contained within the GCM subspace, the residual \( r_{i}^{(i)} \) between \( s_{Zi}^{(i)} \) and its reconstruction via the GCM subspace basis must be computed. This can be written in matrix form as

\[
C_{Si} = S_C^T S_{Zi},
R_{Si} = S_{Zi} - S_C C_{Si}
\]

where \( C_{Si} = \{c_{Si}^{(i)}\} \) and \( R_{Si} = \{r_{i}^{(i)}\} \). For ELQ compression, the quantization method developed in the previous section is applied to \( R_{Si} \) to obtain \( \tilde{R}_{Zi} \), whereas \( C_{Si} \) is saved directly in floating-point format to maintain accuracy. Typically, the size of \( C_{Si} \) is much smaller than that of \( S_{Zi} \), and the entropy of \( \tilde{R}_{Zi} \) is significantly lower than that of \( S_{Zi} \); thus the combined storage required is often significantly reduced compared to entropy-coding each \( S_{Zi} \) independently.

The mean appearance vector of each OSM \( \mu_{Zi} \) can be similarly compressed if the mean vector of the GCM \( \mu_C \) is subtracted from it first. The resultant coefficient and residual vectors, \( c_{\mu}^{(i)} \) and \( r_{\mu}^{(i)} \), can be written as:

\[
c_{\mu}^{(i)} = S_C^T (\mu_{Zi} - \mu_C),
\]

\[
r_{\mu}^{(i)} = \mu_{Zi} - (S_C c_{\mu}^{(i)} + \mu_C)
\]

Thus each OSM \( S_{Zi} \) can be written in the form of \( (C_{Si}, R_{Si}, c_{\mu}^{(i)}, r_{\mu}^{(i)}) \) as given in Eqs. (10) and (11); after losslessly quantizing and entropy-coding the residuals, we arrive at the final compressed representation of \( (C_{Si}, \tilde{R}_{Si}, c_{\mu}^{(i)}, \tilde{r}_{\mu}^{(i)}) \), thus achieving effectively lossless compression with GCM as prior knowledge (GCM-ELC).

3.2 Recovering OSMs

Given a GCM consisting of \( (S_C, \mu_C) \) and a set of compressed OSMs \( \{ (C_{Si}, \tilde{R}_{Si}, c_{\mu}^{(i)}, \tilde{r}_{\mu}^{(i)}) \} \), the original
OSMs \{\{S_{z_i}, \mu_{z_i}\}\}

 can be recovered by the reverse

application of the compression process:

\[
\begin{align*}
\hat{S}_{z_i} &= S_c C_{\mu_i} + \hat{R}_{z_i}, \\
\hat{\mu}_{z_i} &= S_c C_{\mu_i} + \hat{\mu}_{\mu_i}
\end{align*}
\]  

(12)

It should be noted that while all discussions within this section have assumed that the GCM was trained

on a union of all available samples used in the training of each OSM, it does not necessarily preclude the use of the GCM in aiding the compression of an OSM trained on data not used for training the GCM. As will be demonstrated in Section 4, we have found that as long as the OSM belongs to the same class of objects used to train the GCM, there is sufficient overlap between their respective subspaces for significant gains in compression ratios to be observed. This is important to many practical applications where online model training and syncing are required, as the GCM can be trained once on currently available data, then distributed onto all application platforms; each instance of the application can then compress newly-trained OSMs independently without the need to update the GCM.

4 Experiments

In order to validate the effectiveness of the proposed method, we have evaluated its performance on the task of the compression of Active Appearance Models (AAMs)\cite{9} for faces. Experiments on both independent compression and GCM-based compression were conducted. Training data were taken from the annotated face dataset Multi-Pie, as well as annotated face video sequences not within Multi-Pie to gauge the effectiveness of GCM-based compression on OSMs trained with samples unseen by the GCM. While AAMs consist of a point distribution model and an appearance model, we are only concerned with the appearance model, since the point distribution model has a negligible storage footprint.

4.1 Independent model compression

For independent model compression experiments, three publicly-available face video sequences (Akiyo, Miss America (http://trace.eas.asu.edu/yuv/), Franck (http://www-prima.inrialpes.fr/FGnet/data/01-TalkingFace/talking_face.html)) were annotated and used to train separate AAMs. The appearance parts of the AAMs were trained with PCA, keeping 99% of the sample variation. They were losslessly coded with ELQ in addition to several other well-known general-purpose lossless compression algorithms; the resulting compression ratios on all three models are shown in Table 1.

4.2 OSM compression using GCM as prior knowledge

In the case of OSMs, we would like to evaluate the performance of GCM-ELC in two scenarios, including: (1) varying the number of GCM basis vectors, and (2) compressing OSMs trained on out-of-database samples. The GCM used for the following experiments is an AAM trained on 4203 annotated face sample images within the Multi-Pie database\cite{14}, with an appearance model trained by PCA keeping 99% sample variation. The OSMs are similarly trained, with the restriction that each OSM was trained on all sample images from only a specific corresponding subject. A total number of 313 OSMs were trained and used in the in-database compression experiment. For the out-of-database experiment, the three AAMs trained in the previous experiment were used.

4.2.1 Varying the number of GCM basis vectors

In this experiment, we consider the case where $N$ OSMs were trained on a collection of data from $N$ object instances. We wish to reduce the total amount of storage required to store the $N$ OSMs by training a GCM on the entire collection of data, then compressing each OSM using GCM-ELC. Since object appearances are far from uniform random distributions, each axis in the appearance basis of the GCM has varying importance in the sense that each explains a differing amount of variation within the training samples. Thus increasing the dimensionality of the GCM has diminishing margins of return. Figure 1 shows the entropy of the prediction residuals of appearance basis vectors from several OSMs, with respect to the dimensionality of the GCM.

On the other hand, increasing the dimensionality of the GCM increases the amount of overhead storage required to store the GCM itself. If care is not taken, it is possible that the total amount of storage required, which is the sum of the sizes of all GCM-ELC compressed OSMs in addition to the independently-
Fig. 1 The entropies of residuals after GCM prediction of OSM basis vectors. The first three basis vectors from models 1, 157, and 312 are shown. Rapidly diminishing returns on entropy reduction can be observed.

compressed GCM itself, may exceed that which is required for storing $N$ independently-compressed OSMs. Fortunately, since the dimensionality of the GCM, $d$, is bounded between 0 and the underlying dimensionality of the appearance subspace, a simple bisection search can be effected to find such $d$ which gives optimal overall compression. Figure 2 shows the overall storage required to compress the 313 face OSMs used in our experiments, as it varies with the number of GCM basis vectors used.

4.2.2 In-database vs. out-of-database OSMs

Here we consider the effectiveness of applying GCM to OSMs of the same class, but trained on different data. This is of particular importance to applications where online data acquisition and model building are performed, since models built on each device often need to be transmitted to other devices. Using the same GCM as in the preceding experiment, we performed GCM-ELC on the three AAMs trained in the independent compression experiment. Figure 3 shows a comparison between independent compression and GCM-ELC, and demonstrates how the size of the compressed model relates to the number of GCM basis dimensions. An illustration of the relationship between the magnitude of the residuals and the number of GCM basis vectors used is found in Fig. 4. Similar to the in-database experiments, the compression ratio continues to improve as more GCM basis vectors are included, albeit at a diminishing rate. However, in this case, if communication costs are much higher than local storage costs, the full GCM should be kept locally on all devices to ensure best GCM-ELC performance. The compressed sizes of the three models used in our experiments after GCM-ELC using all GCM basis vectors are respectively 1.05 MB, 1.61 MB, and

Fig. 2 Total compressed size vs. number of GCM basis vectors used.

Fig. 3 Compressed size of out-of-database OSMs after GCM-ELC vs. percentage of GCM basis vectors used. 0% corresponds to independent compression.
1.67 MB, showing a 5-fold increase in compression ratio compared to existing compression methods.

5 Conclusions

In this paper, we studied the problem of subspace appearance model compression in two successive steps. Firstly, we established an effectively lossless criterion for subspace appearance models, and proceeded to show that a fixed-width quantization method can be formulated to satisfy the criterion, making compression of individual models more effective. Secondly, for object-specific models, we proposed a method to utilize the prior knowledge able to be obtained on the whole class of the concerned object instances to reduce inter-object redundancy and further increase the compression efficiency. Experiments have shown compression ratio improvements of approximately 300%–400% in the case of independent compression, and more than 500% in the case of GCM-ELC. Future work include the establishment of rate-distortion formulations for the lossy compression of subspace appearance models.

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References

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