Tracking Facial Features Using Mixture of Point Distribution Models

Atul Kanaujia, Yuchi Huang, and Dimitris Metaxas

Department of Computer Science, Rutgers University

Abstract. We present a generic framework to track shapes across large variations by learning non-linear shape manifold as overlapping, piecewise linear subspaces. We use landmark based shape analysis to train a Gaussian mixture model over the aligned shapes and learn a Point Distribution Model(PDM) for each of the mixture components. The target shape is searched by first maximizing the mixture probability density for the local feature intensity profiles along the normal followed by constraining the global shape using the most probable PDM cluster. The feature shapes are robustly tracked across multiple frames by dynamically switching between the PDMs. Our contribution is to apply ASM to the task of tracking shapes involving wide aspect changes and generic movements. This is achieved by incorporating shape priors that are learned over non-linear shape space and using them to learn the plausible shape space. We demonstrate the results on tracking facial features and provide several empirical results to validate our approach. Our framework runs close to real time at 25 frames per second and can be extended to predict pose angles using Mixture of Experts.

1 Introduction

Tracking deformable shapes across multiple viewpoints is an active area of research and has many applications in biometrics, facial expressions analysis and synthesis. Accurate reconstruction and tracking of 3D objects require well defined delineation of the object boundaries across multiple views.

Landmark based deformable models like Active Shape Models(ASM)[1]have proved effective for object shape interpretation in 2D images and have lead to advanced tools for statistical shape analysis. ASM detects features in the image by combining prior shape information with the observed image data. A major limitation of ASM is that it ignores the non-linear geometry of the shape manifold. Aspect changes of 3D objects causes shapes to vary non-linearly on a hyperspherical manifold. During tracking, the shape change is mostly smooth but in certain cases there may be discontinuities. For example, during a head rotation to the full profile face, some of the facial features may get occluded causing a drastic change in the shape. Besides the shape, the correspondences between the local 2D structures and the 3D object structures changes for the landmark based deformable models. The local grey level profiles at these landmarks also exhibit dramatic variations.

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There have been several efforts in the past to represent non-linear shape variations using kernel PCA and multi-layer perceptron[2,3]. The results from non-linear approaches largely depend on whether all the shape variations have been adequately represented in the training data. Discontinuities in the shape space may cause these models to generate implausible shapes. Kernel methods suffer from a major drawback to learn pre-image function for mapping shape in the feature space to the original space.

In this work we present a generic framework to learn non-linear shape space as overlapping piecewise linear subspaces. Our objective is to accurately track facial features across large head rotations. We use the Point Distribution Models(PDM) to represent the facial feature shapes and use ASM to detect them in the 2D image. The contribution of our work is: (1) Improve the specificity of ASM to handle large shape variations by learning non-linear shape manifold. (2)Real time framework to track shapes, and (3) Learning non-linearities for accurate prediction of 3D pose angles from 2D shapes. Our generic framework enables large scale automated training of different shapes from multiple viewpoints. The model can handle larger amount of variability and can be used to learn non-linear continuous shape manifold.

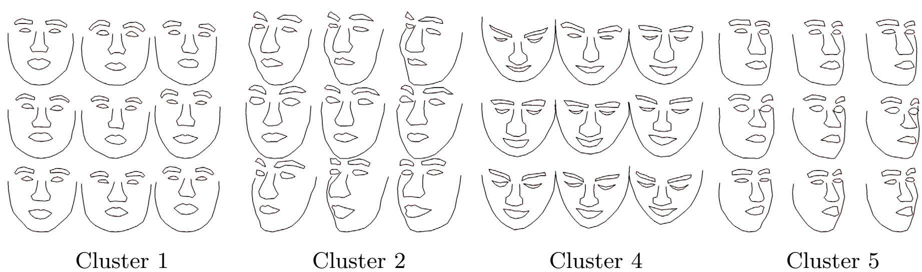


Fig. 1. Shapes from 4 different clusters of the training data set. Cluster 1 contains primarily frontal poses whereas Cluster 5 contains pose with head rotated to right.

2 Related Work

A large segment of research in the past decade focused on incorporating non-linear statistical models for learning shape manifold. Murase et. al. [4] showed that pose from multiple viewpoint when projected onto eigenspaces generates a 2D hypersphere manifold. Gong et. al [5] used non-linear projections onto the eigenspace to track and estimate pose from multiple viewpoints. Romdhani et al. [6] proposed an ASM based on Kernel PCA to learn shape variation of face due to yaw. More recently [7] has proposed a multi-view face alignment algorithm to infer visibilty of feature points across large rotations. The work stresses more on Bayesian estimation to learn shape parameters without providing insight into the shape space. Moreover their EM algorithm is impractical for real time shape fitting applications. Several prominent work exist on facial feature registration and tracking use appearance based models(AAM)[8,9]. [8] uses multiple independent 2D AAM models to learn correspondences between features of different viewpoints. We prefer ASM model over more accurate AAM model as shape based models can be easily generalized to a specific class of objects and is more robust to variations occurring due to changes in appearance and illumination compared to AAM. Most notable work in improving ASM to learn non-linearities in the training data is by Cootes et. al[3] in which large variation is shapes is captured by parametric Gaussian mixture density, learned in the principal subspace. In order to constrain the shape to lie within plausible shape subspace, the probability density is increased using gradient ascent. Our work differs from it in 2 aspects. Firstly we learn multivariate gaussian mixture density on the original shape space and not the parameteric subspace. Consequently the shape non-linearities are preserved across the clusters. We learn PDM within each cluster by projecting shapes of the clusters onto independent tangent spaces. Secondly we explicitly ensure that the learned sub-spaces are overlapping. This is required for efficient search and tracking of the shapes. In this respect our work follows from [10,11] although they primarily focus on shape analysis and surface learning. Unlike [8], our framework does not require explicit modeling of head pose angles. Although we use multivariate gaussian mixture model to learn initial clusters of the shape distribution, our subspaces are obtained by explicitly overlapping the clusters. ASM can be easily generalized to a specific class of objects and is more robust to variations occurring due to changes in appearance and illumination compared to Active Appearance Model(AAM). The faster convergence of ASM gives significant advantage over other shape analysis methods based on level sets and snakes.

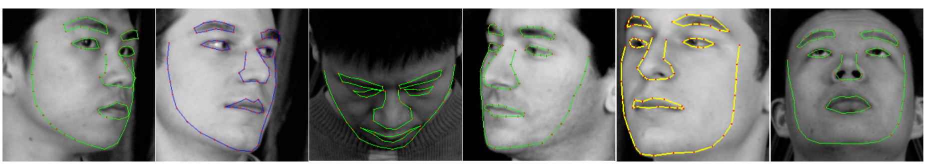


Fig. 2. *(Best Viewed in Color)*Shape fitting results on multiple Subjects across large head movement. The model recovers the pose irrespective of the initial cluster.

3 Learning Shape Manifold

Active Shape Model(ASM) is a landmark based model that tries to learn a statistical distribution over variations in shapes for a given class of objects. Changes in viewpoint causes the object shapes to lie on a hyper-sphere and cannot be accurately modeled using linear statistical tools. Face shape variation across multiple aspects is different across human subjects. A 30^o head rotation will produce more distinctive shape variation for the face with raised features(eyes and nose) as compared to face with flat features. Hence learning independent ASM models and switching the models based on the learned pose, tends to generate abrupt shape changes and inaccurate fitting. Tracking shapes across multiple aspects requires modeling and synthesis of paths between the source and target shapes lying on a non-linear manifold. A complex, non-linear region can be approximated as a combination of multiple smaller linear subregions. Each subregion defines a hyper-ellipsoid within which a shape instance is constrained to lie. The search iteratively modify the shape by searching along the normals of the landmark points and simultaneously constraining it to lie on the shape manifold. The path between the source shape and the target shape is traversed by searching across multiple subspaces that constitute the non-linear shape surface. Tracking of features can be successfully leveraged by taking advantage of the heterogeneous nature of shape variations due to pose changes thereby causing these subregions overlap. The extent of overlap can be improved by having a fixed minimum mahalanobis radius for each subregion and including points across the cluster boundaries to learn the principal subspace. As a pre-requisite for shape analysis, all the 2D planar shapes are aligned to the common co-ordinate system using Generalized Procrustes Analysis[12]. The aligned shapes obtained from Procrustes analysis lie on a hyper-sphere. The tangent space approximation $\mathbf{T_s}$ projects the shapes on a hyper-plane normal to the mean vector and passing through it. Tangent space is a linear approximation of the general shape space so that the Procrustes distance can be approximated as euclidean distance be-

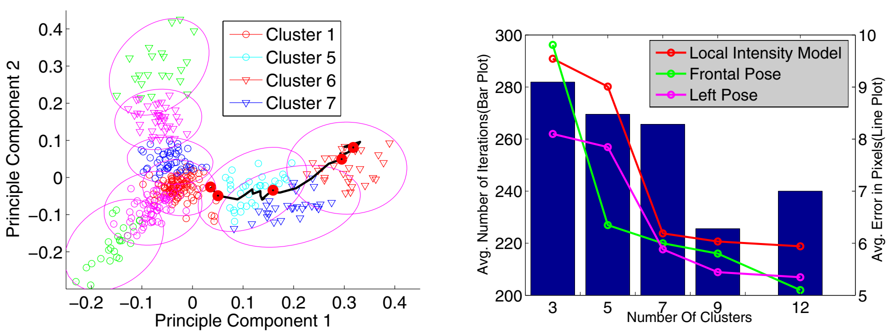


Fig. 3. *(Best Viewed in Color)***(Left)**The 9 overlapping subspaces (projected onto 2 Principal components) learned using GMM. The red cluster in the center is for the frontal pose. The other clusters corresponds to right, left and down movement. Iterative ASM search in fig.4 is shown as black path.**(Right***(Line Plot)***)** Increasing the number of clusters increases the accuracy of ASM for both the frontal and left head pose images. This is due to more accurate representation of the non-linear surface by piecewise linear regions. Increasing the number of gaussian components for the local intensity profile models(IPM) also improves the accuracy(red plot). **(Right***(Bar Plot)***)** The average ASM iterations(over 4 levels of gaussian pyramid) also improves with more gaussian components of the local intensity models but shows erratic increase for more than 10 components due to noise.

tween the planar shapes. The cluster analysis of shape is done in the global tangent space.

We assume a generative multivariate Gaussian mixture distribution for both the global shapes and the intensity profile models(IPMs). The conditional density of the shape $\mathbf{S_i}$ belonging to an N-class model $p(\mathbf{S_i}|\text{Cluster}) =$

$$\sum_{j=1}^{N} \gamma_j (2\pi)^{-(\frac{N}{2})} \|\mathbf{C_j}\|^{-1/2} \exp\{-\frac{1}{2}(S_i-(\mu_j+P_j b_j))^T \mathbf{C_j}^{-1}(S_i-(\mu_j+P_j b_j))\} \quad (1)$$

We assume diagonal covariance matrix $\mathbf{C_j}$. γ_j are the cluster weights and (μ_j, P_j, b_j) are the mean, eigen matrix and eigen coefficients respectively for the principle subspace defined for each cluster. The clustering can be achieved by EM algorithm with variance flooring to ensure sufficient overlapping between the clusters. For each of the N clusters we learn a locally linear PDM using PCA and using the eigenvectors to capture significant variance in the cluster(98%). Unlike the method proposed in [3] where clustering is done in the PCA subspace, we use clustering in the global tangent space to decide class membership of the original shapes. Consequently the shape non-linearities are preserved across the clusters. We learn independent PDM within each cluster. Our algorithm allows more accurate modeling of the non-linear shape manifold using piecewise linear hyper-ellipsoid subspaces. The intensity profiles for the landmark points also exhibit large variation when trained over multiple head poses. The change in face aspects causes the profiles to vary considerably for the feature points that are occluded. The multivariate Gaussian mixture distribution(1) is learned for the local intensity profiles model(IPM) in order to capture variations that cannot be learned using a single PCA model.

Overlapping between Clusters: It is important that the adjacent clusters overlap sufficiently to ensure switching between subspaces during image search and tracking. The amount of overlap can be controlled by variance flooring during EM algorithm for clustering the data set. Setting minimum variance to a fixed value $\mathbf{V_{floor}}$ during the Maximization step, enables clusters to have larger expanse. Eventually the mahalanobis distance is used as a classification cost. The number of clusters also affect the degree of overlap. We can ensure subspace overlap by using boundary points between adjacent clusters to learn the subspace for both the clusters. These points can be obtained as nearest to the cluster center but not belonging to that cluster.

4 Image Search in the Clustered Shape Space

The search is done over 4 levels of Gaussian image pyramid. Conventional ASM uses Alternating Optimization(AO) technique to fit the shape by searching for

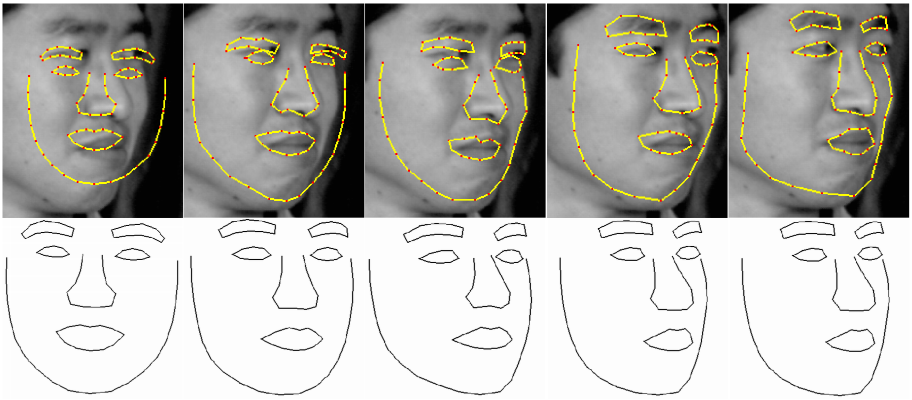


Fig. 4. Iterative search across multiple clusters to fit the face.The frames correspond to iteration 1(Cluster 1), iter. 3(Cluster 5), iter. 17(Cluster 7), iter. 23(Cluster 6) and final fit at iter. 33(Cluster 6) for level 4 of the Gaussian pyramid. The lower row shows the shapes of the cluster centers. Cluster 5 and Cluster 7 contain smaller head rotations while Cluster 6 contains extreme right pose. Fig. 3 shows the corresponding path of the iterative search.

the best matched profile along the normal followed by constraining the shape to lie within the learned subspace. The initial average shape is assumed to be in a region near to the target object. We use robust Viola-Jones face detector to extract a bounding box around the face and use its dimensions to initialize the search shape. The face detector has 99% detection rate for faces with off-plane and in-plane rotation angles $\pm 30^o$. We assign the nearest Cluster$_i$ to the average shape based on mahalanobis distance between the average shape and the cluster centers in the global tangent space. The image search is initiated at the top most level of the pyramid by searching IPM along normals and maximizing the mixture probability density (1) of the intensity gradient along the profile. The model update step shifts the shape to the current cluster subspace by truncating the eigen coefficients to lie within the allowable variance as $\pm 2\sqrt{\lambda_i}$. The shape is re-assigned the nearest cluster based on the mahalanobis distance and the shape coeficients are re-computed if the current subspace is different from the previous.

The truncation function to regularize the shapes usually generates discontinuous shape estimates. Bregler et. al. [11,3] suggests a continuous constrain function that can be maximized using gradient ascent to ensure that the shape lies within the subspace of the nearest cluster. A major limitation of their approach is the use of thresholding to discriminate a valid shape from an invalid shape. We use the truncation approach, due to its low computational requirement and faster convergence. The above steps are performed iteratively and converges irrespective of the initial cluster of the average shape. We present the algorithm steps below:

ASM Train in Clustered Shape Space

1. Align all the shapes $\mathbf{Y_i}$ to the average shape $\overline{\mathbf{X}}$ using procrustes analysis as $\mathbf{Y_{i,a}}$
2. Project the aligned shapes $\mathbf{Y_{i,a}}$ in the common tangent space of $\overline{\mathbf{X}}$ by scaling as $\mathbf{Y'_{i,a}} = \mathbf{Y_{i,a}}/(\mathbf{Y_{i,a}}.\overline{\mathbf{X}})$. This ensures that procrustes distance can be approximated as euclidean distance.
3. Cluster the rescaled shapes $\mathbf{Y'_{i,a}}$ to N Clusters using EM algorithm with minimum covariance $\mathbf{V_{floor}}$ to ensure overlapping clusters.
4. Generate the subregions from the original shapes using the cluster membership. Realign the shapes locally and project the shapes to tangent space of the cluster mean as $\mathbf{Y_{i,a,c}}$
5. Learn locally linear PCA models within each cluster as $\mathbf{Y_{i,a,c}} = \overline{\mathbf{X}}_\mathbf{c} + \mathbf{P_c b_{c,i}}$
6. Learn Gaussian mixture density for the Intensity Profile Model(IPM) for each landmark.

ASM Search in Clustered Shape Space

1. Assign initial cluster Cluster$_{init}$ to the global average shape $\overline{\mathbf{X}}$ based on Mahalanobis Distance.
2. Search IPM along normal for the intensity profile that maximizes the mixture density probability (eqn. 1) to get new shape $\mathbf{Y_s}$
3. Constrain the shape $\mathbf{Y_s} = \overline{\mathbf{X}}_\mathbf{init} + \mathbf{P_{init} b_{init,s}}$ by truncating $\mathbf{b_{init,s}}$ within the subspace of the current cluster to get new shape $\mathbf{Y'_s}$.
4. Re-assign Cluster$_i$ by projecting the new shape $\mathbf{Y'_s}$ onto global tangent space and finding the nearest cluster based on mahalanobis distance.
5. Re-estimate the parameter $\mathbf{b'_{i,s}}$ for the new cluster Cluster$_i$ by projecting the new shape $\mathbf{Y'_s}$ onto cluster mean shape tangent space.
6. Iterate until convergence.

5 Tracking Framework

Running ASM at every frame is computationally expensive and causes feature points to jitter strongly. We track the features using Sum of Squared Intensity Difference(SSID) tracker across consecutive frames[13]. The SSID tracker is a method for registering two images and computes the displacement of the feature by minimizing the intensity matching cost, computed over a fixed sized window around the feature. Over a small inter-frame motion, a linear translation model can be accurately assumed. For an intensity surface at image location $\mathbf{I}(\mathbf{x_i}, \mathbf{y_i}, \mathbf{t_k})$, the tracker estimates the displacement vector $\mathbf{d} = (\delta\mathbf{x_i}, \delta\mathbf{y_i})$ from new image $\mathbf{I}(\mathbf{x_i} + \delta\mathbf{x}, \mathbf{y_i} + \delta\mathbf{y}, \mathbf{t_{k+1}})$ by minimizing the residual error over a window $\mathcal{W}$ around $(\mathbf{x_i}, \mathbf{y_i})$ [13]

$$\int_{\mathcal{W}} [\mathbf{I}(\mathbf{x_i} + \delta\mathbf{x}, \mathbf{y_i} + \delta\mathbf{y}, \mathbf{t_{k+1}}) - \mathbf{g}.\mathbf{d} - \mathbf{I}(\mathbf{x_i}, \mathbf{y_i}, \mathbf{t_k})]\, d\mathcal{W} \tag{2}$$

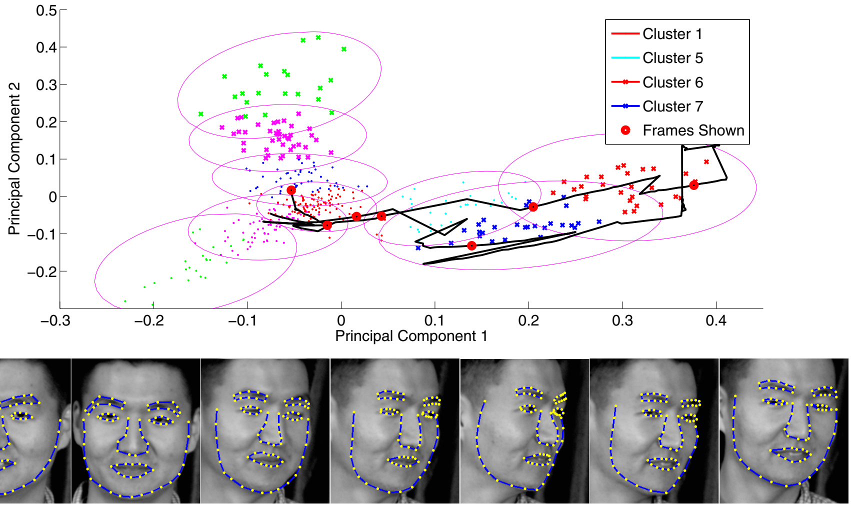


Fig. 5. *(Best Viewed in Color)*Tracking the shapes across right head rotation.**(Top)** The cluster projections on 2D space using 2 principal modes(for visualization)and the bounded by hyper-ellipsoid subspace. The right head rotation causes the shape to vary across the clusters. The red circles corresponds to the frames 1, 49, 68, 76, 114, 262 and 281. The entire tracking path lies within the subspace spanned by the hyper-ellipsoids.**(Bottom)** The images of the tracking result for the frames shown as red markers in the plot.

The inter-frame image warping model assumes that for small displacements of intensity surface of image window $\mathcal{W}$, the horizontal and vertical displacement of the surface at a point $(\mathbf{x_i}, \mathbf{y_i})$ is a function of gradient vector $\mathbf{g}$ at that point. During tracking, some features(ASM landmarks) eventually lose track due to blurring or illumination changes. To avoid this, at every frame we re-initialize the points which have lost track by searching along the normal and maximizing the intensity profile mixture density1). At every frame we ensure that the shape $\mathbf{Y_t}$ obtained from tracking is a plausible shape by constraining the shape to lie on the shape manifold. We align the new shape $\mathbf{Y_t}$ to the global average shape $\overline{\mathbf{X}}_{\mathbf{init}}$ and re-assign it to the nearest Cluster_i based on mahalanobis distance. The new shape $\mathbf{Y_t}$ is constrained to the subspace of the assigned Cluster_i. This ensures switching between the overlapping subspaces that form the non-linear shape manifold. Fig. 5 shows the path (projection on 2 principal components) of a shape for a tracking sequence when the subject rotates the head from frontal to full right profile view and back. The figure also illustrates the cluster switching as the person rotates the head. The entire path remains within the plausible shape manifold spanned by the 9 hyper-ellipsoid subspaces.

6 Pose Angle Estimation

The proposed framework does not use head pose angles for tracking features across large head rotations. In order to deal with discontinuities in shape space and adapting ASM model according to pose change, it may be required to predict pose angles. The current tracking framework can be extended to support pose angle prediction using mixture of experts(ME).

The mapping from 2D shape to 3D pose angle is intrinsically non linear. Inverse mappings from observations to 3D states cannot be functionally approximated due to ambiguities caused by perspective projection and the lost degree of freedom. Mixture of Experts(ME) provide a modular framework for learning non-linear mappings by clustering the dataset and simultaneously learning function approximators locally in the cluster. The EM algorithm for training ME decouples the optimization task into regressor fittng and multi-way classifier learning. In order to learn point distribution models for the shape $\mathbf{X}$, and the corresponding pose angles $\mathbf{A}$, ME formulates the problem as likelihood maximization. The Expectation step involves soft clustering:

$$P(\text{Cluster} = i|\mathbf{X}, \mathbf{A}) = \frac{p(\mathbf{A}|\mathbf{X}, \mathbf{F_i}(\mathbf{X}))P(\text{Cluster} = i|\mathbf{X})}{\sum_j^N p(\mathbf{A}|\mathbf{X}, \mathbf{F_j}(\mathbf{X}))P(\text{Cluster} = j|\mathbf{X})} \tag{3}$$

The density $P(\text{Cluster} = i|\mathbf{X})$ is the gate distribution for classifying shapes to the i^{th} Cluster. The gate distribution is a multi-category classifier learned using softmax function. The pose angle predictions is done by the function approximators $\mathbf{F_i}(\mathbf{X})$ fitted locally to each cluster and are represented using Gaussian distribution $p(\mathbf{A}|\mathbf{X}, \mathbf{F_i}(\mathbf{X}))$. The likelihood is a binomial distribution $\prod_j^N \{p(\mathbf{A}|\mathbf{X}, \mathbf{F_i}(\mathbf{X}))P(\text{Cluster} = i|\mathbf{X})\}^{I(\text{Cluster}=j)}$ where $I(\text{Cluster} = j)$ is the indicator function for the class to which shape $\mathbf{X}$ belongs. The EM iteratively learns the parameters by independently maximizing the gate and the regressor distributions in the log likelihood $\mathcal{L}$ as the Maximization step.

$$\begin{aligned}\textbf{Log Likelihood:}\ & \textstyle\sum_i^M \sum_j^N \mathbb{E}[I(\text{Cluster} = j)] \log(P(\text{Cluster} = j|\mathbf{X_i})) \\ & + \mathbb{E}[I(\text{Cluster} = j)] \log(p(\mathbf{A}|\mathbf{X_i}, \mathbf{F_j}(\mathbf{X_i})))\end{aligned} \tag{4}$$

Where $\mathbb{E}$ denotes the expected value. In effect the EM algorithm does soft clustering of the shapes $\mathbf{X}$ at each step and learns a pose predictor $\mathbf{F_j}$ locally in the cluster. We used linear regressors with softmax gate distribution in our framework. We experimented on the data set containing large shape variations due to yaw with pose angles varying from -90^o to $+90^o$. The pose angles for the training set were estimated within an error of $\pm 5^o$ by linear interpolation between the full profile $\pm 90^o$ and frontal 0^o poses and assuming constant angular velocity during the head rotation. The use of ME gave an average improvement in the prediction accuracy by $\mathbf{8.34^o}$ over single regressor on our data set. More number of experts usually improves the prediction accuracy. However they need to be regularized to avoid overfitting the training dataset. Fig.6 illustrates the ME fitting to the non-linear data. Mixture of Experts incorporates pose angles

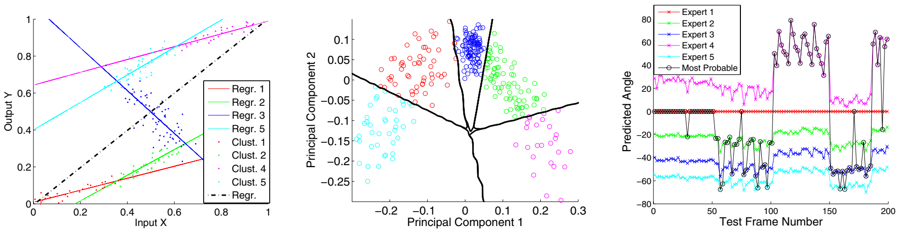
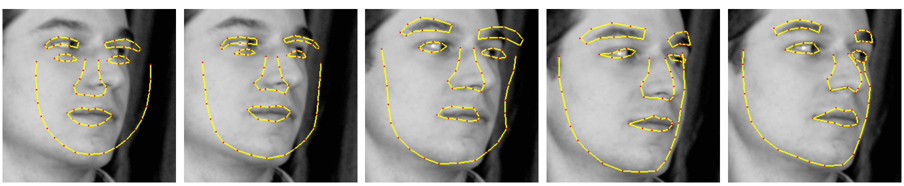


Fig. 6. *(Best Viewed in Color)* **(Left)** A non-linear toy dataset generated from the inverse mapping $x = y + 0.3\sin(2\pi y) + \epsilon$ where ϵ is zero mean Gaussian noise. Multiple locally learned linear regressors(shown in color) gives better predictions compared to single regressor(shown as black). **(Middle)** 5 Shape clusters(projected on 2 principle components) obtained from the learned gate distribution using Mixture of Experts. The data set contained right, frontal(blue points) and left head poses. **(Right)**Pose angle prediction on test data set using 5 Experts. The plot in black indicates the most probable expert. Notice how the most probable expert switch between different experts. The experts predict different range of pose angles and fit well locally.

information to cluster the shapes based on similarity between the aligned shapes and generates meaningful clusters that are based on pose variations. The gating network discriminatively classifies the data set into multiple classes. The overlapping subspaces are learned directly from the clusters.



1.668^o, Init $\quad$ 17.97^o, Iter. 1 $\quad$ 27.95^o, Iter. 20 $\quad$ 45.29^o, Iter. 40 $\quad$ 55.53^o, Iter. 47

Fig. 7. Iteratively fitting ASM using clusters obtained from the Mixture of Experts. The lower row indicates the predicted angles at each of the iteration.

Full Profile and Self Occlusion: The case of full profile has been loosely handled in the past. Zhou et al. [7] presents a model for handling self occlusion and demonstrates the results only on the head poses with yaw $\sim 40^o - 50^o$. Romdhani et al. [6] does not discuss about the self occlusion. Unlike appearance based approaches, the shape undergoes drastic change during full profile head movement. The correspondence between face features and landmark points changes for the outer contour, the eyes and the eyebrows. Depending upon the targeted application the full profile has to be handled by either turn off the visibility of the landmark points which are occluded, or allowing the landmark points to lie along the boundary of the features of the face. Former approach induces discontinuities in the shape space and has to be handled by discrete model switching using stochastic methods [10]. We adopt the latter approach in our framework. The plausible shape space remains continuous in this case. The pose angle prediction enables us to identify the clusters which are full profile (clusters with pose angle in the range $90^o \pm 10^o$). For the full profile image search, we do not match local intensity along the normals for the occluded landmarks. Fig. 8 shows the results obtained from our framework. Occluded landmarks are shown as points.

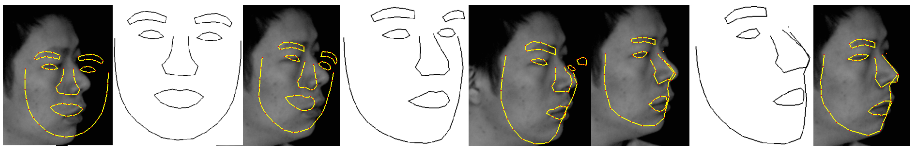


Fig. 8. Shape fitting results on a full profile pose initialized with the average frontal shape. The above frames correspond to iterations 1, 16, 74, 94 and 114 of level 4 of the gaussian pyramid. The initial average shape is in Cluster 1(cluster center shown as the 2^{nd} image). The cluster switch during iteration 74 to Cluster 4(cluster center shown as the 4^{th} image). The cluster switches to the profile cluster (cluster center shown as the 7^{th} image)during iteration 94.

7 Conclusion

In this work we have presented a generic real time framework for detecting and tracking the deformable shapes across non-linear variations arising due to aspect changes. Detailed analysis and empirical results have been presented about issues related to modeling non-linear shape manifold using piecewise linear models. A composite method for pose angle estimation using Mixture of Experts is also proposed. The full profile shape is handled in a special way to ensure continuous shape space modeling.

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Patent Pending

The current technology is protected by patenting and trademarking office. No part of this technology may be reproduced or displayed in any form without the prior written permission of the authors.

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