# Incremental Robust Learning an Active Shape Model [1)]

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*Abstract:*

*Active Shape Models are commonly used to recognize and locate different aspects of known rigid objects. However, they require an off-line learning stage, so that the extension of an existing model requires a completely new re-training phase. Furthermore, learning is based on principal component analysis (PCA) and requires perfect training data that is not corrupted by partial occlusions or imperfect segmentation. The major contribution of this paper is twofold: First, we present a novel robust Active Shape Model that can handle corrupted shape data. Second, this model can be expanded on-line through the use of a robust incremental PCA algorithm. Thus, an already partially learned Active Shape Model can be used for segmentation of a new image and the result of this segmentation process contributes to an on-line update of the robust model. Our experimental results demonstrate the robustness and the flexibility of this new model, which is at the same time computationally much more efficient than previous ASMs using batch or iterated batch PCA.*

## 1 Introduction

Prior knowledge of the object contour/shape is used to improve the result in many computer vision approaches dealing with segmentation, object/face detection or tracking. A common approach, to model different aspects of rigid objects in a shape prior formalism, is the use of Active Shape Models (ASMs) proposed by Cootes and Taylor [4,5]. The standard ASM framework consists of two stages: (1) the modeling/learning and (2) the segmentation/detection stage.

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In this paper we use a level set segmentation framework. Level set representation [13] is an established technique for image segmentation. Over the years several different level set models of ASMs have been presented (i.e., [6,16]). In particular, we use the level set representation of Rousson and Paragios [16]. To avoid unnecessary computation time and numerical errors, we work with the level set shape representation and avoid a conversion to the classical landmark point representation used in [5].

In the learning stage, a set of registered training shapes is used to model different aspects of a model. Generally ASM approaches use a batch (off-line) version of Principal Component Analysis (PCA) [10, 14] for learning, that has two main disadvantages: (1) the approach is not robust in the recognition nor in the training (but, we receive data that is corrupted by partial occlusions or imperfect segmentation) and (2) all training data has to be provided a priori, thus, the shape model cannot be incrementally extended as new segmentations become available.

Various approaches have been proposed to introduce robustness in the recognition stage (e.g., [1, 11, 15]). For these methods it is assumed that the samples in the learning stage are undisturbed. Robust learning is a more difficult problem, since there is no previous knowledge that can be used to estimate outliers. Thus, several methods have been proposed to robustly extract the principal axes in the presence of outliers [7,21]. Other approaches use robust M-estimator [7] or are based on the EM formulation of PCA [17, 18, 20]. Using such a robust approach in our system has two advantages: (1) the robust reconstruction from the ASM allows a much better segmentation of occluded objects and (2) robust learning on the better segmentation results provides a much better ASM.

Not all input data may be given in advance and huge data sets can not be processed by the standard ASMs using batch PCA. To solve this problem, we use an incremental PCA approach in our ASM. Applying an incremental method, we can efficiently build and update an ASM that is used for the segmentation process, i.e., we can use the partially learned ASM to perform segmentation and use the segmentation result to retrain the ASM. Different incremental PCA approaches have been proposed that are based on incremental SVD-updating (e.g., [2, 3, 8]). Recently even robust and incremental [12, 19] approaches have been proposed. In particular we apply a simplified version of the approach of Skočaj and Leonardis [19] to learn the Active Shape Model that will be explained in Section 2.2.

Applying this incremental and robust PCA method, we need only a small data set to initialize our ASM. This first consistent model provides shape priors for the segmentation process. Furthermore, the Active Shape Model can be successively updated with new, even corrupted data from the segmentation process.

The outline of the paper is as follows: Section 2 shows our system and gives a short description of its components. In Section 2.1, we describe the shape registration. In Section 2.2, we introduce in detail the Robust Incremental PCA. Experiments are presented in Section 3 and finally, conclusions are drawn in Section 4.

# 2 Incremental Robust Active Shape Model

Figure 1 depicts our proposed method, which is split into two components: The segmentation module based on the level set segmentation framework by Rousson and Paragios [16] and our novel ASM module.

The output of the segmentation module is the distance function $\Phi(\mathbf{x})$, $\Phi : \Omega \rightarrow \mathbb{R}$, with $\Phi(\mathbf{x}) > 0$, if $\mathbf{x}$ lies in the shape and $\Phi(\mathbf{x}) < 0$, if $\mathbf{x}$ lies out of the shape. $\Omega$ is the image domain and $\mathbf{x}$ denotes a pixel in $\Omega$. In our system, we use this shape representation by Rousson and Paragios [16] instead of the landmark representation used in [4,5] to have the same shape representation in both modules, avoiding unnecessary computation time and numerical errors. However, our ASM can be easily adapted to other shape representations for use with other segmentation approaches.

In a first step, the ASM module is initialized with a training set of non corrupted, aligned shapes characterizing different aspects of an object to learn a first Active Shape Model. This learned ASM is then used in the segmentation process. After each level set iteration step the current result $\Phi_i$ is passed from the segmentation module to the ASM module. A registration process (Section 2.1) applies a transformation $\mathcal{A}$ on $\Phi_i$ to map it with $\Phi_M$ in the best way. $\Phi_M$ is the mean shape calculated over the already learned shapes. $\Phi_i$ is then projected to the eigenspace and robustly reconstructed (Section 2.2). The reconstruction $\tilde{\Phi}_i$ is passed to the segmentation module and used as shape prior in the next level set iteration step. This is repeated until the segmentation process ends. The final result is used to update and improve our ASM (Section 2.2).

## 2.1 Shape registration

For the shape registration, we assume a global deformation $\mathcal{A}$ between $\Phi_M$ (the mean shape) and $\Phi$ (the new shape) that involves the parameters $[\mathcal{A} = (s; \theta; \mathbf{T})]$ with a scale factor $s$, a rotation angle $\theta$ and a translation vector $\mathbf{T}$ [16]. The objective function

$$E(\Phi_M, \Phi(\mathcal{A})) = \int_{\Omega} \rho(s\Phi_M - \Phi(\mathcal{A}))d\mathbf{x}, \tag{1}$$

where $\rho$ is a dissimilarity measure, can be used to recover the optimal registration parameters.

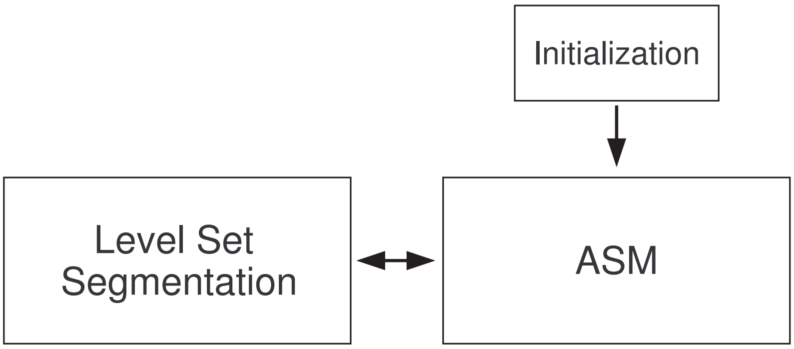



**Figure 1: Our System consisting of 2 components: The level set segmentation [16] and our novel Active Shape Model.**

The rigid transformation $\mathcal{A}$ is dynamically updated to map $\Phi_M$ and $\Phi$ in the best way. For the dissimilarity measure $\rho$, we use the square differences

$$\forall \mathbf{x} \in \Omega : \rho(s\Phi_M - \Phi(\mathcal{A})) = (s\Phi_M - \Phi(\mathcal{A}))^2. \tag{2}$$

Thus, the calculus of variations for the parameters of $\mathcal{A}$ yields the system

$$\begin{aligned}
\frac{\partial s}{\partial t} &= 2\int_\Omega (s\Phi_M - \Phi(\mathcal{A}))(\Phi_M - \nabla\Phi(\mathcal{A})\frac{\partial}{\partial s}\mathcal{A})d\mathbf{x} \\
\frac{\partial \theta}{\partial t} &= 2\int_\Omega (s\Phi_M - \Phi(\mathcal{A}))(-\nabla\Phi(\mathcal{A})\frac{\partial}{\partial \theta}\mathcal{A})d\mathbf{x} \\
\frac{\partial \mathbf{T}}{\partial t} &= 2\int_\Omega (s\Phi_M - \Phi(\mathcal{A}))(-\nabla\Phi(\mathcal{A})\frac{\partial}{\partial \mathbf{T}}\mathcal{A})d\mathbf{x}.
\end{aligned} \tag{3}$$

Figure 2(a-c) shows three example shapes. Figures 2(d) and 2(e) show all three shape contours before and after the registration process.

(a) (b) (c) (d) (e)

**Figure 2: Three example shapes before and after registration.**

### 2.2 Robust Incremental PCA

For batch PCA all training images are processed simultaneously. Therefore a fixed set of input images $\mathbf{X} = [\mathbf{x}_1, \ldots \mathbf{x}_n] \in \mathbb{R}^{m \times n}$ is given, where $\mathbf{x}_i \in \mathbb{R}^m$ is an individual image represented as vector; it is assumed that $\mathbf{X}$ is mean normalized. Let $\mathbf{Q} \in \mathbb{R}^{m \times m}$ be the covariance matrix of $\mathbf{X}$, then the subspace $\mathbf{U} = [\mathbf{u}_1, \ldots, \mathbf{u}_n] \in \mathbb{R}^{m \times n}$ can be computed by solving the eigenproblem for $\mathbf{Q}$ or more efficiently by solving SVD of $\mathbf{X}$.

For incremental learning, the training images are taken sequentially. Assuming that an eigenspace was already built from $n$ images, at step $n+1$ the current eigenspace can be updated in the following way [19]: First, the new image $\mathbf{x}$ is projected in the current eigenspace $\mathbf{U}^{(n)}$ and the image is reconstructed: $\tilde{\mathbf{x}}$. The residual vector $\mathbf{r} = \mathbf{x} - \tilde{\mathbf{x}}$ is orthogonal to the current basis $\mathbf{U}^{(n)}$. Thus, a new basis $\mathbf{U}'$ is obtained by enlarging $\mathbf{U}^{(n)}$ by $\mathbf{r}$ that represent the current images as well as the new sample. Next, batch PCA is performed on the corresponding low-dimensional space $\mathbf{A}'$ and the eigenvectors $\mathbf{U}''$, the eigenvalues $\boldsymbol{\lambda}''$ and the mean $\boldsymbol{\mu}''$ are obtained. To update the subspace the coefficients are projected in the new basis $\mathbf{A}^{(n+1)} = \mathbf{U}''^{T} \left(\mathbf{A}' - \boldsymbol{\mu}''\mathbf{1}\right)$ and the subspace is rotated: $\mathbf{U}^{(n+1)} = \mathbf{U}'\mathbf{U}''$. Finally, the mean $\boldsymbol{\mu}^{(n+1)} = \boldsymbol{\mu}^{(n)} + \mathbf{U}'\boldsymbol{\mu}''$ and the eigenvalues $\boldsymbol{\lambda}^{(n+1)} = \boldsymbol{\lambda}''$ are updated. In each step the dimension of the subspace is increased by one. To preserve the dimension of the subspace the least significant principal vector may be discarded [9].

This method can be extended in a robust manner, i.e., corrupted input images may be used for incrementally updating the current model. Therefore outliers in the current image are detected and replaced by more confident values: First, an image is projected to the current eigenspace using the robust approach [11] and the image is reconstructed. Second, outliers are detected by pixel-wise thresholding (based on the expected reconstruction error) the original image and its robust reconstruction. Finally, the outlying pixel values are replaced by the robustly reconstructed values.

## 3 Experiments

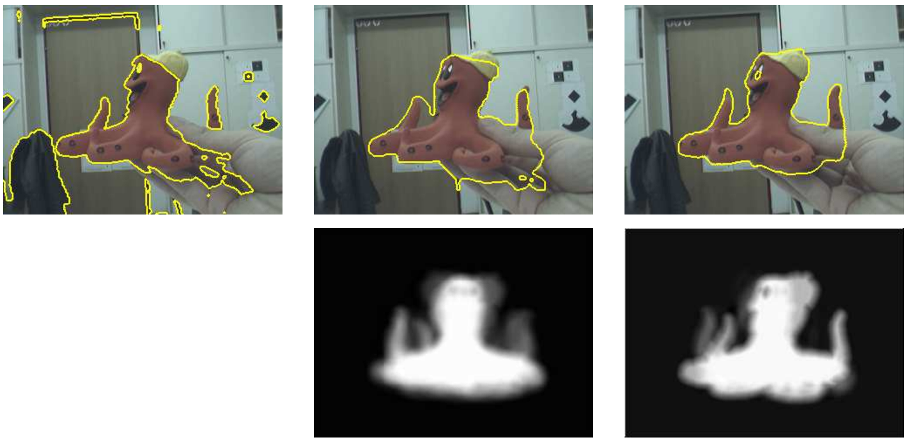
For the experiments, we have created several different data sets: *African man*, *elephant* and *octopus* (Figure 3). For initialization we used 40 to 80 images that are obtained using a turn-table and a homogeneous background, such that we can use the level set segmentation without any shape-prior (Figure 3(a)-(c)). Additionally, more complex images (hand held presentations of the objects with cluttered background) are acquired and used to demonstrate the incremental update and robustness of the method (Figure 3(d)-(e)).

First, we show the increasingly better segmentation results when incrementally updating the current model with new obtained shapes. Thus, Figure 4 depicts different level set segmenta-

(a) (b) (c) (d) (e)

**Figure 3: Examples of our data sets: *A*frican man, *e*lephant and *o*ctopus.**

tion results using our ASM in different training stages. For Figure 4(a), the segmentation is done without a trained ASM. For this case the segmentation fails completely. In Figure 4(b), we show the final shape prior provided from the initialized ASM (40 training shapes) and the corresponding segmentation. The segmentation has been improved significantly but still some errors are present. Afterwards, our ASM is incrementally updated with new training shapes. Figure 4(c) shows the results after 80 training shapes. The segmentation is perfect and the segmentation result depicted in Figure 4 can then be used to add a new aspect to our ASM.

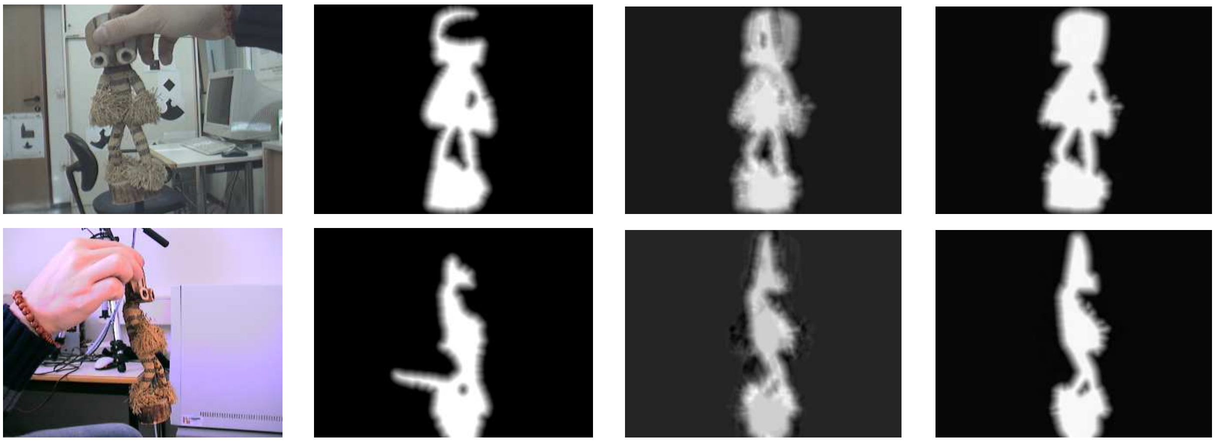


(a) (b) (c)

**Figure 4: Estimated shape prior and corresponding level set segmentation: (a) without an ASM, (b) with an ASM learned from 40 training shapes and (c) with an ASM learned from 80 training shapes.**

Next, the robust extension of the approach was evaluated on the *African man* data set. As can be seen in Figure 5(a) the object was presented in a realistic scenario with background clutter by hand from varying views and under different lighting conditions. The registered segmentations in Figure 5(b) contain holes and over-segmentations. Thus, the standard reconstruction depicted in Figure 5(c) is corrupted. But as can be seen in Figure 5(d) the robust approach provides a perfect reconstruction that can be used for updating the ASM.

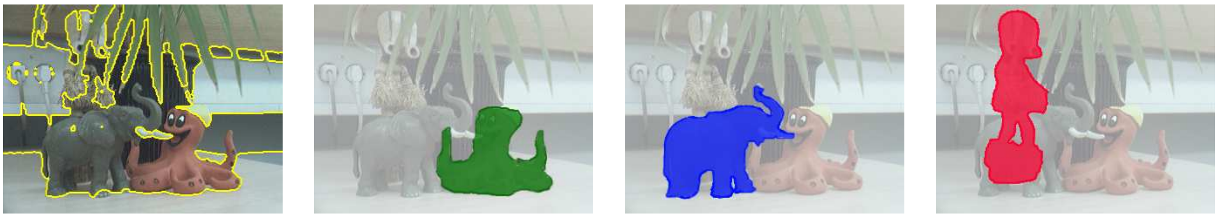
Finally, we show some examples of segmentations using previously trained Active Shapes Models. In Figure 6(a), we use the level set segmentation based on [16] without any shape information. The other three Figures 6(b)-(d) are segmented with three different ASMs. On all three objects, we achieve excellent segmentation results, even for Figure 6(d), where the



(a) (b) (c) (d)

**Figure 5: Robust PCA on *A*frican man data set: (a) original data, (b) segmentation and registration, (c) reconstruction, (d) robust reconstruction.**

lower part of the object is highly occluded, our robust ASM is able to segment the object correctly.



(a) (b) (c) (d)

**Figure 6: Level set segmentation results based on [16]: (a) segmentation without a shape prior; (b)-(d) segmentation using different ASMs.**

## 4 Conclusion

We have introduced a novel robust Active Shape Model, that can be updated on-line. Using a robust, incremental PCA allows us a successive update of our ASMs even with non perfect data (i.e., corrupted data by partial occlusions or imperfect segmentation). For the segmentation and shape representation, we use the work of Rousson et al. [16] but our ASM can easily be adapted to other segmentation approaches and shape representations. We performed experiments on various data sets with different objects. The advantages of the robust, incremental PCA over the standard batch PCA were shown, and we also showed the excellent results using different ASMs for segmentation. Even highly occluded objects in a cluttered background can be segmented correctly.

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