Gait Sequence Synthesis and Reconstruction

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We describe a new technique to synthesize the boundary of a walking subject, with ability to predict movement in missing frames.

The fact that real world images are mostly complex, noisy and occluded makes the implementation of a segmentation algorithms a serious challenge due to the difficulty in segmentation of those images. Some of these difficulties can be tackled via the introduction of prior knowledge, due to its capacity to compensate for missing or misleading image information [1, 2, 6, 7]. Accordingly a robust gait prior shape should enable improved segment ation of walking subjects.

The construction of Human gait prior shape knowledge is inherently more challenging, because the deformation of shapes is non-Gaussian and gait is self occluding.

Two main directions under the title of statistical shape priors have been suggested and employed so far in order to deal with these issues. Some authors suggest the use of kernel density [3] to decompose a shape's deformation modes. The problem however with this approach is that the kernel is chosen regardless of how the data is distributed in feature space [4]. An alternative is to use traditional linear PCA, accompanied with some mechanism to synthesize new shapes [2].

Motivated by the above, we describe a new approach to shape reconstruction which can reconstruct moving shapes in image sequence: the interpolation with cubic spline, and then the application of our proposed method to estimate accurate shapes in a human gait sequences. In our

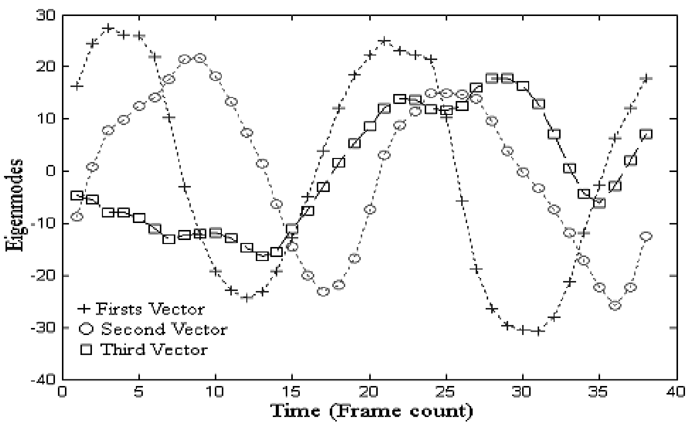

Figure 1: The First three coefficient vectors (eigenmodes) of 38 training shapes

paper we use a level sets representation of the training shapes to compute the statistical model of the shapes deformation. A set of coefficients α_i (see Figure1) is computed to quantify the contribution of each eigenmode to the i^{th} shape[5]:

$$\alpha_k(i) = (\varrho_k)^T (u(i) - \mu), \tag{1}$$

where ϱ_k is the matrix of the first k eigenvectors, $u(i)$ is the i^{th} training shape, and μ is the mean shape. $\alpha_k(i)$, the i^{th} vector of k eigenmode represents the shape metric.

Interpolating cubic spline is proposed to model the oscillation of the eigenmodes and generate new shapes:

$$\alpha_k(t) = spline(\alpha_k(i)) \quad \text{for } i := 1-N,\ t \in [1,N], \tag{2}$$

where $\alpha_k(t)$ is the estimated vector of eigenmodes modeled by the cubic spline at any time in the interval $[1,N]$, and N is the number of training shapes.

Accordingly an estimated valid shape $\hat{u}(t)$ belonging to the class of the training shapes u, can be estimated using k principal components con-

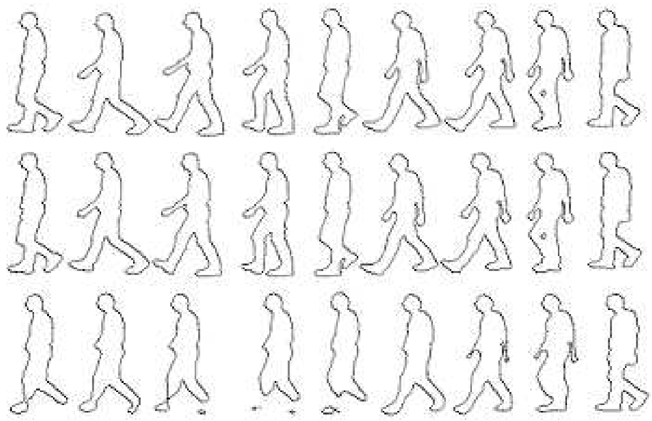

Figure 2: The estimation of the training shapes. Top row is a sample of the training sequence. Middle row is the same shapes reconstructed by cubic spline. Bottom row is the shapes estimated by AR

strained by a k-dimensional vector of eigenmodes, $\alpha_k(t)$:

$$\hat{u}(t) = \varrho_k \alpha_k(t) + \mu. \tag{3}$$

Our contribution is to use a continuous representation of the feature space variation with time.

The experimental results demonstrated in the paper (see Figure 2 for example) show that this level set-based technique can be used reliably in reconstructing the training shapes, estimating in-between frames to help in synchronizing multiple cameras, compensating for missing training frames, and the recognition of subjects based on their gait.

In conclusion the interpolating cubic spline proposed in our paper performs better by modeling the shape variations over one walking cycle.The numerical results demonstrate that the accuracy of the present method is more superior than the autoregressive system used in the literature for the same purpose. The technique proposed here succeeded in capturing the key variability modes which led to success in the reconstruction of walking cycle shapes identical to the training set.

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