INTRODUCTION

given image의 low level intensity or color information을 disambiguate하기위해 hight level knowledge about expected objects를 exploit 하는게 advantageous.

Much research effort(of image segmentation)는 prior knowledge를 machine vision algorithms에 intergrating 하는데 devoted.

focus on prior knowledge about the shape of objects of interest.

Explicit vs Implicit shape representations

Shape : closed contours defined implicitly as the zero level set of embedding function $\phi : \mathbb{R}^2 \Rightarrow \mathbb{R}$.

Introduce "shape dissimilarity measures" for implicit contours which are by construction invariant under the action of certain transformation groups.

Most research on statistical shape modeling has been devoted to explicit contour representations.

The concept of considering shapes as points on an infinite dimensional manifold, representing shape deformations as the action of Lie groups on this manifold and computing statistics on the space of diffeomophisms

do not claim that implicit boundary representations are superior to explicit ones.

want to clarify why we believe the statistical modeling of implicitly represented shapes to be worth investigating.

Explicit parameterizations allow for 'compact representations of shapes' in terms of a few landmarks or control points.

Advantage of Explicit

1. define easily correspondence of parts and the notion of contour shinking and stretching

Disadvantage of Explicit

1. factoring out the reparameterization group and identifying an initial point correspondence(in matching shapes) are busy work numerically, especially higher dimensions(surface matching)
2. extenstions of explicit representations to model multiply-connected objects are not straightforward

Finally the notion of pointwise correspondence can be introduced into implicit boundary representations as well.

∴ adopt the implicit shape representation given by the level set framework.

Prior shape knowledge in level set segmentation

level set has been adapted to segmentation images based on numerous low-level criteria

1. edge consistency
2. intensity homogeneity
3. texture and motion information

prior knowledge about the shape of expected objects를 the level set framework에 통합!!

A training shape set을 signed distance function sampled on a regular grid(or fixed dimension)으로 표현

to apply PCA to this set of training vectors.

enhanced a geodesic active contours segmentation process by adding a term to the evolution equation which draws the level set function toward the function which is most popular distribution.

performed PCA to obtain a set of eigenmodes and subsequently reformulated the segmentation process to directly optimize the parameters associated with the first few deformation modes.

- to impose prior knowledge onto the segmenting contour 추출됨 after the level set function의 매 반복.

  이 방법이 shape information을 segmentation process중에 쓸수 있게 해주지만,

  이건 level set scheme이 아님 since the shape prior가 contour의 역할을 하고, modeling topological changes가 불가능함

shape information을 the variational formulation of the level set scheme에 추가해

1. a model of local(spatially independent) Gaussian fluctuations around a mean level set function
2. global deformation modes along the lines

An excellent study regarding the equivalence of the topologies induced by three different shape metrics and meaningful extensions of the concepts of sample mean and covariance can be found in the work of C.

More recently, level set formulations were proposed which allow to impose dynamical shape priors and concepts of tracking,

to apply shape knowledge selectively in certain image regions

to impose 충돌하는 여러개의 shape priors so as to simultaneously reconstruct several independent objects in a given image sequence.

The above approaches allow to improve the level set based segementation of corrupted images of familiar objects.

Yet, existing methods to impose statistical shape information on the evolving embedding function suffer from

Three limitations (distribution, distance, transformation and optimizer)

- based on the assumption that the training shapes are distributed according to a Gaussian distribution.
- work under the assumption that shapes are represented by signed distance functions.

  Yet, for a set of training shapes encoded by their signed distance function,

  neither the mean level set function nor the linear combination of eigen modes will in general

  correspond to a signed distance function,

  since the space of signed distance function is not a linear space.
- 특정한 transformation에대한 shape prior의 차이는 is introduced by adding a set of explicit parameters and numerically optimizing the segmentation functional by gradient descent.

  requires a delicate tuning of associated gradient descent time step sizes, not clear in what order and how frequently one is to alternate between the various gradient descent evolutions.

  In particular, we found in experiments that the order of updating the different pose parameters and the level set function affects the resulting segmentation process.

Overcome (invariance of the shpae prior 적용하여 transformation 에 영향을 들 받음, staistical shape prior 를 적용하여 distribution 타파)

- introduce invariance of the shape prior to certain transformations by an intrinsic registration of the evolving level set function.

By evaluating the evolving level set function in coordinates of an intrinsic reference frame attached to the evolving surface, we obtain shape distances which are by construction invariant.

Such a closed form solution removes the need to iteratively update local estimates of explicit pose parameters.

Moreover, we will argue that this approach is more accurate because the resulting shape gradient contains an additional term which accounts for the effect of boundary variation on the pose of the evolving shape.

- We propose a statistical shape prior by introducing the concept of kernel density estimation to the domain of level set based shape representations.

  this prior works well approximate arbitrary distributions.

  Moreover, our formulation does not require the embedding function to be a signed distance function.

  Numerical results demonstrate our method applied to the segmentation of a partially occluded walking person.

∴ 여기서 소개한 방법이 계산적 이점 + high dimension 도 커버함

Overview

2. Mumford-Shah functional 의 two-phase level set 수식을 보겠다
3. level set functions으로 표현된 two shapes를 의한 dissimilarity measure 보겠다
4. model pose invariance의 기존 접근법을 보고 intrinsic alignment에 의한 invariance를 유도하기 위한 해법을 소개한다
5. 소개된 invariant shape dissimilarity measure와 연관된 Euler-Lagrange 방정식의 계산

   invariance properties와 additionally emerging term in the shape gradient on the segmentation of a human sihouette의 효과를 검증했다
6. non-parametric kernel density estimation to the domain of level set based shape representations의 개념을 확장함으로서 novel(multi-model) statistical shape prior 를 소개한다
7. 제안된 shape distribution as prior on the level set function을 통합하기위해 level set segmentation 을 Bayesian inference의 문제로 formulate
8. nonparametric shape prior 을 segmentation of a partially occluded walking person in a video sequence 와 the segmentation of the left ventricle in cardiac ultrasound images 에 적용해서 얻은 양적 질적 결과를 제공