

Classification of multivariate medical datasets using deformable models - A work in progress

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Abstract—This paper presents an overview of the project “Classification of multivariate medical datasets using deformable models” and the current work within the project. The project is a joint venture between the Department of Biomedical Engineering (Linköping University), the Center for Medical Image Science and Visualization (Linköping University) and Sectra Imtec AB (Linköping) and focuses on extending a deformable model approach, named the Morphon, to 3D and to utilize multi-variate data with multiple priors. Recent work in the project includes evaluating different methods for estimating the displacement field and automatic scale control.

I. INTRODUCTION

Computer systems tailored for diagnostic tasks can help increase resource efficiency in the health care. With systems that help in classifying medical image data, the time spent on time-consuming manual tasks can be cut and diagnostic accuracy can be increased. The recent development of new imaging techniques and scanners, such as synthetic MR and dual-energy CT, has given rise to datasets that comprise of several measurements at a single spatio-temporal position. The added information presents new possibilities to extract relevant features from the data.

The goal of this project is to develop methods for clinically relevant classification that can benefit from the added information in these datasets. For a classification system to be successful it is our belief that the user’s vast domain knowledge has to be put at the core. In order to include user domain knowledge in this project we propose to use a deformable model approach based on the Morphon algorithm. We intend to extend the Morphon to work with the new multi-variate data. We further intend to strengthen the use of user domain knowledge by using multiple models that are learned through user interaction over time. Of special interest is classification that can help in diagnosing neurodegenerative diseases, such as MS and Alzheimer’s. The task of classifying brain tissue is very complex and has a lot to gain from the incorporation of multiple variates.

II. PROJECT DESCRIPTION

Using user domain knowledge for classification in medical image datasets has proven to be a very powerful tool. As

the complexity of the datasets increases and includes multiple variates of the data the user domain knowledge will be even more important to succeed in classifying datasets. The focus of the Morphon approach on intuitive ways to include prior information makes this an ideal starting point for developing tools for classification of multi-variate medical data. In the following the three main additions to the Morphon approach that will be developed in this project are outlined: a 3D extension of the existing Morphon implementation, an extension to multiple variates and a new way to utilize multiple priors in the Morphon framework.

A. Extension to 3D

Although the framework for the Morphon is easily extended to 3D¹ this extension will still require a substantial effort. Issues like user interface for describing priors, visualization of intermediate and final results and computational complexity must be handled with care since these tasks are much more complex in 3D than in 2D.

B. Extension to multiple variates

The variates in a multi-variate dataset are often related to each other. The value of one variate can impose restrictions on the admissible values of other variates at the same position in the dataset. Using the relationship between variates a more robust classification can be achieved. The intention is to focus on this and develop multi-variate Morphons where the classifications of the different variates are allowed to influence each other to ensure that the a priori knowledge of the admissible variate values are incorporated. How to best utilize the information from the different variates and how to transform different variates within the Morphon algorithm in different scenarios will be one of the big challenges in the project.

C. Extension to multiple priors

To further extend the integration of a priori information our intention is to include anatomical atlases that consist of

¹The Morphon has already been shown to work in 3D but there still remain work to complete the robustness of this extension, see [5].

multiple priors. The use of multiple priors will help overcome the problems with atlas based approaches in cases where there are large variations in the feature of interest. As more variations of the feature appear the intention is to dynamically include these and, over time, build a set of “base-morphons” that span the feature space of interest. This will introduce a feed-back loop in the system and will provide the system with a learning or evolutionary feature.

III. THE MORPHON

The Morphon is essentially an algorithm where a model (prototype image) is iteratively deformed until it fits a target image². The strength of the Morphon lies within its built-in ability to handle different a priori information (priors) associated to the model. The priors can be grouped into the following three groups.

- Material - a parameter field determining the local “material” properties. Typical properties are elasticity, viscosity and anisotropy.
- Context - a parameter field holding information that support the interpretation of the image data. Examples of this are local scale, orientation, anisotropy and certainty.
- Program - a global definition of what to do, how to use the priors and data and what outputs to produce.

The algorithm itself consists of the following three steps: *displacement estimation, deformation field accumulation, deformation*. The algorithm is iterated a number of times on different scales, starting on a coarse scale and moving to finer scales.

A. Displacement estimation

The first step of the Morphon is to estimate the displacement between the model and the target image. There exists a number of different algorithms for doing this, for instance methods based upon gradients and polynomial expansions. The current work is based upon a phase based estimation of the displacement field. This is done by filtering the model and the target image with a set of quadrature filters (N filters with different directions, $\hat{\mathbf{n}}_k$). The filters provide outputs in N different directions ($\mathbf{q}_{M_k}, \mathbf{q}_{T_k}$) describing how edge- or line-like the local neighborhood is (determined by the phase of the filter output) coupled with a certainty measure (determined by the magnitude of the filter output). The outputs are used to compute the local phase difference between the model and the target image based on conjugate products of the filter responses, see [2]. The phase differences d_k and the coupled certainties c_k are then used to compute an incremental displacement field \mathbf{d}_i and certainty c_i for the current scale and iteration.

B. Deformation field accumulation

The incremental displacement field and certainty are then added to the accumulated displacement field \mathbf{d}_a and certainty c_a according to:

²The Morphon can both be utilized for registration but the primary focus of the Morphon is to segment the target image based upon a model/multiple models, see [6] for an example using multiple models.

$$\mathbf{d}_a = \frac{c_a \mathbf{d}_a + c_i (\mathbf{d}_a + \mathbf{d}_i)}{c_a + c_i} \quad (1)$$

$$c_a = \frac{c_a^2 + c_i^2}{c_a + c_i} \quad (2)$$

Important to note here is that the incremental displacement field is regularized before it is added to the accumulated displacement. The regularization is performed by normalized convolution using a Gaussian low pass kernel g as filter and c_i as certainty, see [1].

$$\mathbf{d}_i = \frac{(c_i \mathbf{d}_i) * g}{c_i * g} \quad (3)$$

The reason for this is to provide a more robust algorithm. There exists several different accumulated displacement fields that provide the same end result but we prefer the most simple displacement field, hence the regularization.

C. Deformation

The final step of the Morphon is to use the accumulated field and to morph the original model. The morphed model is used as the model in the next iteration.

IV. CURRENT WORK

A. Different displacement estimation solutions

As noted earlier the current work is based on a phase based approach for estimating the displacement. There exists a number of ways for first computing d_k and c_k and then computing \mathbf{d}_i and c_i . Recent work within the project has focused on the computation of \mathbf{d}_i and c_i .

1) *Least square problem*: Previously it has been suggested that \mathbf{d}_i is computed by finding the solution of a least square problem, see for instance [4].

$$\min_{\mathbf{d}} \sum_{k=1}^N [c_k \hat{\mathbf{n}}_k^T \mathbf{T}_M (\hat{\mathbf{n}}_k d_k - \mathbf{d})]^2 \quad (4)$$

Where:

$$c_k = \sqrt{|\mathbf{Q}_k|} \cos^2 \left(\frac{\arg(\mathbf{Q}_k)}{2} \right)$$

$$\mathbf{Q}_k = \mathbf{q}_{M_k} \mathbf{q}_{T_k}^*$$

\mathbf{T}_M = Local structure tensor of the model, see [1], [3]

$$d_k \propto \arg(\mathbf{Q}_k)$$

\mathbf{d} = Estimated displacement

However, the least square problem defined in equation 4 is not unique. Other suggestions exist such as:

$$\min_{\mathbf{d}} \sum_{k=1}^N [c_k (\hat{\mathbf{n}}_k d_k - \mathbf{d})]^2 \quad (5)$$

$$\min_{\mathbf{d}} \sum_{k=1}^N [c_k \mathbf{T}_M (\hat{\mathbf{n}}_k d_k - \mathbf{d})]^2 \quad (6)$$

2) *Vector summation*: A more intuitive method, here presented for the first time, for finding \mathbf{d}_i and c_i given d_k and c_k is to simply add these as vectors according to:

$$\mathbf{d} = \frac{\sum_{k=1}^N c_k d_k \hat{\mathbf{n}}_k^T \mathbf{T}_M \hat{\mathbf{n}}_k \hat{\mathbf{n}}_k}{\sum_{k=1}^N c_k \hat{\mathbf{n}}_k^T \mathbf{T}_M \hat{\mathbf{n}}_k} \quad (7)$$

$$c = \sum_{k=1}^N c_k \hat{\mathbf{n}}_k^T \mathbf{T}_M \hat{\mathbf{n}}_k \quad (8)$$

In equation 7 we have included the tensor \mathbf{T}_M describing the local structure of the model. An obvious extension of this is to include the tensor \mathbf{T}_T describing the local structure of the target image according to:

$$\mathbf{d} = \frac{\sum_{k=1}^N c_k d_k c_k \hat{\mathbf{n}}_k^T \mathbf{T}_M \hat{\mathbf{n}}_k \hat{\mathbf{n}}_k^T \mathbf{T}_T \hat{\mathbf{n}}_k \hat{\mathbf{n}}_k}{\sum_{k=1}^N c_k \hat{\mathbf{n}}_k^T \mathbf{T}_M \hat{\mathbf{n}}_k \hat{\mathbf{n}}_k^T \mathbf{T}_T \hat{\mathbf{n}}_k} \quad (9)$$

$$c = \sum_{k=1}^N c_k \hat{\mathbf{n}}_k^T \mathbf{T}_M \hat{\mathbf{n}}_k \hat{\mathbf{n}}_k^T \mathbf{T}_T \hat{\mathbf{n}}_k \quad (10)$$

This can also be done without the tensors \mathbf{T}_M and \mathbf{T}_T , according to:

$$\mathbf{d} = \frac{\sum_{k=1}^N c_k d_k \hat{\mathbf{n}}_k}{\sum_{k=1}^N c_k} \quad (11)$$

$$c = \sum_{k=1}^N c_k \quad (12)$$

B. Automatic scale control

Another recent focus area has been the development of an automatic scale control (ASC). Previously the Morphon algorithm has started on a coarse scale and iteratively worked its way through finer and finer scales with a set a number of iterations per scale. The multi scale approach is implemented by iteratively averaging and sub sampling the images in order to obtain the wanted scale. Although the Morphon can handle sub pixel displacement estimations there is a limit for this. Taken this into account the current method for handling different scales suggests that instead of performing a set number of iterations per scale we should only perform another iteration on the same scale as long as the last incremental displacement field adds a substantial displacement to the accumulated displacement field. A suggestion for a change scale criteria is given by:

$$\begin{aligned} \text{change scale if } \max(\|\mathbf{d}_{a_n} - \mathbf{d}_{a_{n-1}}\|) &\geq 2^{sc} \\ \text{where } c_{a_n} &\geq \epsilon \text{ and } sc \text{ is current scale} \end{aligned} \quad (13)$$

The scale sc equals 0 for the original scale/resolution and $sc = 1$ when the scale/resolution has decreased a factor 2. It also seems reasonable, based on the previous approach with a set number of iterations per scale, to still limit the maximum number of iterations per scale.

V. RESULTS

In the following section the model image and target image in figure 1 have been used. To the target image uniform noise have been added, according to figure 2. The results presented in this section are preliminary since the evaluation only has been performed on a limited set of images.

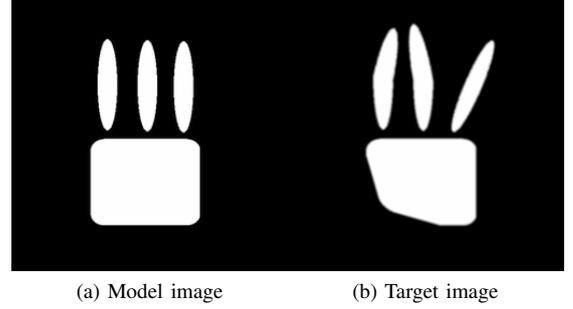


Fig. 1: Model and target images

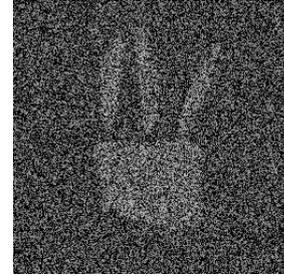


Fig. 2: Target image with low SNR

A. Comparing least square and vector summation solutions

Comparing the least square and vector summation solutions reveals no evident differences, see figure 3. This comparison is cumbersome to perform since the step size is dependent on the selected solution and thus requires manual tweaking, if not one of the solutions will tend to not work properly.

In the following comparison the solutions specified in equations 4 and 9 have been used.

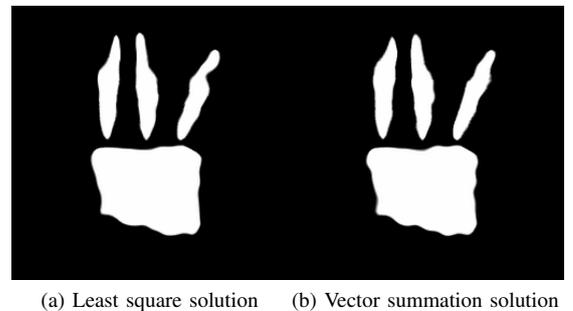


Fig. 3: Comparing least square and vector summation solutions

B. Comparing vector summation solutions with or without \mathbf{T}

The tensor \mathbf{T} is included in order to provide a more robust solution for images with a low SNR. The idea is that the information about the local structure will force the estimated displacement field to also consider the local structure in the neighborhood. However, our preliminary results do not support this assumption but instead suggest that adding the tensor \mathbf{T} provides no extra information, see figure 4.

In the following comparison the solutions specified in equations 9 and 11 have been used.

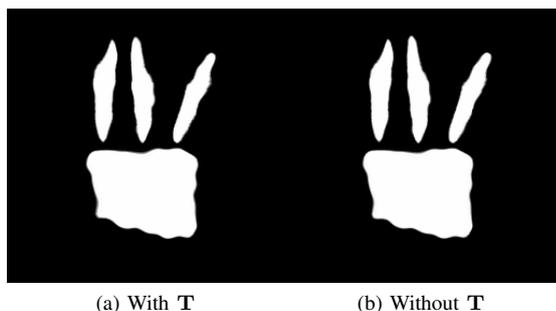


Fig. 4: Comparing vector summation with or without \mathbf{T}

C. Comparing ASC with a set number of iterations per scale

Enabling the ASC as specified in equation 13 and setting the maximum number of iterations to same number of iterations as when performing a fixed number of iterations per scale results in a decrease by 30 % in the number of iterations needed. If using the sum of squared intensity differences and the normalized cross-correlation as similarity measures reveals that the ASC has a slightly worse similarity than using a fixed number of iterations.

In the following comparison the solution specified in equation 9 has been used.

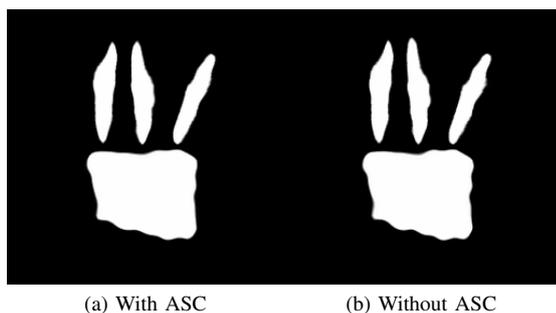


Fig. 5: Comparing vector summation with or without ASC

VI. DISCUSSION AND CONCLUSION

There are a few things that are to be noted regarding the results presented in the previous section.

- The results from the evaluation are only preliminary since it has been performed on a very limited set of images.

- A problem when comparing different solutions for displacement estimation is that today there is no automatic way of determining the step size based upon the estimated phase difference. Instead each solution must be manually tweaked in order to have a suitable step size and this makes the comparison of different displacement estimation solutions rather cumbersome.
- The results from the comparison of least square and vector summation solutions are difficult to evaluate since the results are varying. In some cases the vector summation solution appear to be more stable but in other cases the least square solution is better.
- Automatic scale control improves the speed of the Morphon without substantially affecting the end result.

VII. FUTURE WORK

Based upon the presented results the following suggestions for future work exist:

- Complete the started evaluation and establish a scheme³ for easier comparison of different solutions.
- Extend the Morphon to better determine the step size when doing the displacement estimation⁴.
- Further investigate the difference between the least square and vector summation solutions.
- Further investigate the difference between the two vector summation solutions.

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³The scheme should include different similarity measures, different image transformations (translation, rotation, scale, skew) and different images (simple objects, models and real images).

⁴The step size is related to the center frequency of the applied quadrature filters and should therefore be possible to use. This is important both for comparing different solutions but also for improving the criteria for the automatic scale control.