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CORRELATION BASED 3-D SEGMENTATION OF THE LEFT VENTRICLE IN PEDIATRIC ECHOCARDIOGRAPHIC IMAGES USING RADIO-FREQUENCY DATA

MAARTJE M. NILLESEN,* RICHARD G. P. LOPATA,† H. J. HUISMAN,‡ JOHAN M. THIJSSEN,* LIVIA KAPUSTA,‡ and CHRIS L. DE KORTE*

*Clinical Physics Laboratory, Department of Pediatrics, Radboud University Nijmegen Medical Centre, Nijmegen, The Netherlands; †Department of Biomedical Engineering, Eindhoven University of Technology, Eindhoven, The Netherlands; ‡Department of Radiology, Radboud University Nijmegen Medical Centre, Nijmegen, The Netherlands; †Pediatric Cardiology, Department of Pediatrics, Radboud University Nijmegen Medical Centre, Nijmegen, The Netherlands; and ‡Pediatric Cardiology Unit, E. Wolfson Medical Center, Holon, Israel

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Abstract—Clinical diagnosis of heart disease might be substantially supported by automated segmentation of the endocardial surface in three-dimensional (3-D) echographic images. Because of the poor echogenicity contrast between blood and myocardial tissue in some regions and the inherent speckle noise, automated analysis of these images is challenging. *A priori* knowledge on the shape of the heart cannot always be relied on, e.g., in children with congenital heart disease, segmentation should be based on the echo features solely. The objective of this study was to investigate the merit of using temporal cross-correlation of radio-frequency (RF) data for automated segmentation of 3-D echocardiographic images. Maximum temporal cross-correlation (MCC) values were determined locally from the RF-data using an iterative 3-D technique. MCC values as well as a combination of MCC values and adaptive filtered, demodulated RF-data were used as an additional, external force in a deformable model approach to segment the endocardial surface and were tested against manually segmented surfaces. Results on 3-D full volume images (Philips, iE33) of 10 healthy children demonstrate that MCC values derived from the RF signal yield a useful parameter to distinguish between blood and myocardium in regions with low echogenicity contrast and incorporation of MCC improves the segmentation results significantly. Further investigation of the MCC over the whole cardiac cycle is required to exploit the full benefit of it for automated segmentation. (E-mail: m.m.nillesen@cukz.umcn.nl) © 2011 World Federation for Ultrasound in Medicine & Biology.

Key Words: Echocardiography, Pediatric, Adaptive filtering, Temporal cross-correlation, Deformable model, Ultrasound, Image segmentation.

INTRODUCTION

Ultrasound is a reliable and fast imaging modality that is pre-eminent in cardiac imaging of children because of its high temporal resolution and bedside application. The introduction of real-time three-dimensional (3-D) echographic imaging techniques has been a major step forward for quantitative analysis of the heart as these techniques provide rich information about the whole structure and 3-D motion of the heart. Three-dimensional echocardiography enables the estimation of clinically important parameters such as cardiac output and ejection fraction without the necessity of making two-dimensional (2-D) geometrical assumptions. These geometrical assumptions generally include a simplified shape of the left ventricle which may lead to inaccurate estimation of the ventricular function (Gopal et al. 1995; Jacobs et al. 2006), especially in children with congenital malformations of the heart. Three-dimensional ultrasound imaging might also facilitate simultaneous estimation of strain in radial, circumferential and longitudinal direction in the heart muscle. Furthermore, inaccurate strain estimates due to out of plane motion (Kallel and Ophir 1997; Konofagou and Ophir 2000) can be prevented.

The availability of 3-D echocardiography has also boosted the urge for automated segmentation methods.
since manual segmentation of 3-D ultrasound image sequences is very time-consuming. Moreover, manual segmentation by an expert is subject to inter-and intra-expert variability. Many approaches for segmenting the endocardial wall in adult echocardiographic images have been proposed. An overview can be found in Noble and Boukerroui (2006).

The inherent speckle noise from randomly backscattered echoes and the poor echogenicity contrast between blood and myocardium in some regions impose strong demands on the segmentation algorithm. If the orientation of the muscle fibers is mainly parallel to the propagation direction of the ultrasound beam, myocardial echogenicity is reduced to within the range of blood echogenicity. Automated segmentation purely based on differences in echogenicity will lead to erroneous segmentation in these low echogenicity regions as the contrast between blood and myocardial tissue is absent. To overcome segmentation errors in these regions, methods using shape and appearance models have been proposed (Bosch et al. 2002; Hansegard et al. 2007). These models incorporate knowledge about the shape and appearance of, for example, the left ventricle by using an average shape and appearance model of the adult heart. These methods rely on implicit knowledge that is also used by expert cardiologists during manual segmentation and are successful in normal adult heart geometries in standardized (apical) views. However, echocardiography in children often aims at detection of congenital deformities of the heart. The use of a priori knowledge about the average shape of the ventricle may lead to incorrect segmentation in these images.

Segmentation in pediatric echocardiographic images faces some additional difficulties. Due to the relatively small intercostal spaces, image quality might be affected negatively by the ribs, causing shadowing and clutter artifacts. Compared with adults, the position of the heart within the thorax is different in such a way that in most 3-D apical images in young children the lateral wall (compare the standard 2-D two-chamber view) is difficult to visualize. Three-dimensional transthoracic short-axis/long axis views lead to much better image quality as the largest part of the muscle fibers is now perpendicular to the ultrasound beam. However, in this different view, it is challenging to visualize the entire left ventricle and often the apex is missing or has a very low echogenicity. Furthermore, most commercial segmentation methods require a standardized apical view and, consequently, inaccurate segmentation is obtained in this different viewing angle with these methods.

To obtain more accurate segmentations in problematic low contrast regions without the necessity of making a priori assumptions on shape/appearance and viewing angle, the addition of temporal information using cross-correlation techniques might be helpful. These techniques build on the underlying principle that echographic data of two successive time frames will correlate less for fast moving blood than for the myocardial tissue. For the analysis of echocardiographic images, an expert cardiologist mentally incorporates the movement of the heart throughout the cardiac cycle to determine the exact geometry of the heart and uses the temporal coherence of structures to resolve ambiguities. In this study, we propose the use of temporal cross-correlation techniques that utilize the rich phase information available in the radio-frequency (RF) signal.

In the field of ultrasound segmentation, most methods are based on using conventional B-mode images (amongst others, Angelini et al. 2001; Corsi et al. 2002; Gerard et al. 2002; Lin et al. 2003; van Stralen et al. 2005), whereas only a few studies are dedicated to segmentation based on the RF-data. Davignon et al. (2005) used statistical parameters, derived from the envelope of the RF-data, representative of the scattering conditions in the tissue in a multiparametric segmentation process and they evaluated these parameters in simulated ultrasound data. Boukerroui et al. (2001) computed the mean central frequency (MCF) and integrated backscatter (IBS) from the local frequency spectra of the RF-signal and used these parameters in a multiparametric and multi-resolution segmentation algorithm. Dydenko et al. (2003) proposed the use of spectral autoregressive parameters and velocity-based parameters and tested these on 2-D simulated and cardiac RF-data. Gerrits et al. (2007) used the temporal decorrelation of Doppler RF-signals for 3-D region based-segmentation of the blood pool in the left ventricle. Yan et al. (2007) investigated several RF-derived parameters as the IBS, the MCF and a 3-D maximum cross-correlation coefficient (MCC) derived from phase sensitive speckle tracking. In the latter study, segmentation based on parametric images obtained from the MCC was promising.

This study aims at 3-D automated segmentation of the endocardial surface in 3-D pediatric echocardiographic images. We propose the use of temporal cross-correlation values of subsequently acquired 3-D volumes. 3-D cross-correlation values were derived from an iterative RF-based coarse-to-fine displacement algorithm that was originally developed for strain estimation. These values were included as external force in a deformable model to segment the endocardial surface and tested against manually segmented surfaces. Cross-correlation values were also combined with and tested against adaptive filtered demodulated RF-data (Nillesen et al. 2007), a feature that only uses differences in echogenicity to distinguish between blood and myocardium.
MATERIALS AND METHODS

Echographic data

Echocardiographic image sequences of the left ventricle were obtained in 10 healthy children (6–15-years-old, mean ± SD: 9 years and 10 months ± 3 years). The protocol was approved by the local ethics committee and both parents and children (if older than 11 years) gave their informed consent. The health status of each child was determined by anamnesis and conventional echocardiographical examination as assessed by an experienced pediatric cardiologist. Routinely, the transducer was placed in the third intercostal space to obtain transthoracic full volume image sequences (3-D + t) in long/short axis views. This view was preferred over the apical view as in children the lateral wall is more difficult to visualize in 3-D apical images. All children were in sinus rhythm (79 ± 12.6 [mean ± SD] beats per minute) and the electrocardiogram (ECG)-triggered, 3-D full volume data were acquired during seven consecutive heart beats. The resulting volume imaging rate varied between 41 and 56 Hz, depending on the image depth. To prevent stitching artifacts due to inaccurate synchronization between two consecutive heart beats, children were asked to hold their breath for the time of acquisition (maximally 10 seconds). RF-data were acquired directly after receive beam forming using an iE33 ultrasound system (Philips Medical Systems, Bothell, WA, USA), equipped with an RF-interface and a pediatric X7-2 matrix array transducer (2–7 MHz). RF-data were sampled at 16 MHz and transmitted to an external hard disk at USB 2.0 interface. The angle between the image lines in lateral as well as elevational direction was either 1.25° or 1.5°. The line density depended on the total angle required to encompass the entire left ventricle, i.e., larger ventricles result in the lower line density. The data were band-pass filtered using a linear phase finite impulse response filter (FIR) least squares filter to prevent disturbance by clutter and noise from frequencies outside the frequency band of the transducer. For visualizing the echograms, the data were amplitude demodulated using the Hilbert transform method and log-compressed. Matlab software (The MathWorks Inc., Natick, MA, USA) was used to perform the RF filtering, Hilbert transform, MCC computations and adaptive filtering. The deformable model was implemented using ITK (v. 2.8) and visualized using VTK (v. 5.0.0).

Since the frame rate of the echo system used for full volume imaging is still limited, only the cardiac phases with low deformation rate of the heart muscle, i.e., the end-diastolic and end-systolic phases, yield optimal correlation and displacement estimates (see paragraph on cross-correlation techniques below). Since the heart muscle was not always entirely visible in the end-diastolic phase, the end-systolic phase was chosen to acquire images for evaluation and validation of the proposed segmentation method.

Maximum cross-correlation computation

The blood flow velocity in the ventricles is higher than the velocity of the surrounding myocardial tissue. So, if successive 3-D ultrasound volumes are compared, the temporal correlation will be higher for the myocardial tissue than for the blood. This difference can be used for segmentation of the walls vs. the blood in the ventricular cavity. For 3-D strain imaging purposes, the cross-correlation function of 3-D windows of RF-data was calculated (Chen et al. 2005; Lopata et al. 2007). We used a 3-D coarse-to-fine displacement estimation algorithm (Lopata et al. 2007) that was based on an earlier developed 2-D algorithm (Lopata et al. 2009b; Shi and Varghese 2007) to estimate axial, lateral and elevational displacements iteratively. The position of the maximum of the cross-correlation function (CCF) corresponds to the local displacement of the tissue between two acquisitions and can, thus, be used for displacement and strain estimation (Ophir et al. 1991). The maximum of the cross-correlation function (MCC) corresponds to the similarity between subsequently acquired RF signals and this similarity is expected to be lower for fast flowing blood than for rather slow-moving myocardial tissue. In this study, the MCC was used as a driving force for the segmentation model.

Displacement estimation

Three-dimensional windows were cross-correlated for two subsequent time frames and the MCC was determined. All cross-correlation computations use line data, i.e., all data were processed along the scan lines in a rectangular matrix representation. Table 1 provides a detailed overview of all window dimensions used in the CCF computations. The 3-D normalized CCF for two successive frames of RF data (I_t and I_{t+1}) was defined as:

$$CCF(w, t, \tau) = \frac{\sum_{w \in K_w} [I_t(w) - \bar{I}_t][I_{t+1}(w+\tau) - \bar{I}_{t+1}]}{\sqrt{\sum_{w \in K_w} [I_t(w) - \bar{I}_t]^2[I_{t+1}(w+\tau) - \bar{I}_{t+1}]^2}} \quad (1)$$

where $w = (w_{ax}, w_{lat}, w_{elev})$ denote the axial, lateral and elevational indices and $\tau = (\tau_{ax}, \tau_{lat}, \tau_{elev})$ denotes the spatial shift between frames $I_t$ and $I_{t+1}$. The maximum absolute shift $\tau$ was limited, hereby limiting the maximum axial and lateral and elevational displacements that could be measured. $K_w$ defines a symmetrical window centered...
around \( w \) and \( I_t \) and \( I_{t+1} \) indicate the mean values for the specified windows for \( I_t \) and \( I_{t+1} \) used in the CCF computation. The peak of the cross-correlation function within the search window revealed the displacement estimate \( \hat{d} = (\hat{d}_{ax}, \hat{d}_{lat}, \hat{d}_{elev}) \) of a 3-D segment of RF-data in the next time frame in 3-D space:

\[
\hat{d}(w, t) = \arg\max_{b} CCF(w, t, \tau)
\]  

(2)

The displacement estimation \( \hat{d} \) was further improved by parabolic interpolation of the cross-correlation function around the peak (Lopata et al. 2009a) (Fig. 1).

**Iterative cross-correlation refinement**

Now we have obtained an initial displacement estimate, this displacement can be compensated for in the CCF computation in an iterative manner. By doing this, the cross-correlation values can be optimized and further refined. The displacement field \( \hat{d} \) estimated in the previous iteration was used as an offset for the CCF computation:

\[
CCF_{iter}(w, t, \tau, \hat{d}_{iter-1}) = \frac{\sum_{w \in K_{w}} [I_t(w) - I_t][I_{t+1}(w + \tau + \hat{d}_{iter-1}) - I_{t+1}]}{\sqrt{\sum_{w \in K_{w}} [I_t(w) - I_t]^2[I_{t+1}(w + \tau + \hat{d}_{iter-1}) - I_{t+1}]^2}}
\]  

(3)

The iterative displacement estimation method was applied using a coarse-to-fine algorithm, as illustrated by Figures 1 and 2. In the first iteration, the envelope data (i.e., demodulated RF-data using the Hilbert transform) were cross-correlated using large windows (coarse) to obtain a coarse displacement field. In the second iteration, the window size (w) and search space (\( \tau \)) were decreased (middle), enabling more precise displacement estimates at a higher resolution. The third iteration used the RF-data at a fine scale enabling even more accurate displacement estimations because of the use of high-resolution phase information (Lopata et al. 2009a). All displacement estimates were smoothed using a median filter. Detailed information on window sizes (\( K_w \)) and search space (\( \tau \)) for the different iterations is given in Table 1. As a final step (iteration 4), the peak of the one-dimensional (1-D) CCF in the axial direction (based on RF-data) was estimated. After compensation for the 3-D local displacement field using 3-D cross-correlations in the first three iterations, we used the 1-D cross-correlation in the fourth iteration since this is a better representation of the actual correlation between the two consecutive volumes. Therefore, more precise and higher cross-correlation values are achieved using the 1-D CCF:

\[
CCF_{1D}(w, t, \tau_{ax}, \hat{d}) = \frac{\sum_{w_{ax} \in K_{w_{ax}}} [I_t(w_{ax}) - I_t][I_{t+1}(w_{ax} + \tau_{ax} + \hat{d}_{ax}, w_{lat} + \hat{d}_{lat}, w_{elev} + \hat{d}_{elev}) - I_{t+1}]}{\sqrt{\sum_{w_{ax} \in K_{w_{ax}}} [I_t(w_{ax}) - I_t]^2[I_{t+1}(w_{ax} + \tau_{ax} + \hat{d}_{ax}, w_{lat} + \hat{d}_{lat}, w_{elev} + \hat{d}_{elev}) - I_{t+1}]^2}}
\]  

(4)

(5)
where $K_{\text{ax}}$ defines a symmetrical axial window centered around $w_{\text{ax}}$. The maximal absolute axial shift $\tau_{\text{ax}}$ was limited between $-5$ and $+5$ samples. The maximum of this 1-D CFF was defined as the MCC parameter that was used as a novel feature in the segmentation process:

$$MCC(w,t) = \max_{\tau_{\text{ax}}} CCF_{1D}(w,t,\tau_{\text{ax}}, \hat{d})$$

(6)

Finally, similar to displacement regularization in strain imaging, a median filter (see Table 1 for specifications) was applied to the MCC values to discard outliers and smooth the data before automated segmentation was executed. Figure 2 illustrates the iterative cross-correlation refinement algorithm by showing MCC values for the four iteration steps in short and long axis views of the left ventricle.
3-D adaptive filtering

Besides estimation of the maximum cross-correlation values, adaptive filtering was used as a more conventional method to optimize the distinction between blood and myocardium. Three-dimensional adaptive mean squares filtering of the amplitude demodulated RF-data was applied in the spatial domain (Nillesen et al. 2007). The 3-D filter window size was related to image speckle size and contained approximately $5 \times 2 \times 2$ (axial $\times$ lateral $\times$ elevational) speckles. Since the speckle size is independent of echo depth while using the image lines instead of scan-converted DICOM images (Valckx et al. 2000), the size of the window was set at a fixed value for all echo depths. Knowledge about speckle statistics (Nillesen et al. 2008) of blood and myocardium are incorporated in an adaptive manner: homogeneous regions are filtered strongly, i.e., speckle noise is reduced, whereas in inhomogeneous regions the degree of filtering is low, such that transitions between blood and myocardial tissue are preserved. The suppression of speckle noise is essential in the case of gradient-based deformable models as speckle introduces multiple incorrect ‘boundaries’ that leads to incorrect segmentation. The AMS filter has been proven to enhance the difference between echo-levels originating from blood and myocardial wall (Nillesen et al. 2007) and to be effective for segmentation of 3-D echocardiographic images when using gradient based deformable models (Nillesen et al. 2009).

Deformable model

A gradient-based deformable simplex mesh model (Delingette 1999) was used for segmentation of the left ventricle. A simplex mesh consists of a set of vertices that forms a discrete non-parametric representation of a surface in $\mathbb{R}^3$. In this model, each vertex of the mesh $p_i = (x_i, y_i, z_i)$ is displaced in an iterative manner according to the discrete approximation of the Newtonian law of motion:

$$p_{i+1} = p_i + \alpha F_{\text{int}} + F_{\text{ext}}$$

$F_{\text{int}}$ is a regularization force and controls the smoothness of the surface (Delingette 1999). $F_{\text{ext}}$ is an external force derived from the image data that steers the simplex mesh onto boundary structures. In this study, $F_{\text{ext}}$ consists of an adaptive filtering based component (AMS) and the newly defined maximum cross-correlation component (MCC):

$$F_{\text{ext}} = \beta F_{\text{gradAMS}} + \delta F_{\text{gradMCC}} + \kappa F_{\text{speedAMS}} + \lambda F_{\text{speedMCC}}$$

Both AMS and MCC values were used to compute gradient and speed forces (Bottger et al. 2007). The gradient force $F_{\text{grad}}$ is defined as:

$$F_{\text{grad}}(p_i) = \nabla \frac{1}{1 + \exp \left( -\frac{\nabla G_s I_{\text{force}}(x_i, y_i, z_i) - \nu_{\text{grad}}}{\eta_{\text{grad}}} \right)}$$

where $I_{\text{force}}$ stands for image intensity (echo level) of either the AMS image (force = AMS) or the MCC image (force = MCC). The parameters $\nu_{\text{grad}}$ and $\eta_{\text{grad}}$ are used to scale the gradient magnitude to the interval [0, 1] by sigmoidal intensity mapping and are based on the minimum and average gradient magnitude value (Ibanez et al. 2003). Gaussian smoothing ($G_s$) with a relatively small $\sigma$ (0.5 mm) is applied to increase the width of the attraction potential and to smooth undesired small gradients inside the left ventricular cavity.

$F_{\text{speed}}$ is an inflating force, into the vertex normal direction $n = (n_x, n_y, n_z)$ and is defined as (Bottger et al. 2007):

$$F_{\text{speed}}(p_i) = \frac{1}{1 + \exp \left( -\frac{\nabla G_s I_{\text{force}}(x_i, y_i, z_i) - \nu_{\text{speed}}}{\eta_{\text{speed}}} \right)} \cdot n$$
The parameters $\zeta_{\text{speed}}$ and $\eta_{\text{speed}}$ are chosen such that $F_{\text{speed}}$ has high values in regions with no gradient information and has low values at boundaries and lies between 0 and 1, to reduce the need for close-to-boundary initialization of the mesh. Unlike the gradient force $F_{\text{grad}}$, the direction of the speed force $F_{\text{speed}}$ is always along the vertex normal direction $n$.

Weighting factors $\alpha$, $\beta$, $\delta$, $\kappa$ and $\lambda$ were used to balance the different forces. Whereas adaptive filtering and computation of the cross-correlation was performed by processing the data along the scan-lines, computation of the external and internal forces, as well as the deformation of the simplex mesh was performed on the data in scan-converted (i.e., sector) format. Initialization of the mesh was done by interactive placement of a small spherical mesh in the center of the left ventricle.

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**Evaluation**

The method was evaluated by comparing left ventricular cavity contours as obtained from the segmentation method with contours obtained from manual segmentation. Segmentation results of three different force types were compared: using AMS force only (original model, $\beta$ and $\kappa \neq 0$, $\delta = \lambda = 0$), using cross-correlation force only ($\beta = \kappa = 0$, $\delta$ and $\lambda \neq 0$) and the combined model ($\beta$ and $\kappa$ and $\delta$ and $\lambda \neq 0$). In the combined model, AMS and MCC are equally weighed forces. For each dataset, the same initial position of the mesh in the center of the left ventricle was used for all three segmentation methods.

Contours were extracted from the 3-D volume segmented by the deformable model and compared to manual segmentation for long axis (LAX) views and short axis (SAX) cross-sections. The endocardial surface was segmented manually by a trained observer for all data sets by drawing 2-D contours for each axial-elevational plane (short-axis view). The observer was blinded to the automatically segmented contours. Papillary muscles were excluded from the left ventricular cavity as the aim of the segmentation method was to distinguish blood from muscle tissue also for the purpose of tissue strain imaging. For each data set, a set of relevant short axis and long axis planes was defined. A plane was considered “relevant” if it contained (part of) the left ventricle. Planes on the periphery of the left ventricle, where it was not possible to draw reliable contours, were left out. Two-dimensional (2-D) similarity indices were computed for all relevant planes in the axial-lateral (long axis) and axial elevational (short axis) planes. The Dice coefficient (Dice 1945) was computed between manual (Ref) and automated segmentation (Seg) to express the similarity:

$$SI_{\text{Dice}} = \frac{2(\text{Ref} \cap \text{Seg})}{\text{Ref} + \text{Seg}}$$

It should be mentioned that this similarity index was applied to 2-D contours as well as to 3-D volumes.
Statistical analysis (Wilcoxon signed rank test) was performed to test whether the 2-D and 3-D SIs for all relevant planes of all data sets were significantly different for the three force types.

**RESULTS**

Three-dimensional segmentation of the left ventricle was performed in full volume images obtained from ten healthy children in the end systolic phase of the heart cycle. Three different force types were tested using the deformable model for each dataset: AMS, MCC and an equally weighed combination of both AMS and MCC.

Figure 3 shows characteristic short and long axis views from a full volume dataset for the two external forces of the deformable model. In general, the contrast between blood and the myocardium is higher for the maximum cross-correlation values than for the adaptive filtered data. MCC values still seem to have contrast between blood and myocardium in low echogenicity regions of the heart muscle, for example in the region where the muscle fibers are parallel to the ultrasound beam (cf. short axis view, compare Fig. 3a and c).

Figure 4 shows segmentation results for the three force types, AMS, MCC and AMS combined with MCC. This figure depicts the scan-converted demodulated RF-data overlaid with contours of the segmented endocardial surface in short axis, long axis views as well as a 3-D volume representation.

To perform a more thorough evaluation of the influence of the MCC on the segmentation results, 2-D and 3-D Dice similarity indices (SIs) between automated and manual segmentation were computed. Two-dimensional SIs for one data set (cf., Fig. 4) are given in Figure 5. Average 2-D SIs over all relevant planes are denoted in brackets for all three force types. Table 2 summarizes the average 2-D similarity indices over all relevant planes of long and short axis views for AMS, MCC and the combination of AMS and MCC. As can be appreciated from this table, the most accurate segmentation was obtained by the combination of AMS and MCC. Especially in the short axis views, in 80% of the cases, the combination of AMS and MCC outperforms segmentation based on AMS or MCC alone. In the long axis view, in 60% of the cases the segmentation outcome of the combination is equally or more accurate than segmentation based on AMS alone.

A Wilcoxon signed rank test on the 2-D similarity indices over all relevant planes of all datasets reveals significant improvement for the combination of AMS and MCC compared with segmentation based on AMS alone, as well for short axis views \( (n = 269, p < 0.001) \) as for long axis views \( (n = 131, p < 0.05) \). The combined force also significantly \((p < 0.001)\) outperforms segmentation based on the MCC force alone for both short and long axis views.

Furthermore, we compared the entire manually segmented 3-D surface with the automatically segmented surface by calculating the 3-D similarity index. Results are shown in Table 3. Although no significant difference was found between the pair-wise comparison (Wilcoxon signed rank test) of 3-D SI of AMS vs. MCC or the

![Fig. 4. Segmentation results for a full volume dataset. Short axis (upper panel, a–d), long axis (middle panel, e–h) and 3-D views (lower panel, i–l) are shown for the three different settings of the deformable model. From left to right: echo- graphic data overlaid with contours of the segmented endocardial surface using adaptive filtering based component (AMS) (first column), maximum cross-correlation coefficient (MCC, second column), an equally weighed combination of AMS and MCC forces (third column) and manual segmentation (reference, fourth column).](image-url)
combination of AMS/MCC, the 3-D SI (Table 3) shows that compared with the use of the AMS force solely, the use of MCC values is advantageous, either as a force on its own or in combination with the AMS force. It should be noted that also planes that are very difficult to analyze are included within the 3-D similarity measure and reference contours might be less reliable for these planes.

In Figure 6, an illustrative example for segmentation of the long axis view is given that shows the additional value of the MCC in low echogenicity regions. It can be clearly seen that for this dataset, segmentation exclusively based on the AMS data resulted in crossing boundaries at the apical side of the long axis view and thus led to overestimation of the left ventricular cavity. Addition of the MCC feature improved the segmentation results and yielded correct dimensions of the left ventricle. This figure illustrates that the MCC (Fig. 6b) is still distinctive in the case of blood vs. myocardium in the apical region whereas the AMS filtered data is not (Fig. 6a). Similarity indices also reflect improved segmentation when using MCC values (SI AMS: 0.73, SI MCC: 0.87, SI AMS and MCC: 0.88).

Segmentation based on maximum cross-correlation led in a limited number of cases to incorrect results and underestimation of the endocardial dimension. This is illustrated by the MCC segmentation in Figure 7 and reflected by the corresponding SI values (AMS: 0.91, MCC: 0.75, AMS and MCC: 0.81). Also, in the combined force setting (AMS and MCC), the endocardial cavity is still underestimated.

**Table 2.** Average 2-D similarity indices (Dice) over relevant planes of the long axis and short axis views for the three different force types

<table>
<thead>
<tr>
<th>Volunteer No.</th>
<th>AMS</th>
<th>MCC</th>
<th>AMS &amp; MCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.80</td>
<td>0.78</td>
<td><strong>0.82</strong></td>
</tr>
<tr>
<td>2</td>
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<td>0.88</td>
<td><strong>0.88</strong></td>
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<tr>
<td>3</td>
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<td>0.83</td>
<td><strong>0.83</strong></td>
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<tr>
<td>4</td>
<td>0.83</td>
<td>0.82</td>
<td><strong>0.81</strong></td>
</tr>
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<td><strong>0.81</strong></td>
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<td>6</td>
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<td>0.81</td>
<td><strong>0.81</strong></td>
</tr>
<tr>
<td>7</td>
<td>0.83</td>
<td>0.78</td>
<td><strong>0.83</strong></td>
</tr>
<tr>
<td>8</td>
<td>0.80</td>
<td>0.81</td>
<td><strong>0.81</strong></td>
</tr>
<tr>
<td>9</td>
<td>0.88</td>
<td>0.86</td>
<td><strong>0.86</strong></td>
</tr>
<tr>
<td>10</td>
<td>0.78</td>
<td>0.73</td>
<td><strong>0.79</strong></td>
</tr>
</tbody>
</table>

**Table 3.** Average 3-D similarity indices (Dice) for the three different force types

<table>
<thead>
<tr>
<th>Volunteer No.</th>
<th>AMS</th>
<th>MCC</th>
<th>AMS and MCC</th>
</tr>
</thead>
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<tr>
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<tr>
<td>2</td>
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<td><strong>0.88</strong></td>
<td>0.84</td>
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<tr>
<td>3</td>
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<td>0.79</td>
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</tr>
<tr>
<td>4</td>
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<td><strong>0.79</strong></td>
<td>0.68</td>
</tr>
<tr>
<td>5</td>
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<td>0.67</td>
<td><strong>0.81</strong></td>
</tr>
<tr>
<td>6</td>
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<td><strong>0.80</strong></td>
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<tr>
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<td>0.76</td>
<td><strong>0.85</strong></td>
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<tr>
<td>8</td>
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<td><strong>0.76</strong></td>
<td>0.73</td>
</tr>
<tr>
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<td><strong>0.87</strong></td>
<td><strong>0.87</strong></td>
<td><strong>0.87</strong></td>
</tr>
<tr>
<td>10</td>
<td>0.72</td>
<td>0.79</td>
<td>0.76</td>
</tr>
</tbody>
</table>

AMS = adaptive filtering based component; MCC = maximum cross-correlation coefficient.
For each data set the method with the highest SI is denoted in bold.

**DISCUSSION AND CONCLUSIONS**

In this study, we investigated a method that enables segmentation of anatomical structures in pediatric hearts by incorporating temporal information. Temporal cross-correlation using the phase information present in the RF-signal was used as an additional feature to distinguish between blood and myocardium. The method was tested on 3-D echocardiographic image sequences of ten healthy children and compared to a more conventional method that only uses echo-amplitude information.

Using the 3-D iterative displacement estimation algorithm, the maximum temporal cross-correlation values were optimized and refined by each iteration step as illustrated by Figure 2. This optimization procedure was necessary to obtain the deformation of the heart
muscle in 3-D and, after compensation for this 3-D deformation field, to obtain accurate MCC values.

According to the preliminary results, maximum temporal cross-correlation values based on the RF-signal have additional value for the segmentation of cardiac tissue. Since the MCC can still be high in (myocardial) regions with low echogenicity (and, thus, low contrast with blood), inclusion of this parameter in the deformable simplex model as an extra feature in general improves segmentation. Quantitative analysis using similarity indices in 2-D image planes (Table 2) reveals that in the majority of cases the combination of the MCC and AMS outperforms segmentation using MCC or AMS only. Especially in the short axis view, the combination is beneficial. This is probably related to the fact that in short axis views the ultrasound beams and the muscle fiber orientation are parallel in a significant part of the myocardium, resulting in low echogenicity. On the contrary, in the long axis view only the apical region suffers from this artifact. As a result, only in 50% of the cases the combination improves the segmentation results in the long axis view.

A deformable model that only uses the cross-correlation force underestimated the blood pool region in some cases (Fig. 7). This might be caused by the blood close to the heart wall “adhering” to the moving cardiac tissue, leading to a higher maximum correlation value, i.e., lower MCC contrast in blood regions close to the endocardial border. A second reason for underestimation of the blood pool region might be the lower resolution of MCC images (compared with adaptive filtering) due to the larger windows used in the calculation of correlation values.

In high quality images (without low contrast regions), segmentation exclusively based on the AMS force already yielded accurate results. This finding corroborates previous findings obtained using open chest animal experiments (Nillesen et al. 2009). In these images, the MCC force did not improve the similarity index or even led to slightly lower SIs in some planes, see for example the SIs for data set 9 in Tables 2 and 3. However, from the 2-D and 3-D similarity indices as shown in Tables 2 and 3, we might conclude that in most subjects, the MCC force does improve the segmentation results. It should be noted that these tables show only average SIs while improvement of the SI for individual planes demonstrates greater differences between the three force types (e.g., see Fig. 5a, short axis views).

Presently, the MCC parameter has been tested in the end-systolic phase because of the limited frame rate of the used echo machine while imaging the entire left ventricle. The limited frame rate results in a limited accuracy of cross-correlation in phases of the heart cycle with fast deformation of the heart muscle. Consequently, we first evaluated the performance in cardiac phases with small
deformation of the heart muscle, \textit{i.e.}, in the end-systolic or end-diastolic phase. However, with the introduction of the latest real-time 3-D echocardiographic scanners, increased frame rates seem to be feasible. For now, the cross-correlation based model could be used in the end-systolic phase as a more robust initialization for segmentation of the other frames in the cardiac cycle. In future, the method will be extended to more frames during the cardiac cycle. Since the temporal behavior of blood is also not constant over the heart cycle, incorporation of this knowledge might be beneficial to improve the proposed approach. In the rare case that the blood flow velocity is very low in a certain phase of the heart cycle, the MCC will be similar for blood and heart muscle and cannot be used as a feature to distinguish blood and myocardial tissue.

A limitation of this study is that only long/short axis views of the left ventricle were analyzed because of the limited visibility of the lateral wall in 3-D pediatric apical images. So, more research is needed to further investigate whether cross-correlation techniques can support automated segmentation in 3-D apical images.

The ECG gated full volume data sets used in this study comprise seven cardiac cycles to build up a complete volume. So-called stitching artifacts may occur due to inaccurate synchronization between two consecutive heart beats, because of heart rate variation or motion of the patient due to respiration. It is clear that this inaccurate synchronization between cardiac cycles will have a severe influence on the temporal cross-correlation values since these are calculated using 3-D volumes. For this reason, full volume datasets that contain severe stitching artifacts are less suitable for MCC based segmentation. It should be mentioned that these stitching artifacts often cause disturbance of the geometry as well and these data cannot be used for quantitative analysis anyway. The data sets analyzed in this study showed no increased decorrelation at the transitions between the seven sub-volumes that build up the complete 3-D volume.

Further research is required to investigate the optimal combination of echo-level and temporal information. In the combined force model that is currently used, AMS and MCC forces are equally weighed. A more sophisticated balance between these two forces might improve the segmentation results. This could be done by implementing a quality measure for transitions between blood and myocardium. For example, in high quality images with high contrast borders, the AMS force should dominate over the MCC force. In contrast, MCC values close to one should be relied on stronger than lower MCC values. Additionally, location specific

Fig. 7. Typical example of inaccurate segmentation of the left ventricle when only maximum cross-correlation coefficient (MCC) values are used for segmentation. In this case, the use of adaptive filtering based component (AMS) force only (c) leads to the most accurate segmentation (compare the reference contour in panel f). Temporal information by using the MCC (d) does not improve the segmentation of the endocardium. Even the combination of AMS and MCC (e) does not lead to correct segmentation results. The left panel shows the AMS (a) and MCC (b) force to explain the differences in segmentation.
weighting might be applied. For example in the apical region, the AMS based segmentation is generally worse than the MCC based one, in contrast to the septal wall that is normally better segmented using AMS values as external force. This information might be beneficial for improving the overall performance of a segmentation method using both MCC and AMS.

In conclusion, temporal information present in the RF signal yields a useful parameter to distinguish between blood and myocardial tissue in regions with low contrast in echogenicity. The MCC value improves segmentation in these regions but further investigation of this parameter is required to exploit the full benefit of it for automated segmentation.

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REFERENCES


