White Paper

Computer-Aided Detection in Echocardiography
Technical Approach for Learned Pattern Recognition

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Technical Approach for Learned Pattern Recognition

Introduction

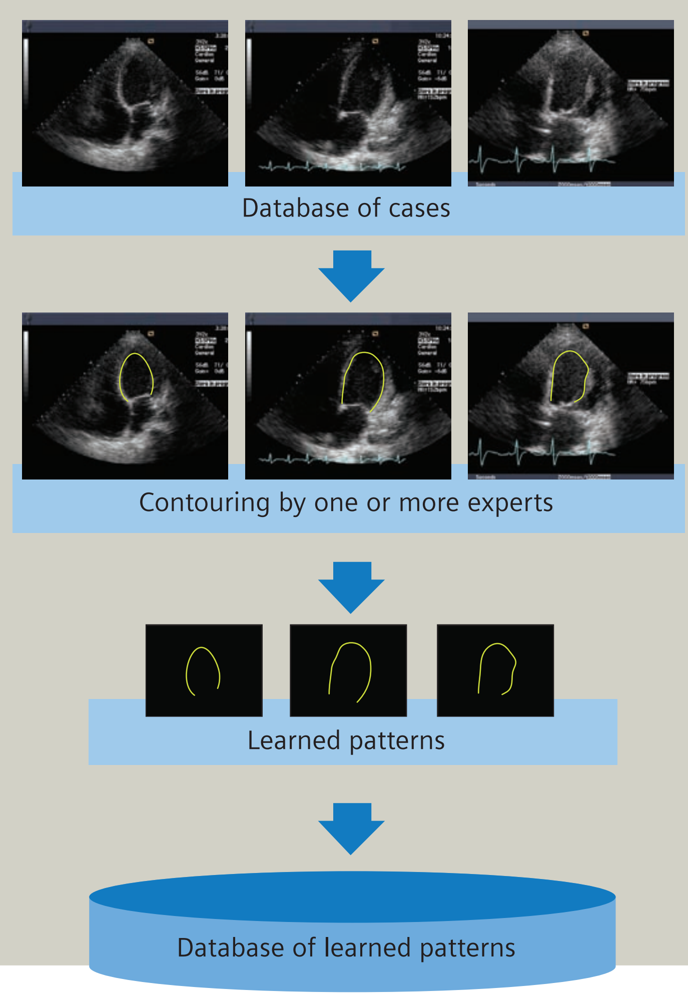
The reliable delineation of the left ventricle (LV) for robust quantification requires years of clinical experience and expertise by echocardiographers and sonographers. Even with acceptable image quality, issues such as trabeculations of the myocardium, fast-moving valves, chordi and papillary muscles, all contribute to the challenges associated with delineation of the LV. Technical issues, such as the fact that a 2D plane is acquired on a twisting 3D object, make this problem even more difficult. Limited success has been achieved in automated quantification based on LV delineation with methods that simply look for a border between black and white structures in an image.

In clinical practice, experienced echocardiographers and sonographers rely on their expertise when viewing a fast-moving object, as well as for understanding individual variations in the heart. As a result, they can apply learned knowledge and experience to confidently locate the border of the left ventricle. Based on this insight, Siemens Medical Solutions has developed a fundamentally new approach to address quantification in echocardiography based on a technology called learned pattern recognition (LPR). This new technology makes it possible for clinicians to automatically identify the endocardium of the left ventricle and track the border through the heart cycle. In fact, the first application in ultrasound for LPR, called syngo® Auto Ejection Fraction, is the automatic measurement of cardiac ejection fraction (EF) in adult patients.

Creating a Database of Learned Patterns

LPR technology is based on a broad concept of artificial intelligence (AI) that attempts to mimic human abilities for reasoning, discovering meaning, generalization and

Figure 1 Creating a database of learned patterns.



the ability to learn from past experiences. In fact, the ability to learn from past experience and to generalize sets Siemens' unique approach apart from previous technical attempts in automated LV quantification. Siemens' AI system is developed from large databases of cases. For example, a database of learned patterns for the computation of EF was created by having experts in the field of echocardiography contour over 10,000 images representing phases throughout the entire cardiac cycle. The cases represent a wide range of patients and disease types typically seen in an adult echocardiography clinic, including patients with various wall motion abnormalities, patients with heart failure, and patients with dyssynchrony. Each of these cases has been painstakingly contoured by one or more experts as the basis for training the system and creating a database of learned patterns.

Endocardial Border Detection in a Single Frame

The first step in automating the EF calculation or analyzing the clinical image is the identification of the endocardium in a single frame. This is done using a technique called database-guided segmentation. Segmentation is guided by the database of learned patterns that helps the system to detect and segment a border. For any given new cardiac image, the computer compares the cardiac image against the database of learned patterns. Every heart image shares some common characteristics, such as the basal mitral annuli and the midseptal region in the apical four chamber view. These characteristics are first used to automatically identify the location of the heart within the image. Then the characteristics are used to identify the learned patterns in the database that are most similar to the current case. After this, the algorithm combines the learned patterns from these similar cases to create a unique model (border) for the current case being analyzed.

This approach is shown graphically in Figure 2, where three learned patterns are found. These patterns are then combined to most closely match the current case. Initially this is done on a coarse scale, followed by finer and finer detail until the model that most closely represents the current case is identified. The points along the border are then combined using a spline to create a smooth representation of the endocardial border. At this point, a distinctive model of the heart in the current case is created. Further information on database-guided segmentation is described in the references.[1]

Figure 2 Endocardial border detection in a single frame using database-guided segmentation.

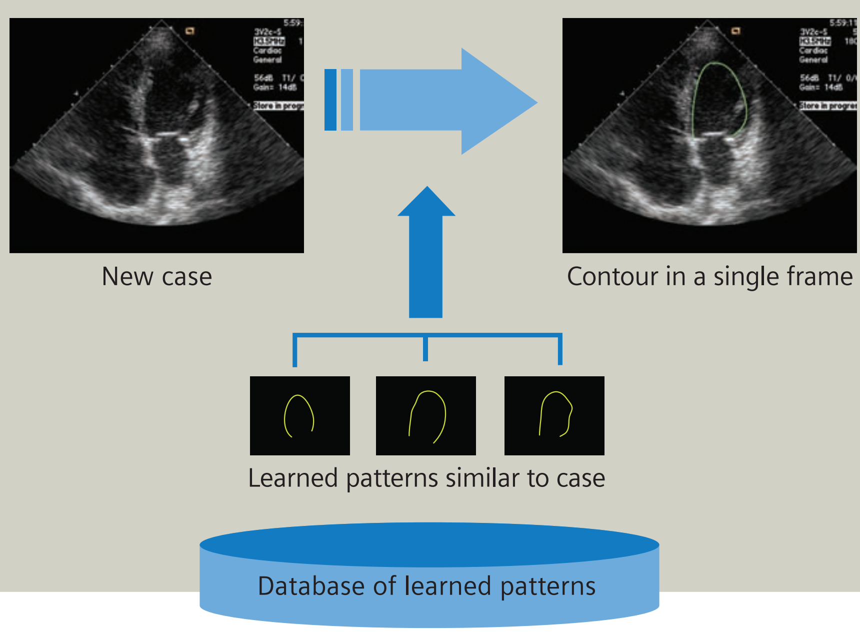
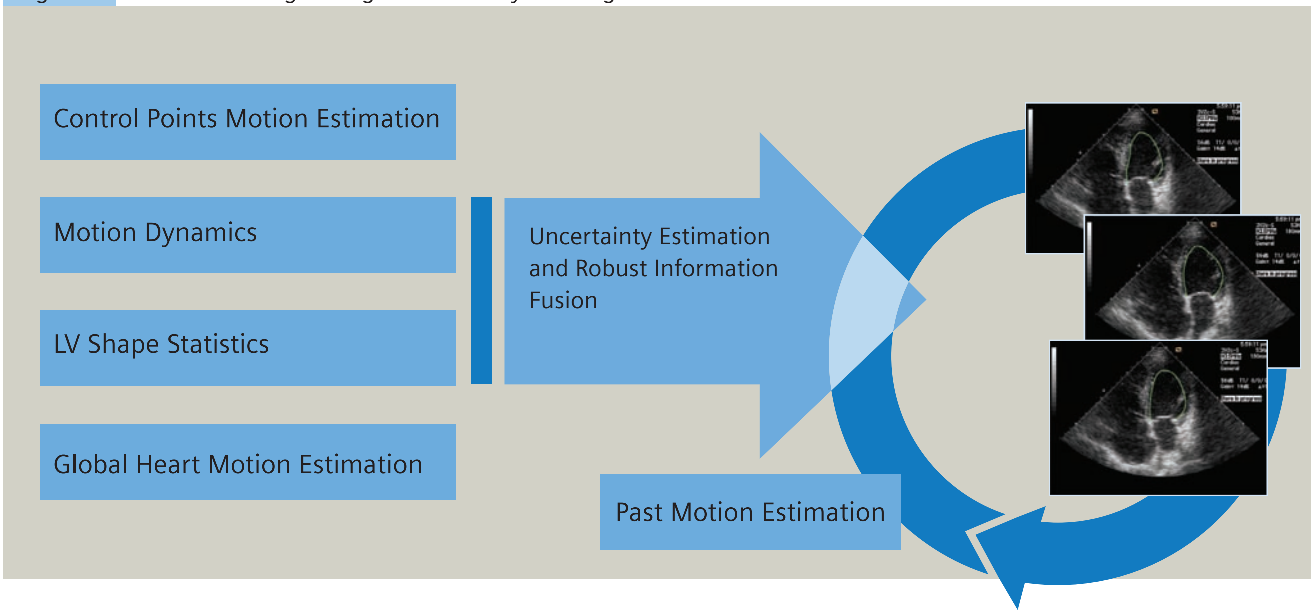


Figure 3 Motion tracking through the heart cycle using robust information fusion.



Motion Tracking Through the Cardiac Cycle

The second step of the process is to track the border throughout the video clip. Once the endocardial border is identified in one frame, it needs to be tracked in all of the other frames within that cardiac cycle. Traditionally, motion tracking in echocardiography has been done using correlation, speckle-tracking or similar techniques. However, there are some unique problems in tracking the endocardium, which are not addressed by these techniques. First, there is the issue of drop-out, particularly in the lateral wall and apex. Second, objects often come in and out of the imaging plane, which can cause uncertainty in individual frames regarding specific location of the endocardium. However, the use of LPR enables the computer to learn how to track the endocardial border despite these problems.

To address the challenges of previous tracking methods, Siemens has developed a technique called robust information fusion. This method incorporates learned shape and motion models of the heart to track the endocardium throughout the cardiac cycle. These models are learned from the database of case patterns, just as detection models were learned for detection. They help to constrain the possible location of the endocardium within the uncertainty estimated by the system. This is shown graphically in Figure 3. Further details of robust information fusion are described in peer-reviewed technical journals and conference presentations.[2,3,4]

Automated Quantification

Once the endocardial border has been detected and tracked, quantification parameters, such as left ventricular volumes and ejection fraction can be calculated. At each frame the volume can be computed from the endocardial border using standard techniques, such as the modified Simpson's rule. This is accomplished by the following: First, the long axis of the heart is computed for each frame. The system is trained to detect the mitral annuli which are represented by the two end-points of the endocardial contour. The end points are connected to create the mitral valve plane. The long axis can then be determined and volumes computed. Next, end-diastole and end-systole are approximately identified by using the ECG. The frame closest to the R-wave is labeled as end-diastole, and systolic duration is estimated based on case characteristics such as heart rate. From these initial estimates the exact location of end-diastole and end-systole are determined using the maximum and minimum values of the volume curve (Figure 4). As a result, ejection fraction can successfully be computed.

Conclusion

Siemens has taken the insights from experienced echocardiographers and sonographers, and designed a new approach to automated adult cardiac EF quantification. This tool is based on a revolutionary new technique called learned pattern recognition (LPR). In this technique, a new clinical image is compared to a series of patterns learned from several clinical cases, and based on the learned patterns, a model of the endocardium is formed. The first application of LPR is automated measurement of ejection fraction, which was developed from a database of over 10,000 images from a wide range of adult patients and disease types. Database-guided segmentation and robust information fusion allow the detection and tracking of the endocardium of the left ventricle with a high degree of accuracy and robustness. Use of LPR and artificial intelligence for image processing and computer vision applications is a new field, and offers potentially significant new opportunities for cardiac quantification in echocardiography exams.

References

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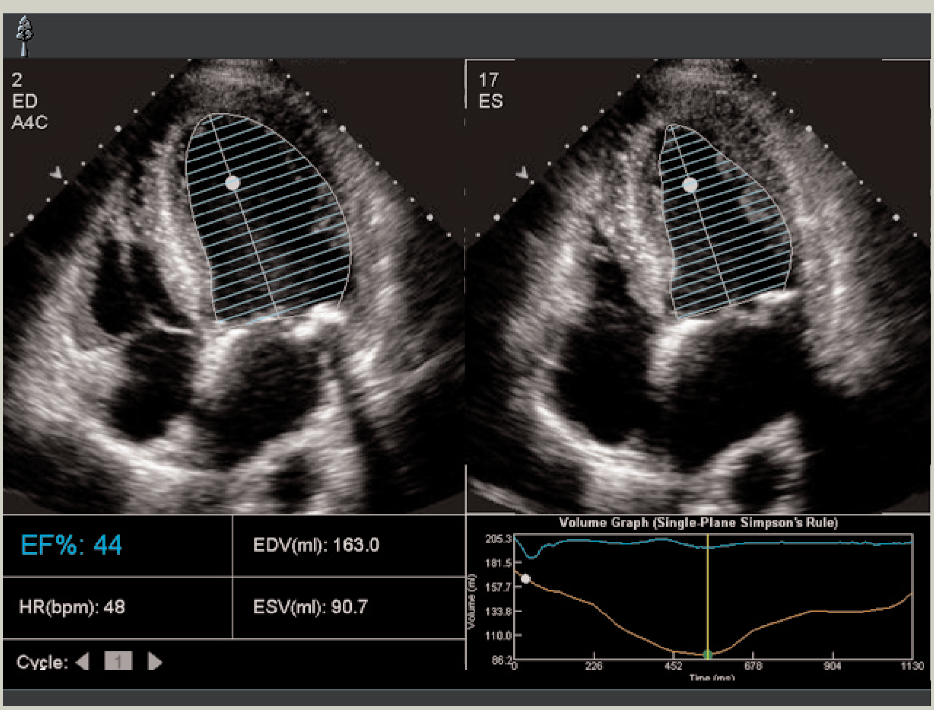
Figure 4 Time-volume curve as the basis for cardiac quantifications such as ejection fraction.



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