Image Processing for Decision Support in Heart Failure

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Abstract: Signal and imaging investigations are currently a basic step of the diagnostic, prognostic and follow-up processes of heart diseases. Besides, the need of a more efficient, cost-effective and personalized care has lead nowadays to a renaissance of clinical decision support systems (CDSS). The purpose of this paper is to present an effective way to achieve a high-level integration of signal and image processing methods in the general process of care, by means of a clinical decision support system, and to discuss the advantages of such an approach. Among several heart diseases, we treat heart failure, that for its complexity highlights best the benefits of this integration. Architectural details of the related components of the CDSS are pro-vided with special attention to their seamless integration in the general IT infrastructure. In particular, significant and suitably designed image and signal processing algorithms are introduced to objectively and reliably evaluate important features that, in collaboration with the CDSS, can facilitate decisional problems in the heart failure domain. Further-more, additional signal and image processing tools enrich the model base of the CDSS.

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1.Introduction

Signal and imaging investigations are currently a basic step of the diagnostic, prognostic and follow-up processes of heart diseases. Not by chance, in the last decades, the development of Computer-Aided Diagnosis (CAD) schemes has attracted a lot of interest and effort within medical imaging and diagnostic radiology, becoming in some cases a practical clinical approach. The basic concept of CAD is to provide a second opinion or a second reader that can assist clinicians by improving the accuracy and consistency of image based diagnoses [1]. Actually, the clinical interpretation of diagnostic data and their findings largely depends on the reader's subjective point of view, knowledge and experience.

Hence, computer-aided methods, able to make this interpretation reproducible and consistent, are fundamental for reducing subjectivity while increasing the accuracy in diagnosis. As such, they are likely to become an essential component of applications designed to support physicians' decision making in their clinical routine workflow. Other important motivations rely on the limits to reader's ability of data interpretation caused by either the presence of structure noise or the vast amount of data, generated by some devices, which can make the detection of potential diseases a burdensome task and may cause oversight errors. Besides, the development of computerized applications for supporting health care givers (an old but still alive quest, started more than 45 years ago in the early 1960s) is experiencing a period of rapid expansion in knowledge, motivated by a renewed interest [2]. The need of a more efficient, cost-effective and personalized care and of a more rational deployment of diagnostic resources is one of the reasons behind this renaissance. Actually, the development and increasing use of hospital or, even, cross-enterprise regional health information systems make possible the design of ambitious integrated platforms of services in order to guarantee the continuity of care across the various stakeholders. Clinical Decision Support Systems (CDSSs) are a natural and key ingredient of such integrated platforms, since they may compete with the increasing bulk of clinical data by providing an integrated approach to their analysis. In addition, CDSSs may foster adherence to guidelines, prevent omissions and mistakes, spread up-to-date specialistic knowledge to general practitioners and so on. This being the general setting, the purpose of this paper is to address the integration of signal and imaging investigations with the wide-ranging services provided by CDSSs. Actually, signal and image processing methods may be understood and embedded as a part of the model base of the CDSS. In such a way an effective high-level integration of signal and image processing methods in the general process of care is achieved. With the aim of avoiding unnecessary generality, the paper addresses the specific yet complex and paradigmatic example of image and signal processing for decision support in heart failure. Indeed, heart failure is a clinical syndrome, whose management requires –from the basic diagnostic workup– the intervention of several stakeholders and the exploitation of various imaging and non-imaging diagnostic resources. The paper is organized as follows. First, heart failure management is briefly described in Section 2.1, including a description of its diagnostic workup which is enlightening to understand the complexity of this syndrome. In Section 2.2 the quest for a decision support system is motivated, describing relevant decisional problems. In Section 3, signal and imaging investigations are justified, highlighting the value added to the CDSS, while suitably designed algorithms for image and signal processing are introduced in Sections 3.2 and 3.3 respectively. In Section 4, the results of architectural design for integration are described both at the IT infrastructure level (Section 4.1) and at the higher level represented by the general CDSS (Section 4.2). Finally, Section 5 ends the paper with some remarks and directions for future work.

2. Background

2.1 Heart Failure

Heart Failure (HF) is a complex clinical syndrome resulting from any structural or functional cardiac disorder which impairs the ability of the ventricle to fill with or eject blood. In its chronic form, HF is one of the most remarkable health problems for prevalence and morbidity, especially in the developed western countries, with a strong impact in terms of social and economic effects. All these aspects are typically emphasized within the elderly population, with very frequent hospital admissions and a significant increase of medical costs. The first, immediate and enlightening proof of HF complexity is represented by its diagnostic workup, which we briefly describe next. Indeed, it can be considered as the first stage of HF patients' management which necessarily requires the acquisition and analysis of signal and imaging data.

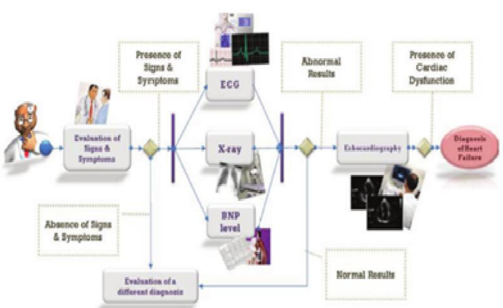


Fig. 1. HF Diagnostic Workflow

Heart Failure Diagnostic Workup. Figure 1 shows the sequence of steps that compose the HF diagnostic workflow [3]: after having assessed the presence of main signs and symptoms, physicians usually require diagnostic examinations such as ECG, chest X-ray and neuroendocrine evaluations (i.e. Brain Natriuretic Peptides - BNP) in order to check out the diagnosis, confirmed eventually by an echocardiography investigation. Supporting such a decision problem requires to encode the workflow into an opportune knowledge base which formalizes, for each step, the set of conditions evaluated by physicians. The first step regards the presence and severity of signs and symptoms such as breathlessness, swelling, fatigue, hepatomegaly, elevated jugular venous pressure, tachycardia, third heart sound and pulmonary crepitations. Then, ECG signals are acquired for investigating the presence of anterior Q waves and left bundle branch block, signs of left atrial overload or left ventricular hypertrophy, atrial fibrillation or flutter and ventricular arrhythmia. If ECG abnormalities are present, HF diagnosis is considered carefully possible and further checked out by analyzing chest X-ray. Such an examination is useful for detecting the presence of cardiac enlargement (cardio-thoracic ratio > 0.50) and pulmonary congestion. In parallel, neuroen-docrine analysis are performed to test out high levels of natriuretic peptides which suggest the presence of a cardiac disease. Whether all these examinations certify the presence of abnormalities, an echocardiographic investigation is per-formed for documenting a cardiac dysfunction. The most important parameter to be evaluated from such a diagnostic modality is the Left Ventricle Ejection Fraction (LVEF); other relevant data are the fractional shortening, the sphericity index, the atrioventricular plane displacement, the myocardial performance index, the left ventricular wall motion index, the isovolumic relaxation time, the early to atrial left ventricular filling ratio, the early left ventricular filling deceleration time, the pulmonary venous atrial flow velocity duration, the ratio of pulmonary vein systolic and diastolic flow velocities, and the pulmonary artery pressures. HF diagnosis is finally concluded if symptoms and signs and ECG / X-ray / BNP level / Echocardiographic abnormalities are all present.

2.2 Decision Support in Heart Failure

Recent studies and experiences have demonstrated that accurate heart failure management programs, based on a suitable integration of inpatient and outpatient clinical procedures, might prevent and reduce hospital admissions, improving clinical status and reducing costs. Actually, HF routine practice presents several aspects in which an automatic, computer-based support could have a favorable impact. A careful investigation about the needs of HF practitioners and the effective benefits assured by decision support was performed: four problems have been identified as highly beneficial of CDSS point-of-care intervention [4]. They can be referred as macro domain problems and listed up as: (i) HF diagnosis, (ii) prognosis, (iii) therapy planning, and (iv) follow-up. Further detailed decision problems were identified for specifying these macro domains, focusing as much as possible on the medical users' needs; explicative examples are:

- severity evaluation of heart failure – identification of suitable pathways

- planning of adequate, patient's specific therapy – analysis of diagnostic examinations
- early detection of patient's decompensation

An accurate analysis highlighted that the needed corpus of knowledge mainly consisted of domain know-how. Nevertheless, the solution of some of these problems seemed still debated in the medical community, due to the lack of validated and assessed evidences. In such cases, computational models appeared the best solution for modelling the decision making, extracting knowledge directly from available data. In this perspective, a CDSS for the management of heart failure, which com-bines several models of reasoning, has been suitably designed. Having the overall organization of the CDSS being reported in [5], the focus in the sections below is on the analysis of diagnostic examinations and on their integration into the CDSS.

3. Signal and Image Processing in Heart Failure

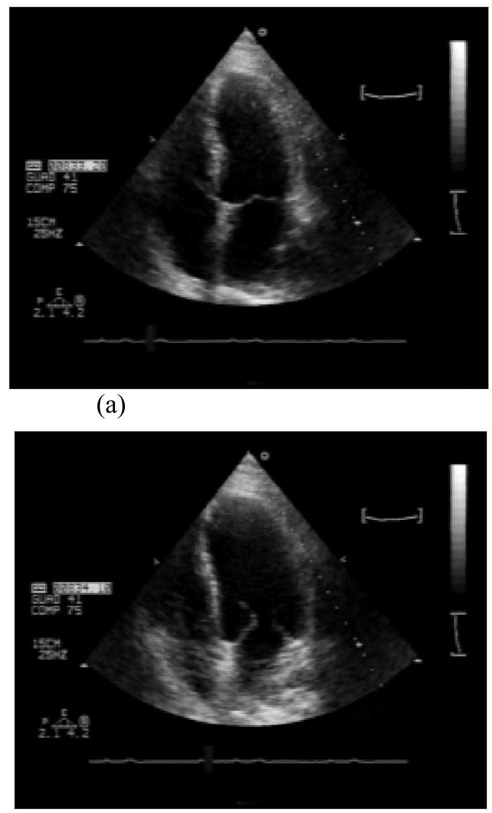
3.1 Significance

During the formalization of the main decisional problems that require the CDSS intervention and, hence, listing up all the pieces of knowledge, data and information relevant for decision making, the importance of considering and interpreting ECG signals and echocardiography images had come forth. Indeed HF diagnostic workup was a straightforward example of the importance of computer-aided data processing in HF decision making, but other significant contributions can be envisaged. Overall, among all the profitable applications into decision support workflows, the following can be listed up:

- automatic or semi-automatic computation of parameters relevant in the decisional problems;
- support of physicians' case-based reasoning processes; – discovery of novel pertinent knowledge.

While the first is typical of routine workflows in relatively simple situations, as described in the diagnostic workup example, the other two can be considered advanced applications that may aid physicians in facing critical cases or critical problems. Actually, not only the parameters extracted from signals and images examinations are significant to physicians for formulating a response but also the data themselves can be useful for having a general overlook of a patient's situation. This means that allowing clinicians to explore data can assure the availability of a lot of other pieces of information hidden in the same data. Moreover, when dealing with a difficult case, comparing the one at hand with assessed responses for other patients' situations can be really helpful [6]. This entails maintaining and making available a database of cases with annotated images and signals which can be retrieved by similarity on a set of computed features (see Section 4.1). Difficult diagnoses and, most of all, prognosis assessment are examples of these situations. For such critical problems, data processing facilities can have further relevance for the discovery of novel knowledge by granting the computation of a wide range of parameters which can be explored and correlated in order to find out new relevant patterns [7].

Finally, from the opposite side, opportune knowledge formalization may represent advantages in personalization of diagnostic imaging and non-imaging investigations. This means that adequate conditions could be encoded within the CDSS in order to suggest which kind of parameters could be more usefully evaluated for a given patient during, for instance, an echocardiography or an ECG session.



(a)

(b)

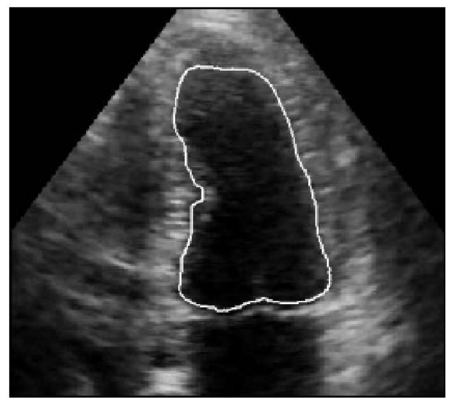
Fig. 2. Typical frames of an image sequence taken from the apical view

3.2 Image Processing Methods

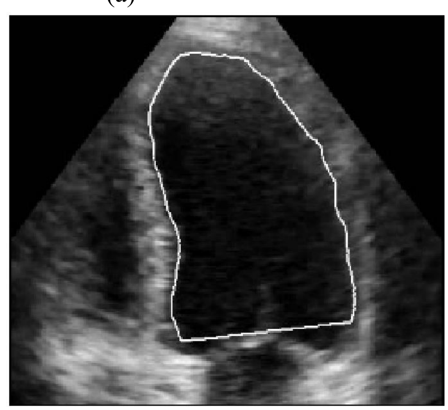
Imaging techniques offer invaluable aid in the objective documentation of cardiac function, allowing for the computation of parameters relative to chamber dimensions, wall thickness, systolic and diastolic function, regurgitations and pulmonary blood pressure. As previously mentioned, chest X-ray and echocardiography should be included in the HF initial diagnostic workup. Further, echocardiography will be regularly repeated to monitor in an objective way the changes in the clinical course of a HF patient. Additional techniques, like nuclear imaging and cardiac magnetic resonance, may be also considered for particular patients, since they have not been shown to be superior to echocardiography in the management of most HF population. Thus, echocardiography and in particular 2-D TransThoracic Echocardiography (TTE) for its portability and versatility is the key imaging technique for the practical management of HF. The most important measurement performed by TTE is LVEF, which permits to distinguish patients with cardiac systolic dysfunction from patients with preserved systolic function. LVEF is given by the normalized (non-dimensional) difference between left ventricle End-Diastolic Volume (EDV) and the End-Systolic volume (ESV). Among different models for the computation of such volumes, the American Society of Echocardiography [8] suggests the use of the so-called Simpson's rule, by which the left ventricle is approximated by a stack of circular (or elliptical) disks whose centers lie in the major axis. Simpson's method, therefore, relies on left ventricle border tracing. It is well-known that manual border tracing, besides being time-consuming, is prone to inter- and intra- observer variability, and thus is unable to provide a satisfactory and reproducible measurement of LVEF. Image processing techniques may reduce variability of human interventions in border tracing, by providing automated or, at least, semiautomated methods for tracing contours of relevant structures found in an image. However, the segmentation problem for ultrasound images is by no means trivial, due mainly to low signal to noise ratio, low contrast, image anisotropy and speckle noise [9]. Nevertheless, some acquisition devices already offer the possibility of automatically computing a set of relevant parameters but are still really expensive and this is the reason why older devices are still very common.

From these considerations, it was early realized that the development of assisted segmentation methods, able to deal with echocardiographic image sequences, could represent a valid support to the physicians in the process of image report formation. Thus a prototypical toolkit [10] –composed of three main modules– for the analysis of apical-view sequences of the heart has been developed. Two typical frames of such sequences are shown in Figure 2. The first module (Region Identification), which takes in input an apical sequence of the heart, is able to identify the left ventricle cavity in every frame of the sequence by means of mimetic criteria, providing a rough segmentation. The second module (Segmentation Refinement), which takes in input an image and a rough segmentation of it, is able to refine the segmentation exploiting a variational formulation of level set methods, which achieves regularization of the boundary of the left ventricle as well as better adherence to image edges [11]. The third module (Feature Extraction) is able to extract significant features from a set of segmented left ventricles, the most important being EDV and ESV (both computed according to Simpson's rule) and, in turn, LVEF. After the integration in a suitable graphical user interface, three possible ways may be foreseen to employ the toolkit. These ways are described below according to the automatism level, starting from the less automatic one.

Case A) Manual Selection of the End-Diastolic and End-Systolic Frames and Rough Manual Contour Tracing. In this case, the toolkit provides a refinement of the manually traced left ventricle contour in the manually selected frames. Instead of using the common free hand selection, the user may just quickly select a polygonal region approximating the left ventricle cavity. The *Segmentation Refinement* module is then triggered. In particular, the manually drawn con-tour is used for the initialization of the level set method. Finally, the third module is used for feature extraction.



(a)



(b)

Fig. 3. Final result of segmentation in an end-systole (a) and in an end-diastole (b) frame

Case B) Manual Selection of the End-Diastolic and End-Systolic Frames and Automatic Contour Tracing. In this case, the toolkit traces automatically the contour of the left ventricle in the manually selected frames. The *Region Identification* module is used to find an approximate left ventricle contour. Then the contour is refined by the level set segmentation step as in Case A).

Case C) Automatic Selection of the End-Diastolic and End-Systolic Frames and Automatic Contour Tracing. In this case the toolkit takes in input the whole image sequence and applies the *Region Identification* module to every frame in order to obtain a rough segmentation of the left ventricle. Then the volume of the cavity is computed on this rough segmentation by using the *Feature Extraction*. The indices of the frames corresponding to the extremal values (i.e. maximum and minimum) of the volume are found and stored. Then, the *Segmentation Refinement* is applied to the contours in the frames which are near to those of extremal values. Computing again volumes on the basis of the refined contours by the *Feature Extraction* module leads to the identification of the end-systole and end-diastole frames and to the computation of related clinical parameters. The final result of segmentation in the automatically identified end-systole and end-diastole frames is shown in Figure 3.

The proposed image processing toolkit could be easily extended in several ways. Besides integrating standard tools for performing graphically image measurements (such as linear measurements) and producing IHE-compliant Simple Image and Numeric Reports, the core segmentation modules may be adapted to deal with other echocardiographic views, so as to perform a complete quantification of heart chambers.

3.3 Signal Processing Methods

ECG is one of the very basic examinations performed in the evaluation and assessment of HF. According to [3], the negative predictive value of normal ECG to exclude left ventricular systolic dysfunction exceeds 90%. The most common ECG examinations are the *Resting ECG* and the *Holter ECG*. While the latter is more commonly used for the discovery of rhythm abnormalities and the computation of the Heart Rate Variability (HRV), the former is more commonly used for the evaluation of morphological abnormalities in the PQRST shape. Considering the crucial role of ECG signals and the various related examinations, it has been immediately judged important to design and implement some *basic*, *robust* and *scalable* algorithms for ECG processing that could be immediately applied to the raw data acquired by ECG devices with different lead numbers and different acquisition periods. After some interviews with the clinicians, it has been identified a significant operative scenario, where the ECG acquired with a non-interpretive electrocardiograph is transferred to the hospital gateway and from there processed in order to:

1. Detect the QRS complexes
2. Identify the dominant beats
3. Evaluate the averaged dominant beat (for all the leads)

In particular, the averaged dominant beat can be used by the cardiologists (with the help of a graphical ECG viewer), for the evaluation of all the measurements of interest for the diagnosis or the follow-up of heart failure patients, like ST de-pression, QRS and QT durations, Sokolow-Lyon index for left ventricular hyper-trophy, presence of left or right branch bundle block and presence of pathological Q waves. Notice that, since the average dominant beat is cleaner from the noise than the original signal, performing measurements on this average beat leads to a more accurate results, thus reducing inter- and intra- observer variability. The algorithms developed for ECG processing are briefly described below.

QRS Detection. The selected approach for QRS detection belongs to the time-domain techniques [12]. The first step consists in a signal pre-filtering using a moving-average linear filter in order to reduce the baseline wandering and the high-frequency noise, and to select the typical frequencies contained in the QRS complexes. Then a QRS enhanced Signal (QeS) is built as the sum of the absolute derivatives of each pre-filtered channel. The filter for the generation of the derivatives has been chosen trying to reduce the effect of the high frequency residual noise. In practice a pass-band filter is used with a derivative behavior in the band of interest. Then, the beginning of a QRS is detected when the QeS overcomes a suitably defined adaptive threshold. Using only the above algorithm the QRS detection results are good enough, especially in recordings with low or medium content of noise. However, when the noise in one or both leads is high, the performances of the detector are significantly reduced. Therefore, a technique for the improvement of the detection performance when the noise is present only in one channel has been introduced. In particular a Noise Index (NI) is associated with every detected QRS on the basis of the T-P interval average power divided by the QRS average power [13].Since the NI can be used as an indicator of the noise in the two different channels and of good QRS detection, the appearance of a number of consecutive noisy QRSs determines the beginning of a noisy interval, which ends once a few consecutive non-noisy QRSs appear. In this way, a procedure for best channel selection can be obtained with significant improvement of the overall QRS detection performance. The results have been evaluated on the 48 records of the MIT-BIH Arrhythmia Database where each ECG record is composed by 2 leads sampled at 360 Hz for a total duration of about 30 minutes. The annotated QRSs are 109494 in total. The results have been very satisfying on all the an-notated QRSs and, with the inclusion of an automatic criterion for ventricular flutter detection, a sensitivity=99.76% and a positive predictive value=99.81% have been obtained.

Construction of the Average Dominant Heart Beat.

A prerequisite for the construction of the average dominant beat is the morphological classification of each detected QRST. In fact, it is necessary to avoid the introduction of extrasystoles or non-dominant beat in the averaging process, since they would alter the quality of the averaged beat. Normally the evaluation of the heart beat type is performed considering its morphology and its occurrence compared to the previous and following beats (rhythm). If the requirement is to obtain a complete rhythm evaluation, then it is necessary an accurate classification of each heart beat based on both morphological and rhythm criteria. However, significant clinical information can be obtained from the analysis of the dominant beat morphology. For the classification algorithm, only the basic morphological parameters were taken into consideration, trying to limit as much as possible the complexity of such a system. For such purpose, the development and the test of the algorithms were made using the records of the MIT-BIH Arrhythmia Database that includes four records acquired from patients with pacemaker. The algorithm is based on a two-stage clustering technique; firstly a possible classification of all beats is performed, and then all clusters but the one that has been identified with the dominant beats of the signal are reprocessed. In particular, the clusters containing non-dominant beats (according to the first stage) that are large in number are split into smaller ones and reconsidered for misjudgment of being non-dominant. Details will appear elsewhere.

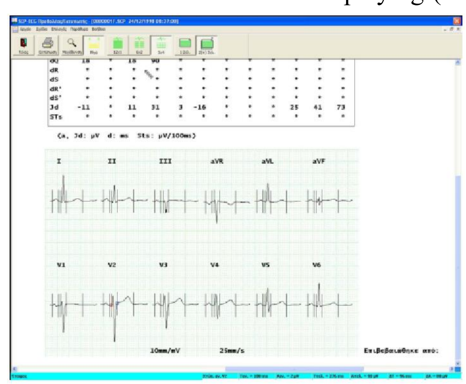
Finally, the averaged dominant beat is represented by the class centroid of the dominant class evaluated on all the QRST assigned to the dominant class after accurate alignment with horizontal and vertical wiggling. Figure 4 shows a graphical interface that, among other functionalities, allows for visualizing the average dominant heart beat and performing linear measurements.

4 Architectural Design and Results

4.1 IT Infrastructure

The signal and image processing methods described in Section 3 have as a result a bunch of clinical parameters together with a new set of annotated images and wave-forms (e.g. the segmented echocardiographic sequences and the computed aver-aged dominant beats). These data should be stored in a structured way in order to trigger CDSS functionalities involving the extracted parameters; further retrieval procedures should be devised to support physicians' case-based reasoning. Aiming at answering these needs, a composite repository has been prepared and standard-compliant network services have been enabled. Apart from a standard database for clinical parameters, a DICOM Image Archive has been included into the composite repository. The Image Archive is used to store the original images deriving from a TTE examination as well as the annotated images produced by the image processing toolkit. DICOM Secondary Capture (DICOM-SC) modality is used for the latter purpose, since it is specifically designed to embed the results of image processing (ranging from the application of enhancement filters to more complex image processing procedures) into a DICOM image [14]. The header of the DICOM-SC image may replicate the patient personal information contained in the original DICOM image which is used as input of the image processing algorithms. Further, the header may be used to add a reference to the original DICOM study: in this way the original images and the processed ones are *persistently linked* together within one DICOM study. However, when DICOM-SC is used for storing the results of a segmentation task, a major limitation is represented by the impossibility to edit the segmentation after exporting to DICOM-SC. This problem will be fixed in future releases of DICOM standard; actually some relevant DICOM supplements are in an advanced status of preparation (such as DICOM Supplement 132 which aims at defining the so-called Surface Segmentation Storage SOP Class). Having obtained in this way an interoperable repository, a second step towards integration consists in embedding network services into the developed prototypical toolkit. Up to now, the image processing toolkit is able to save its results in DICOM-SC format with a meaningful header. The header may replicate the personal details of the patient contained in the original images and other pieces of information which are not altered during processing. A new series UID is associated to the segmented images, while the study UID (if available in the original images) is kept. Further, DICOM utilities (based on the JAVA implementation of DICOM provided by the DCM4CHE toolkit [15]) have been

Fig. 4. A screen of the ECG viewer displaying (in zoom



mode) additional information including the reference (average) beats. The caliper (ruler) is active and the amplitude and intervals can be accurately measured.integrated in the toolkit; in particular, the segmented images are sent to the Image Archive directly from the image processing application.

4.2 Integration in the General CDSS Architecture

The intervention of signal and image processing methods into the management of care delivery, as detailed in the previous sections, has been carefully and deeply investigated while designing the CDSS, identifying its functionalities and modeling its architecture. The CDSS has been devised for processing patients' related information by exploiting the relevant medical knowledge which has been opportunely elicited from medical experts and extracted from clinical guidelines. The symbolic paradigm has been selected for formalizing such knowledge into an *ontology-* and *rule-based Knowledge Base* [4]. During the knowledge representation process, the integration of both signal and image processing methods has been conceived in order to embody parameters extracted from different data acquisition modalities into the more general process of health care management. In particular, the integration has been focused on two main issues, i.e. (i) sup-plying relevant parameters to the inferential processes and (ii) personalizing the diagnostic investigations by suggesting which parameters should be extracted. An example can be used for better explaining the implications of these two is-sues: while processing a patient's information for identifying the causes of his worsening, the CDSS may need a number of routine parameters not yet avail-able. In such a case, a suggestion will be issued by the system asking the clinician to perform additional examinations, such as an ECG or a TTE, in order to obtain the missing parameters. On the other side, it can happen that such routine parameters are not able to completely explain patient's status and thus the sys-tem can require the extraction of other non standard features that can enlighten patient's peculiar conditions. In both cases, the inferential process pauses, waiting for additional information. Reactivating the inferential process requires data processing algorithms to be performed. The CDSS has been hence carefully and specifically designed for incorporating this kind of functioning. Figure 5 shows the CDSS architecture defined according to a multilevel conceptualization strategy which distinguishes between the knowledge and processing components. Such conceptualization division makes the organization of knowledge inside the sys-tem explicit, providing an implementation-independent description of the role that various knowledge elements play during the decision supporting process.

The CDSS is then composed by the following components:

- the Domain Knowledge Base which maintains the domain knowledge, formalized from the guidelines and from the clinicians' know-how. It consists of a suite of ontologies and a base of rules;
- the Model Base which contains the computational decision models, signals and images processing methods and pattern searching procedures;
- the Meta Knowledge Base which is composed by the strategy knowledge about the organization of the CDSS tasks;
- the Brain which is the system component endowed with the reasoning capability. It is divided into (i) a meta level composed by a Strategy Controller that manages and orchestrates the object level according to what stated into the Meta KB; and (ii) an object level that contained both an Inference Engine for reasoning on the Domain KB and a Model Manager for handling and applying computational reasoning and data processing models.

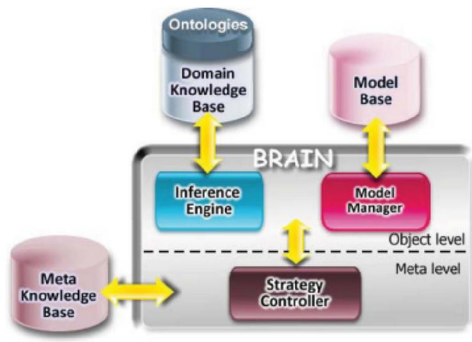


Fig. 5. The CDSS architecture

In particular, the integration of signal and image processing models are, first of all, assured by a dedicated formalization of the relevant acquisition modalities, diagnostic examinations and computable parameters within the ontologies of the Domain KB. Moreover, inferential rules able to process parameters extracted from both signals and images are encoded into the same KB. Finally, the Meta KB contains suitable procedural rules for integrating the application of the data processing methods into the inferential reasoning process. More precisely, when the Inference Engine stops into a crisis status due to the missing values of specific parameters, the Strategy Controller is able to solve the problem by requiring the application of the opportune processing methods triggered by the Model Manager.

5 Conclusions

In this paper we have presented a high-level integration of diagnostic signal and image processing into the wide-ranging services provided by a CDSS for the management of heart failure. In particular, we have motivated the choices made in designing suitably image and signal processing algorithms and we have shown how they can be deployed in decisional problems –and hence in the global process of care– by the CDSS. Future activities will focus on the extension of the already developed signal and image processing toolkit as well as on the realization of an integrated interface for their easy usage in conjunction with the CDSS.

References

1. Doi, K.: Computer-aided diagnosis in medical imaging: Historical review, current status and future potential. Computerized Medical Imaging and Graphics 31, 198– 211 (2007)
2. Greenes, D.: Clinical Decision Support: The Road Ahead. Academic Press, London (2007)
3. Swedberg, K., et al.: The Task Force for the diagnosis and treatment of CHF of the European Society of Cardiology, Guidelines for the diagnosis and treatment of Chronic Heart Failure: full text (update 2005). European Heart Journal, 45 pages (2005)
4. Colantonio, S., Martinelli, M., Moroni, D., Salvetti, O., Perticone, F., Sciacqua, A., Chiarugi, F., Conforti, D., Gualtieri, A., Lagani, V.: Decision support and image & signal analysis in heart failure. A comprehensive use case. In: Azevedo, L., Londral, A.R. (eds.) First International Conference on Health Informatics. HEALTHINF 2008. Proceedings, Funchal, Madeira, Portugal, INSTICC - Institute for Systems and Technologies of Information, Control and Communication, pp. 288–295 (2008)
5. Colantonio, S., Martinelli, M., Moroni, D., Salvetti, O., Perticone, F., Sciacqua, A., Gualtieri, A.: An approach to decision support in heart failure. In: Semantic Web Applications and Perspectives (SWAP 2007). Proceedings, Bari, Italy, Dip. di Informatica, Universit`a di Bari (2007)
6. Perner, P.: Introduction to Case-Based Reasoning for Signals and Images. In: Case-Based Reasoning on Signals and Images. Studies in Computational Intelligence, vol. 73, pp. 1–24. Springer, Heidelberg (2007)
7. Perner, P.: Image mining: Issues, framework, a generic tool and its application to medical-image diagnosis. Engineering Applications of Artificial Intelligence 15, 193–203 (2002)
8. Lang, R.M., et al.: Recommendation for Chamber Quantification: A Report from the American Society of Echocardiography's Guidelines and Standards Committee and the Chamber Quantification Writing Group, developed in conjunction with the European Association of Echocardiography, a branch of the European Society of Cardiology. J Am Soc Echocardiogr. 18, 1440–1463 (2005)
9. Noble, J., Boukerroui, D.: Ultrasound image segmentation: a survey. IEEE Trans. Med. Imag. 25, 987–1010 (2006)
10. Barcaro, U., Moroni, D., Salvetti, O.: Left ventricle segmentation in ultrasound sequences for the automatic computation of ejection fraction. In: Open German Russian Workshop on Pattern Recognition & Image Understanding. Proceedings, Ettlingen, Germany, Forshungsinstitut fur Optronik und Mustererkennung (2007)
11. Barcaro, U., Moroni, D., Salvetti, O.: Left ventricle ejection fraction from dynamic ultrasound images. In: Submitted to Pattern Recognition and Image Analysis, Pleiades Publishing House (2007)
12. Chiarugi, F., Sakkalis, V., Emmanouilidou, D., Krontiris, T., Varanini, M., Tollis, I.: Adaptive threshold QRS detector with best channel selection based on a noise rating system. In: Proc. of Computers in Cardiology, vol. 34, pp. 157–160 (2007)
13. Talmon, J.L.: Pattern recognition of the ECG: a structured analysis. PhD thesis, Vrije Universitet of Amsterdam (1983)
14. Zhou, Z., Liu, B.J., Le, A.H.: CAD-PACS integration tool kit based on DICOM secondary capture, structured report and IHE workflow profiles. Computerized Medical Imaging and Graphics 31, 346–352 (2007)
15. DCM4CHE: A Java implementation of the DICOM Standard (2008), http://www.dcm4che.org/

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