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Patient Specific Cardiovascular Risk Assessment and Treatment Decision Support Based on Multiscale Modelling and Medical Guidelines

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***Abstract*—In this work we present an enhanced medical workflow and a decision support system for atherosclerotic risk assessment and treatment, that is based both on existing medical guidelines and on patient specific multiscale data. The medical expert that uses the system is able to apply both existing medical guidelines as well as to take into account additional information for the patient by inspecting the 3D geometry of an arterial segment or the arterial tree, model the blood flow in the patient specific arterial model and predict the progression of the plaque. Moreover, the user is able to apply plaque characterization techniques in Intravascular Ultrasound images (IVUS) and Tomography Images (CT). The combination of the medical guidelines with the patient specific multiscale data provides a detailed view in the patient status for risk assessment and treatment suggestion.**

I. Introduction

Coronary artery disease (CAD) is the development of atherosclerotic plaques in coronary arteries, resulting in coronary luminal narrowing, and subsequently, occlusion, and thus leading to myocardial infarction (MI) or sudden cardiac death. The CAD is the leading cause of death in western countries. The understanding of the pathophysiology of CAD, the prevention of its development, the identification and effective modification of cardiovascular risk factors, its diagnosis and treatment in early, and reversible stages are of great importance [1]. The identification and stratification of patients of no prior CAD but with high or intermediate risk (for CAD) is a major diagnostic task for medical experts with high clinical value.

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Patients with intermediate risk for CAD can be either asymptomatic or symptomatic. Asymptomatic patients are initially assessed with tools such as the Framingham scoring system [2], which has become the clinical standard for initial patient CAD risk categorization. Many tools for further risk stratification exist and can be used in patients categorized as at intermediate risk [3-5].

Patients at intermediate risk could be candidates for further risk stratification through non-invasive procedures that test for the presence of myocardial ischemia or coronary atherosclerotic burden. To test presence of ischemia in asymptomatic patients exercise stress test is applied. The purpose of coronary atherosclerotic burden procedures is another way to assist the physician in better defining absolute risk of intermediate-risk patients. Although these non-invasive procedures have traditionally been used for diagnosis of coronary artery disease for the purpose of invasive intervention, the emphasis suggested by the Prevention Conference V was on their use to predict future major coronary events (unstable angina and myocardial infarction).

Different is the case of symptomatic patients. Additional testing to determine the possible induction of myocardial ischemia is considered. Coronary angiography could be indicated to determine the extent and severity of obstructive CAD. Global, prognostic, and ischemic risk scores are factored in with coronary angiography results to optimize patient management. Myocardial ischemia, even in patients with normal angiographic results, indicates poor prognosis and is managed with attention to risk factors and aggressive medical management.

Decision support systems, mainly for the diagnosis of CAD have also been proposed in the literature. These methodologies can be divided into various categories. Methods that provide diagnosis of CAD based on the ECG signal [6], medical images such as Single Photon Emission Computed Tomography (SPECT) [7], methods based on heart sounds [8], Doppler ultrasound [9], methods employing demographic, history, and laboratory data (subject's data) [16]; and methods combining more than one type of data such as ECG, and subject's data [10]. On the other hand, methods have been proposed for the assessment of the cardiovascular risk of patients. In this category, the most commonly used methods are the Framingham [11] score and the Assign score [12]. Another recent approach is being developed within the HEARTCYCLE project [13]. They proposed a risk assessment tool that models the medical guidelines, using data from the health record, images and biosignals and provides treatment and follow-up suggestions.

In this work we extend the currently developed decision support systems, by adding patient's data obtained from multiscale modeling. The proposed decision support system provides suggestions for medication and follow-up, based on medical guidelines and additional patient specific knowledge, obtained from multiscale modeling. In addition, the decision is supported by knowledge extracted using data mining techniques.

II. THE TREATMENT DECISION SUPPORT SYSTEM

A. Architecture

The architecture of the proposed treatment decision support system is presented in Figure 1.

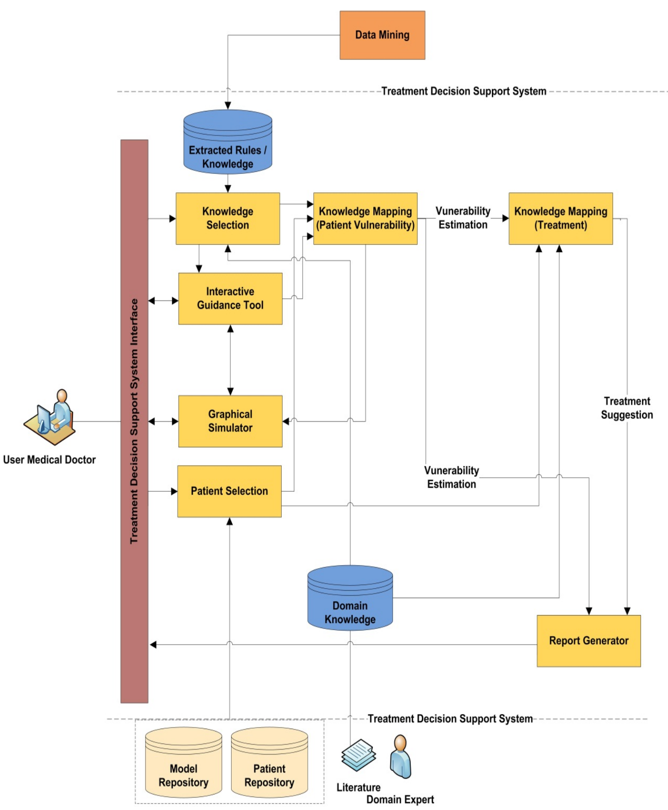

Fig. 1. The architecture of the Treatment Decision Support System

The Knowledge Selection component informs the user on the level of knowledge that could be used for risk estimation.

The Interactive Guidance Tool is an tool that assists the medical professional in the examination process by: (i) pointing the needed input for reasoning and (ii) seamlessly modelling the medical examination/diagnosis workflow (according to guidelines). Input requirements are presented to the user through the TDSS GUI. Using this Tool the medical professional is not needed to provide a full patient record, but only the data needed at the specific stage of the examination/diagnosis process. It is activated through the TDSS user interfaces.

The Patient Selection component allows the medical professional to select a patient for Treatment Decision Support, gets his/her record from the Patient Repository and performs necessary data manipulations for the Knowledge Mapping. It is activated from the TDSS GUI and it provides output (i.e. patient records) to the two Knowledge Mapping components.

The Knowledge Mapping components are the core components of the TDSS. They provide reasoning on the patient vulnerability/risk and on the treatment suggestion and the scheduling of the next visit. More specifically, the Knowledge Mapping for patient vulnerability estimation provides an estimation of the patient vulnerability/risk based on the knowledge selected through the Knowledge Selection component. The main output, i.e. the vulnerability/risk estimation, is provided to the Knowledge Mapping for treatment suggestion and to the Report Generator component. The Knowledge Mapping for treatment suggestion provides a treatment suggestion (including therapy / medication/ next visit scheduling) according to the patient data, the domain knowledge and the vulnerability estimation. The output is provided to the Report Generator.

The Report Generator generates comprehensive reports on treatment decision support and vulnerability for the medical professional. It receives the output of the two Knowledge Mapping components. It is activated after the completion of both Knowledge Mappings.

The Graphical Simulator produces estimations on the patient risk for specific cases and risk factor corrections. It provides suggestions to the patient for the improvement of his risk of CAD.

Apart from the external patient repository and the models repository (where patient specific models are stored), two main repositories are used by the TDSS. The Extracted rules/ Knowledge repository which includes the outcome of the Data Mining component. The knowledge in this repository is considered as "red" knowledge as it is not validated but is only automatically extracted from previous patient records.

The Domain Knowledge repository is used for the Knowledge Mappings (vulnerability estimation/treatment suggestion). It includes modelling of medical guidelines, expert knowledge and knowledge extracted from clinical trials and literature.

The above components are complemented by the Treatment Decision Support GUI which is the front-end application of the TDSS through which specific components are activated and the input and requests of the medical professionals are acquired.

B. Workflow

The Treatment Decision Support System (TDSS) combines the diagnosis workflow with additional data derived from patient specific modeling (Fig. 2): 3D geometry (Fig. 3), blood flow modeling for wall shear stress (WSS) distribution (Fig. 4), low density lipoprotein (LDL) transport (Fig. 5), plaque progression (Fig. 6) and plaque characterization (Fig. 7).

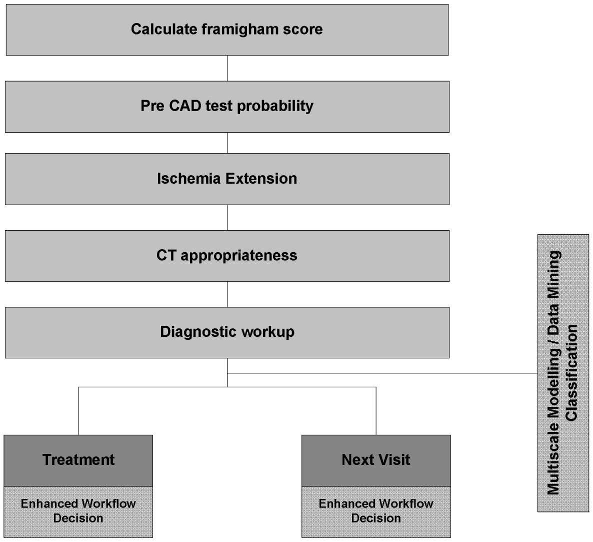

Fig. 2: The enhanced diagnostic workflow.

Data mining on a series of history patient data provides new, data driven, knowledge / rules that can further support patient stratification, risk and severity assessment.

In our enhanced workflow the starting point is the calculation of the Framingham score. Based on it, a patient risk is estimated (low, intermediate or high). Next, the Pretest Probability of CAD is estimated [11]. Then, the ischemia extension of the patient is computed using MPI or stress echo. The possible different outcomes of this ischemia extension test are: (i) ischemia not present (NP), (ii) ischemia extension 0%, (iii) ischemia extension less than 10%, (iv) ischemia extension from 10-15%, (v) ischemia extension more than 10% [14]. The next step is the system to propose a diagnostic workup for the patient, either coronary angiography or CT. But before that, the system performs a CT appropriateness test in order to identify if it is meaningful to perform a CT to the patient [15]. Finally, after the proposal of the diagnostic work up, and based on its results, the system proposes possible treatments and the next patient visit.

In parallel to this flow, the medical expert has the possibility to perform a data mining classification of the patient into severe or non severe state of CAD. The result of the data mining classification is combined with the result of the normal workflow. In case a patient case is characterised as "severe", a revised schedule for the next visit is suggested. Modelling results (as shown in Figs. 3-7) are also presented to further support medical decisions. Figures 3-6 present the results of the patient specific multiscale modeling, regarding 3D arterial tree reconstruction, WSS, LDL and macrophages distribution. Finally, Figure 7 presents the plaque characterization for a specific IVUS frame.

Our workflow uses three different types of knowledge according to the level of credibility: (i) "Green" knowledge that includes all knowledge considered by medical professionals in clinical practice and in accordance to clinical guidelines; (ii) "Orange" knowledge which is knowledge supported by some studies but is not validated by large scale clinical trials and (iii) "Red" knowledge which includes very new knowledge which still lacks validation. (e.g. new medical knowledge automatically extracted through data mining and multiscale modeling). In this way the medical researcher can extend everyday practice experimenting with new knowledge.

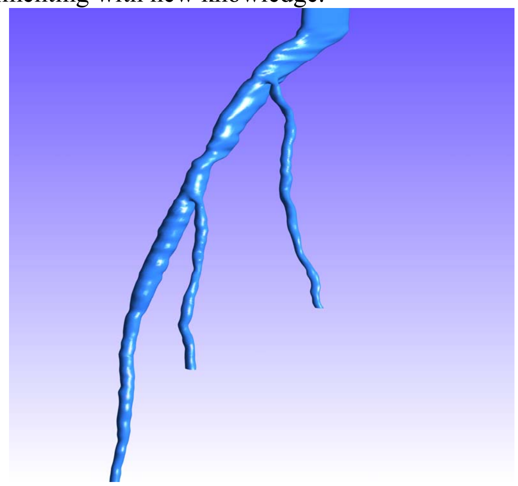

Fig. 3: 3D reconstructed model of an arterial tree.

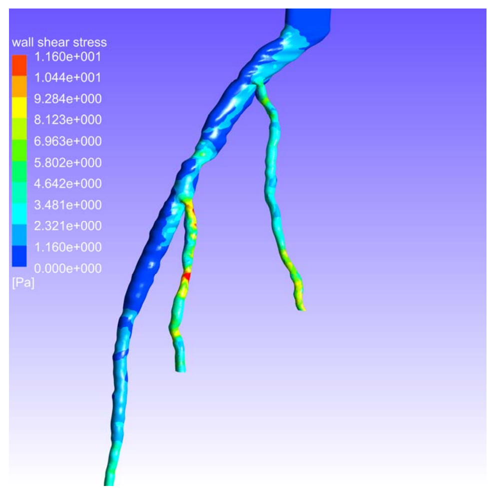

Fig. 4: Wall Shear Stress Distribution in a 3D model.

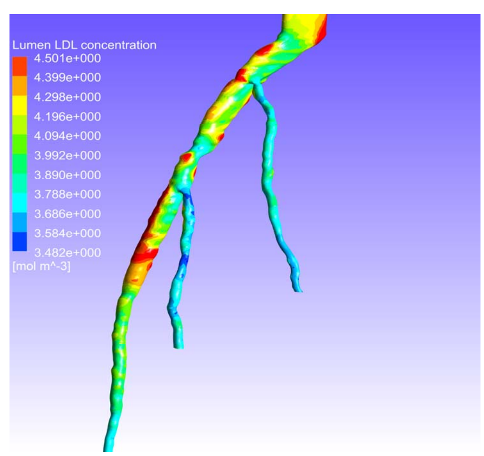

Fig. 5: LDL distribution in a 3D model.

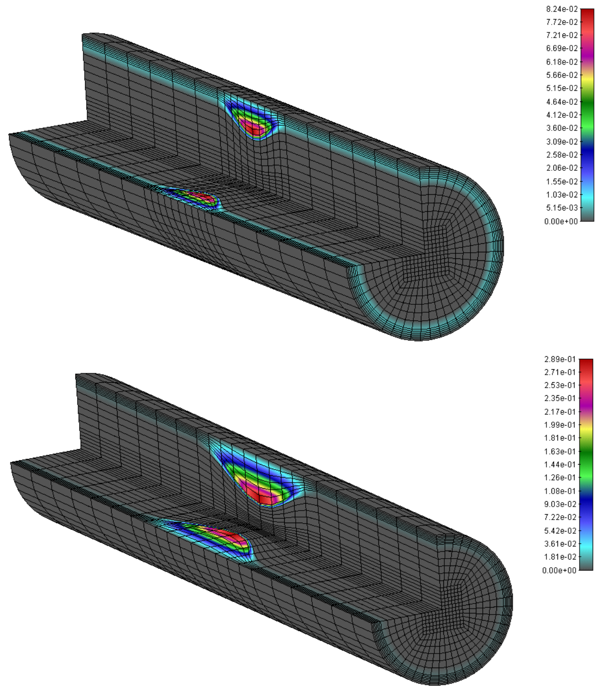

Fig. 6: Plaque progression in a 3D model (macrophages distribution in the intima for an initial mild stenosis 30% constriction by area and after 107 sec[units mg/mL]

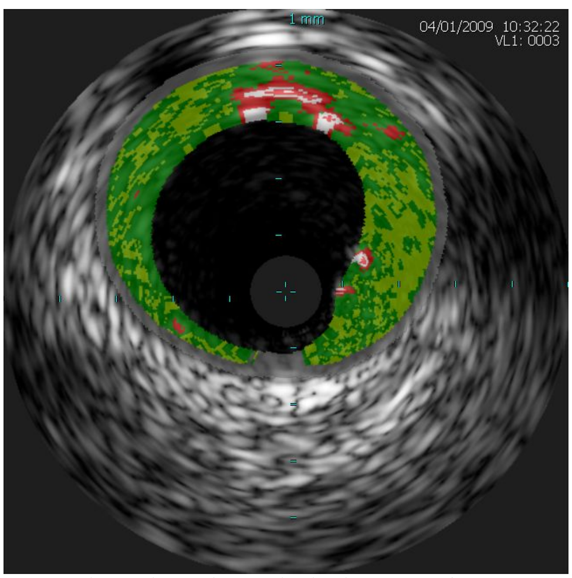

Fig. 7: Plaque characterization in an IVUS frame

III. Conclusions

A novel workflow for CAD diagnosis and treatment suggestion and the respective decision support system are presented. This approach enhances current practice with patient specific modelling data and new knowledge derived through data mining. Validation in real clinical settings will prove the added value in medical diagnosis and treatment selection and its efficiency in early and more accurate patient characterization and management.

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