Toward Decision Support System for Lower Limb Endovascular Revascularization

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***Abstract*—Vascular surgeons take decisions on the revascularization technics when surgery is needed for patients with Lower Extremities Arterial Disease (LEAD). This decision requires experience, good knowledge of official recommandations and new technics and an exhaustive description of the patient status. The Case Based Reasoning (CBR) is a good candidate to clinical decision support. To assess its applicability to LEAD, this study proposes a numerical modelization of patient data in this context, application of hierarchical and heterogenous similarity measures on retrospective data. We showed that similar pathological contexts of patients induce similar revascularization technics, which confirms CBR is usable for our purpose. These experiments need to be reproduced in the future to confirm these results on prospective data.**

***Index Terms*—Decision Support System, Case Based Reasoning, Modelization, Vascular Surgery**

I. Introduction

Atherosclerosis is an arterial pathology that describes the accumulation of plaques on arterial walls. At some point, it can lead to obstruction of arteries: this phenomenon is called ischemia. This work focuses on arteries of lower limbs where the pathology is the Lower Extremeties Arterial Disease (LEAD). Four different stages were identified by Leriche and Fontaine [1] depending of the severity of the symptoms: stage I is the asymptomatic stage, stage II when pain is felt while walking, stage III when pain is felt at rest and stage IV for the combination of pain at rest and trophic disorders (i.e. ischemic wounds).

To avoid amputation, vascular surgeons can revascularize the lower limb with different technics: endovascular surgery and open surgery are the two main types of revascularization that exist with different level of invasivity. Endovascular revascularization is minimally invasive surgery that consists in treating the obstruction by introducing the tools directly through the arterial lumen. Different technics exist, angioplasty and stenting for instance that can be combined. Open surgery, is more invasive as the technics usually involve opening the tigh to access the artery.

The revascularization has three goals: the wound healing, the relief of pain, and the maintenance of the ambulatory status. As patients concerned by LEAD are usually patients over 60 years old with numerous comorbidities, the recovery and thus the invasivity are important parameters to consider.

The choice of a technic or another relies on Patient Data, Official recommandations, surgeon experience and the experience of their peers. However, these decision factors are not always available: patient data in the hospital informatic system is scattered in several databases, redundant and unstructured ; official recommandations are not always up to date with newest technics and leave space for interpretations; the experience of other surgeons is not always fully available nor explicit.

To help overcoming these limits, Decision Support tools have already proved their efficacy in other medical domains, [2]. There are two main types of algorithms : the training based algorithms and knowledge based algorithms [3]. Among training based ones, we can count neural networks, bayesian networks as example, that have already been used for clinical decision support [4]. However, when using training based methods, knowledge is acquired through training, which requires large and exhaustive databases. In addition, as the whole pathological context of patient needs to be considered, the LEAD database uses much more descriptive variables compared to the number of observations. Therefore, statistical significance cannot be reached. In this study, we focus on knowledge based methods where the knowledge is given to the system.

Among knowledge-based methods, the Case Based Reasoning (CBR) uses experience of past surgeries as the source of knowlegde. It has already been used in other clinical contexts [5]–[7].

It is called 'Case Based' because it uses a certain amount of already solved cases, here past surgeries. It works in a four steps cycle: when a new case to solve enters the system, it will first retrieve the most similar case(s) among the case base thanks to similarity measures. The solution(s) of these similar cases give the suggested solution(s). The revise step aims to adapt the suggested solution(s) to the given problem, thanks to adaptation rules, to obtain the confirmed solution(s). Once a solution is confirmed, it is tested and the result obtained, the retain step will integrate this new case into the case base to enrich the system.

This algorithm mimics the human reasoning as it solves a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation [8]. This functionning and its explanability make it an interesting method for our purpose.

The CBR works by retrieving the most similar cases.

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Thus, we will need to measure similarity which is a quantity reflecting of how much two elements are alike. Numerous similarity measures already exist [9]. It can be defined as a function that quantifies either the distance i.e. the dissimilarity or the correlation i.e. the strentgh of the link between two elements. Helène Feuillâtre et. al. [5] defined a hierarchical and heterogenous distance between patients in the context of aortic valve replacement.

This study aims to assess the applicability of CBR to the context of revascularization of lower limbs. After detailing the data model needed, we illustrate how it is used to measure similarity between cases.

II. METHODS

To evaluate the pertinence of CBR, we focus on the following clinical question : " For a given patient, what would be the most efficient revascularization technic to relief pain, heal wounds and maintain patient mobility ?". To answer this question thanks to CBR methods, we need to design the model of a numerical patient using raw clinical data. Thus, we first need to define how to describe cases, i.e. the attributes necessary to describe patient pathological context. Secondly, we need to define what are similar cases.

A. Definition of a Case

A case comprises three elements: the attributes describing the problem, which include the list of variables detailing a patient's symptoms and overall pathological context; the solution that was selected and applied, representing the most effective revascularization method for a given patient, either through endovascular or open surgery techniques; the outcome of the solution, indicating success or failure. Success can be defined by technical success, signifying immediate restoration of blood flow during surgery, as well as clinical success, encompassing pain relief, wound healing, and restored mobility. Conversely, failure entails either reintervention or amputation on the same side, perioperative death, or technical complications during surgery.

B. Data Structure

In the context of vascular surgery, defining a case involves identifying the necessary variables for our numerical model. We undertook this task with precision, guided by official recommendations, pertinent clinical studies, and the invaluable insights of expert surgeons.

1) Hierarchy of data model: Our variable selection process adhered to established guidelines and clinical decision-making frameworks specific to our pathology.

For preoperative data, we embraced the PLAN concept endorsed by the Society of Vascular Surgery [10]. This entails prioritizing three key aspects for each patient in the following order: *Patient risk estimation*, encompassing comorbidities and risk factors. (for example chronic kidney failure, bronchopneumopathies, cardiac pathologies) [11], [12]; *Limb staging* evaluated through the WIfI score [13], [14] to gauge amputation risk and revascularization benefits.; *ANatomical pattern* based on interpretation of CT scans and scoring .

Regarding the solution attributes, we also delineated attributes related to revascularization techniques employed, categorized into three levels: the type of surgery (endovascular or open surgery) ; Specific techniques or their combinations (angioplasty, stenting, bypass).; Detailed aspects of the techniques, such as stent size, balloon diameters, and prosthesis materials.

Attributes concerning surgical outcomes were meticulously defined, focusing on achieving revascularization goals. Success or failure was assessed based on postoperative evaluations of pain, wound progression, and ambulatory status at various intervals.

2) Type of data model: Ensuring consistency and comprehensiveness in our model demanded careful consideration of data types. Clinical data encompassed a diverse range, including quantitative, binary, qualitative, ordinal data, and images.

To enhance uniformity, qualitative data were converted into binary variables. For example, rather than having a variable where the possible values are the different cardiopathies, each possible values became a binary variables.

Ordinal data, are between qualitative and quantitative: they are categories representing a scale. They are often used in medical domain for diagnosis: as an example ranges of hemoglobin concentration values to give the grade of anemia. We retained raw quantitative measurements whenever feasible, prioritizing precision in patient comparisons.

Regarding images, CT scans are the examination helping surgeons to determine the complexity of the arterial tree of a given patient. We chose to use CT scan interpretations providing essential variables such as lesion localization, calcification presence, and stenosis degree.

3) Handling Missing data: Missing data is an important characteristic of clinical data. Indeed, depending on the context, the patients arrive with different amount of information. Moreover during patient interrogation some data is considered as implicit. For example,when nothing is mentionned concerning the smoking status on a patient file, we can either assume that the patient is not a smoker, or that we do not know. To avoid that confusion, we defined a ternary format of variables—where values could be True, False, or Unknown—we mitigated ambiguity and ensured clarity in data interpretation. This approach effectively distinguished between explicitly absent information and instances where data were simply undisclosed or uncertain.

In summary, our meticulous approach resulted in the identification of over 650 variables comprising our patient model. This comprehensive framework integrates diverse data types, aligns with clinical best practices, and addresses the complexities inherent in vascular surgery data analysis.

C. Data Collection

To build a database following the data structure described above, we develop a software to collect data. The first objective is to design this tool in a user-centered way, the first users being the surgeons. The whole organization of the forms is

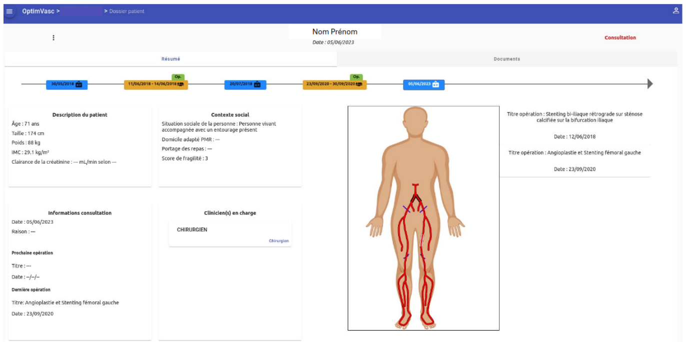

Fig. 1. View of a patient file on the data collection software

based on vascular surgeons workflow. The second objective is the collection of data in a exhaustive and structured way allowing access to anonymized these clinical data. This is achieved by integrating the patient data model in the forms.

D. Similarity Measures

To retrieve contexts which are the most alike, we need to measure similarity between surgeries with distances. Among various distance metrics, we have chosen to implement the Hierarchical Weighted and Heterogenous Similarity Measure (H-WHSM) [5] as it accommodates the diverse formats of data encountered in the clinical context. This measure incorporates the hierarchical structure of variables, along with the weighting derived from clinical decision trees, particularly the PLAN concept outlined earlier. The weighting scheme is specifically applied to preoperative variables. This tailored approach ensures that the measurement accounts for the specificities of the clinical context and is well-suited for decision support systems.

III. Results

To verify the applicability of CBR to LEAD, we developped a software to collect structured, normalized and exhaustive data and performed preliminary studies on retrospective data.

A. Data collection software

We developped prospective data collection system integrated in a web application in figure 1.

This tool is currently deployed in the Centre Hospitalier Universitaire Grenoble Alpes.

B. Retrospective data

The retrospective database used for our preliminary experiments was collected for technical and legal studies between 2018 and 2020 with patients going under lower limb revascularization. As They were not intended for CBR, simplifications hypothesis of the data model had to be made.

Concerning missing data, the ternary format can only be used for prospective data collection. As quantitative measurements as were not all available, we used ordinal variables (scales and grades). Regarding images, interpretations of surgeons were not available. Thus, we used interpretations of reports made by radiologists instead.

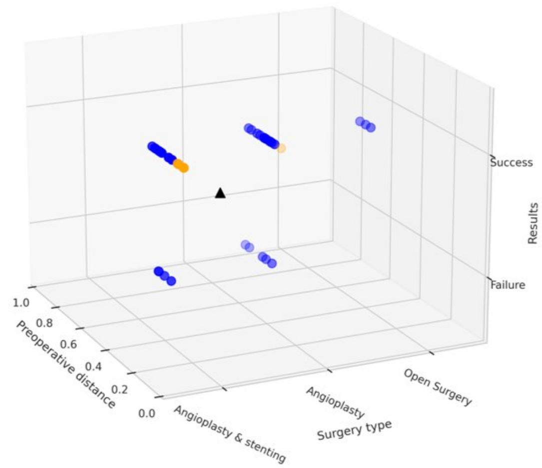

Fig. 2. Example1: 3D plot of the distance between patients and their solution and results

Another element impacting our data collection was the chronicity of LEAD: even after revascularization obstruction can happen again, at the same location or a different one. Hence, we considered only one surgery per patient.

With these simplifications, from 675 variables in the proposed model, we kept 75 variables: 45 are preoperative attributes, 9 are surgical solution attributes, and 17 are results attributes. These retrospective data on surgeries were used to perform preliminary studies on similarity measures.

The solution, surgical technic, could be described by multiple variables. To simplify the result display and interpretation, we defined three categories for surgery types: pen surgery, angioplasty or angioplasty and stenting.

The result of a revascularization procedure is a combination of multiple factors. We chose to define the result as binary: success or failure. The success is the non-occurrence of re-intervention, amputation or death within 3 months after surgery. The failure is the occurence of at least one of these events.

The case base constituted includes 38 cases to perform preliminary studies.

C. Similarity measure on retrospective dataset

We used H-WHSM on preoperative attributes as similarity measure to retrieve the most similar cases to a test case. The test case is a known case not included in the case base. Among the closests, we represented the surgery type that was used for the patient and the result (success or failure.)

The figure 2 represents for a given patient the distance regarding the preoperative variables on x axis, the type of surgery applied on the y axis, and the clinical result of the surgery on the z axis. The triangle represents the patients of reference i.e. the patient for which we retrieve the most similar ones. In orange, we represent the 5 most similar patients. The test case went under endovascular surgery for Angioplasty with stenting and it was a success. The 5 most similar patients went under endovascular surgery with success as a result and

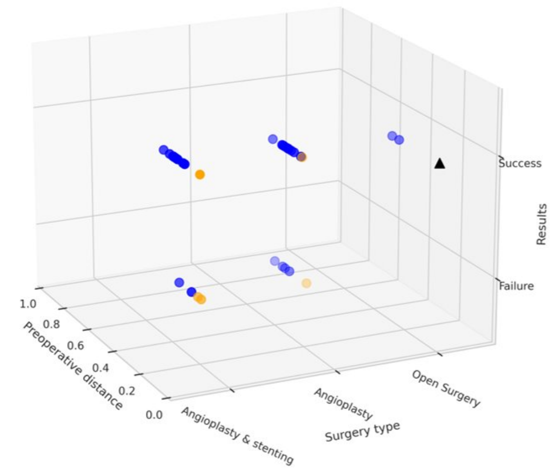

Fig. 3. Example2: 3D plot of the distance between patients and their solution and results

among these 5 patients, 4 received an angioplasty with stenting exactly as the patient of reference. Hence, the pathological context described by the attributes seems to indicate an endovascular technic.

On the second example (figure 3), the test case went under open surgery for revascularization and it was a success. The most similar patients did not go under open surgery but 3 of the 5 most similar patients went under endovascular surgery (angioplasty and/or stenting) with clinical failure. Nevertheless, 2 of the 5 most similar patients went under endovascular surgeries with a successful outcome.

IV. Discussion

These preliminary results show that CBR could be applied to the context of endovascular revascularization. However, we observe disparities, in solutions and results, for some cases.

As retrospective dataset was not designed for a CBR application, simplification hypothesis were made compared to the proposed model. The exhaustivity planned in the proposed model could bring more accuracy on the patient model with a prospective database. This is why, such experiment should be reproduced with a prostective and exhaustive dataset.

The case base used here might not be representative of the whole spectrum of pathological context.

Definition of success and failure of a surgery were made binary in our preliminary results. However, in a clinical context and especially concerning chronical diseases, success or failure of a solution is not binary. We also need to consider other variables impacting the results such as the evolution of wounds and of the ambulatory status. These postoperative variables could be combined to use a success score of a revascularization intervention.

The objective here was not to elect the best distance metric but only to assess the feasability of Case Based Reasoning in the specific context of LEAD. We chose the H-WHSM distance for our preliminary study, however other similarity measures should be tested to identify the one that is the most efficient on retrieving the most similar cases in our field of application.

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