Visual Assistance in Clinical Decision Support

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Abstract

*Clinical decision-making for complex diseases such as cancer aims at finding the right diagnosis, optimal treatment or best aftercare for a specific patient. The decision-making process is very challenging due to the distributed storage of patient information entities in multiple hospital information systems, the required inclusion of multiple clinical disciplines with their different views of disease and therapy, and the multitude of available medical examinations, therapy options and aftercare strategies. Clinical Decision Support Systems (CDSS) address these difficulties by presenting all relevant information entities in a concise manner and providing a recommendation based on interdisciplinary disease- and patient-specific models of diagnosis and treatment. This work summarizes our research on visual assistance for therapy decision-making. We aim at supporting the preparation and implementation of expert meetings discussing cancer cases (*tumor boards*) and the aftercare consultation. In very recent work, we started to address the generation of models underlying a CDSS. The developed solutions combine state-of-the-art interactive visualizations with methods from statistics, machine learning and information organization.*

CCS Concepts

• ***Human-centered computing*** → ***Visual analytics;*** • ***Applied computing*** → ***Life and medical sciences;***

1. Introduction

Therapy decision-making mainly considers (i) patient-specific information entities, (ii) clinical guidelines, and (iii) the physician's knowledge and experience. Based on that, a physician is able to recommend a treatment for standard patient cases. For complex cancer cases, an additional multidisciplinary discussion with experts from different domains, the so-called *tumor board*, is required. Domains include but are not limited to surgery, radiology, pathology, radio-, and chemo therapy. Experts from other specialties may be needed in case of comorbidities. In this context, however, some of the physicians in the tumor board have to discuss the case without a patient consultation beforehand. They have to rely on the available patient information in the hospital information systems (HIS) and the case introduction by the attending physician. Next to this, changing clinical guidelines, distributed data storage, and diversity of treatment options complicate the decision-making.

After therapy, the patient is monitored in aftercare to watch for tumor recurrences and long-term side effects. Aftercare consultations require an overview of patient status and development including so-called *patient-reported outcomes* (PRO) and may benefit from comparing both with similar patients. However, overview and comparison are inadequately supported by existing HIS.

To address these challenges and gaps, we have developed approaches blending interactive visualizations with methods from statistics, machine learning, in particular, probabilistic models, and information organization to provide an overview and timeline of the patient's clinical pathway, to allow for comparison of an individual with patient cohorts, and to prepare and explain an initial treatment recommendation. A crucial prerequisite for the acceptance of and the trust in such a computed recommendation is its explainability. The physicians have to be able to understand and justify the recommendation generation process in order to trust the clinical decision support system (CDSS) [VMW*19]. In our work we showed that visual assistance is beneficial in getting an improved understanding of process and results.

Our solutions have been developed and thoroughly evaluated within different clinical settings at the University Hospitals of Leipzig and Magdeburg, Germany. They are to a certain degree tailored to specific types of cancer and the local treatment procedures but large parts can be readily transferred to other types and sites. One research prototype for PRO visualization is currently being integrated in the commercial software "Oncofunction" [ZMW*20] for cancer aftercare consultations. Another prototype tailored to explainable clinical decision support for laryngeal cancer therapy forms the basis for a submitted Dutch grant proposal in the context of endometrial cancer. In the remainder, we focus on the visualization aspects of our work but considerable effort was also spend on integrating the solutions into hospital environments [GSOO18].

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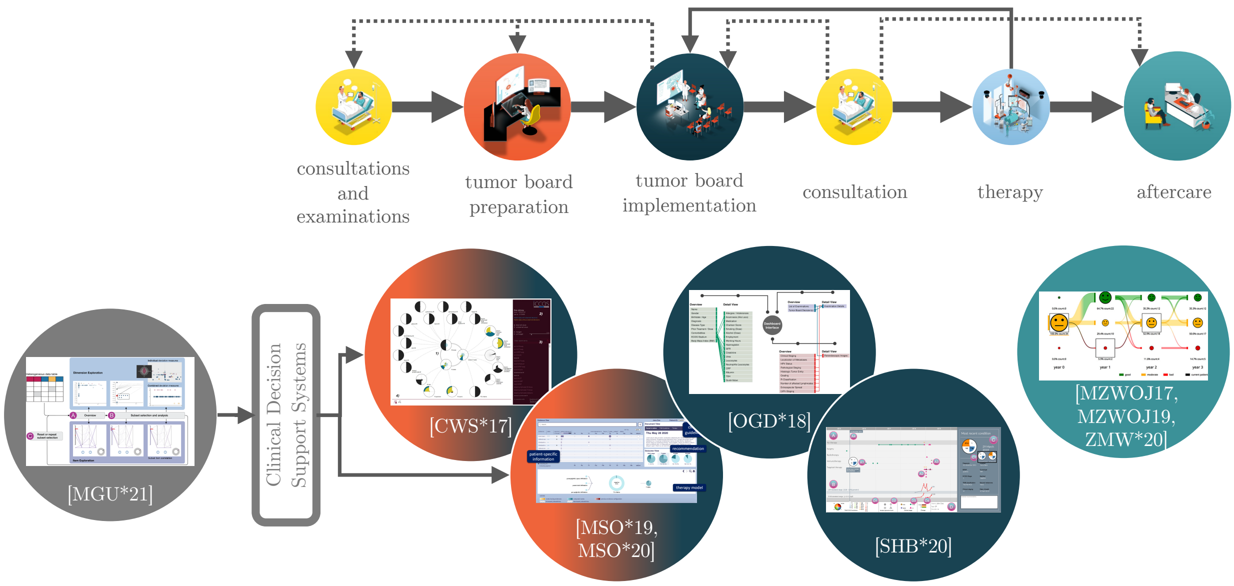

Figure 1: *Schematic pipeline of the treatment decision-making workflow for solid cancer diseases [CWS*17]. Clinical Decision Support Systems can assist physicians in finding the optimal patient-specific treatment.*

2. Clinical Background

The common treatment decision-making workflow for cancer patients starts with *clinician consultations and examinations* to identify the patient's health condition (Fig. 1). The results are stored in a distributed and often, machine-unreadable form across multiple HIS and/or on paper-based case sheets.

At the tumor centers of the University Hospitals of Leipzig and Magdeburg, Germany, an initial treatment recommendation for the tumor board is elaborated by the attending physician in the *tumor board preparation* step. The physician searches for and collects all relevant patient information from the HISs and the paper records and copies them to the tumor board case sheet. This sheet is then distributed to all physicians within the *tumor board implementation*. The meeting starts with the attending physician introducing the patient and presenting the initial treatment recommendation which is then, discussed by all attending colleagues. During the discussion, the radiologist displays the recorded patient images, such as CT or MRI scans, on a large screen. It usually takes only a few minutes, depending on the complexity of the patient case, for the physicians to discuss and agree on a treatment plan. Following the tumor board implementation, the treatment plan is communicated to the patient in a clinician *consultation*. In case the patient agrees with the treatment plan, the *therapy*, e.g., surgery, starts. Otherwise, the case is discussed in a tumor board again. If problems occur during therapy, the case may be re-introduced to the tumor board. After the therapy, the patient is followed up in *aftercare* for multiple years to identify tumor recurrences at an early stage.

The treatment-decision workflow involves lots of patient-specific data from diagnostic examinations, treatment procedures, imaging examinations, etc. The data is partially narrative and partial semi-structured. Often, the data quality also varies, so that information may be unreliable or delayed. To assist physicians in decision-making, we developed interactive visual tools inspired by decision-making processes within a therapy-life-cycle of cancer patients and, therefore, specifically adjusted to the clinicians' needs.

3. Technical Background

A large part of our work on visual assistance for tumor board preparation and implementation is related to laryngeal cancer and based on a Bayesian Network (BN) model of its treatment [CS19]. BNs are probabilistic models based on a directed acyclic graph structure [Pea88]. They consist of a set of nodes, edges indicating relations of nodes, and a conditional probability table (CPT) per node constituting its *if-then* relations on the parent nodes [Pea88]. Each node is a random variable and takes on a probability distribution of states. For example, the node "Laryngeal Cancer" in Figure 2 takes on a probability distribution of the states "true" and "false" depending on the presence of "Tobacco" and "Alcohol" abuse. In the context of BNs, *evidence items* are observed information available for the patient and impacting the recommendation generation process. BNs are especially suited for reasoning under uncertainty

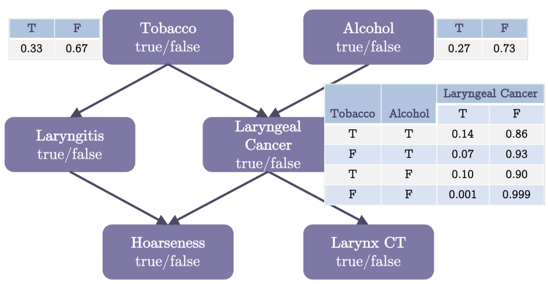

Figure 2: *Oversimplified Bayesian network representing a diagnostics decision reduced to Laryngitis and Laryngeal cancer.*

and missing values and therefore, are well designed for application in treatment decision-making [RGV*20]. In the medical context, we showed that BNs can be developed using clinical guidelines as well as epidemiological and clinical study results [CS19] and/or learnt from data using machine-learning algorithms [MNC*18].

4. Visual Assistance in Tumor Board Preparation

A key influence for the treatment recommendation for solid tumors, such as laryngeal cancer, is the TNM classification (*T*umor size and type, lymph *N*ode infiltration, and distant *M*etastasis) [BGW17]. It is manually determined based on TNM staging guidelines. The last updated TNM classification is extracted by the attending physician in the tumor board preparation step from the patient records and copied to the tumor board case sheet. In the tumor board however, it may have to be reworked due to recent patient-specific information, such as pathology or features derived from medical images, which were entered into the patient records after the last TNM classification. This costs the time of multiple experts and may lead to postponing the case to the next tumor board.

To assist the attending physician in determining the most recent TNM classification, we support its on-the-fly computation and verification using the respective part of the BN model for laryngeal cancer treatment [CS19]. This network part consists of 303 nodes and 334 causal relations (Sec. 3). To allow for an application within clinical routine, we developed an interactive graph view for the structured verification of a computed TNM staging (Fig. 1 [CWS*17]). Our approach includes tailor-made glyphs for encoding the probability distributions, interaction techniques for BN graph exploration, and comparative visualizations of two TNMs resulting from two sets of evidence items. By using a force directed graph layout and interaction techniques allowing for investigation of nodes, node relations, and node probabilities by dragging nodes under investigation in the centered circular focus region, the users are able to explore the whole BN. We evaluated our visual system and TNM verification approach with five experienced clinicians. Although the participants were able to verify the TNM staging using our approach, key limitations were identified in the unstructured and unordered presentation of nodes using a force-directed layout which resulted in an average TNM verification time of 10 minutes. Still, this time is acceptable if it saves the time of multiple experts in the tumor board implementation.

5. Visual Assistance in Tumor Board Implementation

With our work, we addressed the explainability of a computed therapy recommendation as well as the concise presentation of both, the current patient status and its development over time during therapy. The latter is crucial if previous therapies failed/were insufficient and the patient is re-introduced to the tumor board.

5.1. Explainable Clinical Decision Support

The entire BN of laryngeal cancer treatment consists of more than 1,000 nodes and 1,300 causal dependencies [CS19]. It became clear quickly, that a graph visualization and exploration approach, as successfully applied to a sub-network during tumor board preparation (Sec. 4), would not fit the tight schedule of tumor board implementation. Instead of inspecting the causal flow in the entire network leading to the computed recommendation, clinicians are rather interested in the certainty of the recommendation and in patient evidence items supporting/contradicting the recommendation.

Hence, we developed a new, award-winning interactive visual approach assisting clinicians in understanding and justifying treatment recommendations computed by BNs (Fig. 1 [MSO*19, MSO*20]). Inspired by decision-making within clinical routine, our approach consists of four parts: *(i)* the *evidence view* representing all available patient-specific information in a structured manner regarding their relevance of influence on the computed recommendation, *(ii)* the *guidelines view* showing related clinical guidelines, *(iii)* the *outcome view* presenting target nodes, such as the node for treatment recommendation, and the computed recommendations, as well as *(iv)* the *network view* allowing for a structured exploration of the underlying BN. The user is able to interactively modify the set of evidence items in case of newly observed information, for simulating patient's conditions, or for predicting a future outcome and can observe the related changes within the probability distributions in comparative bar, donut or pie charts. In an evaluation study with six experienced Otorhinolaryngologists using the BN for TNM staging of laryngeal cancer patients outside the tumor board, we assessed the usability, medical relevance, and applicability within healthcare as very important and useful. Before application within clinical routine, however, our approach must be fully integrated and evaluated within the tumor board. Based on our approach, the Radboud University, the Netherlands, in collaboration with us submitted a grant proposal for the development and implementation of BNs as CDSS within clinical routine for patients suffering from endometrial cancer.

5.2. Patient Overview Presentation for the Tumor Board

The patient information available to the physicians in the tumor board is limited since the tumor board case sheet contains information filtered by the attending physician only. Some board participants bring their own (paper) records, which are then, however, not available to all participants. Hence, we developed overview visualizations of patient status and development that can be populated by the HISs and be shown to the entire board on a large screen next to the medical images.

5.2.1. Head and Neck Cancer Tumor Board

We shadowed the head and neck cancer tumor board at the University Hospital Leipzig, Germany, and developed a questionnaire to find out which information entities are considered crucial in decision-making by all board participants. By means of multiple interview cycles with eight participants from different disciplines, we achieved consensus and identified three main content groups for head and neck cancer tumor board dashboards: (i) *patient metrics*, (ii) *therapy metrics*, and (iii) *disease metrics* (Fig. 1 [OGD*18]). In each group, information entities were ranked by the interviewees as crucial and potentially relevant. Grouping and ranking were organized in a *map of information* based on which the patient information from the HISs is structured and displayed in the dashboard. Crucial information is visible in an overview while potentially relevant information is shown on demand.

5.2.2. Dermatological Tumor Board

Based on our developments for head and neck cancer, we designed a dashboard for the dermatological tumor board at the University Hospital Magdeburg, Germany (Fig. 1 [SHB*20]). The focus was on melanoma patients with brain metastases under immunotherapy. A specific requirement was the concise display of therapy history and the impact of therapy steps on patient status since most of these patients have a complex history of standard and rather experimental therapies. Following our approach for map of information generation, we identified three main content groups: (i) *general patient data*, (ii) *prognostic parameters*, and (iii) *therapy data*. Visual mappings of these content groups are orchestrated in a timeline representation in combination with glyphs encoding the patient's condition, applied treatments, and TNM staging. Thus, the user can easily observe changes in the patient's condition. Five experienced dermatologists assessed our approach as applicable within the dermatological tumor board.

6. Visual Assistance in Aftercare

After treatment, head and neck cancer patients regularly attend follow-up consultations over five years to detect tumor recurrences at an early stage, manage therapy-associated side effects and cancer-related comorbidities. Within these consultations, physicians assess the patient's current condition as well as verify and update the aftercare treatment. In this context, they are usually less attentive to the documentation of functional impairments and quality of life perceptions. Especially for head and neck cancer patients, however, the disease and the treatment are mostly accompanied with a wide variety of related functional impairments, such as swallowing, voice, pain, etc., which have a huge impact on the patient's daily life and their perceived quality of life. To assess and react to these problems at an early stage, supplementation of aftercare consultations with Patient-Reported Outcome (PRO) measurements is recommended to ensure a patient-centered aftercare.

A PRO is defined as "any report of the status of a patient‘s health condition that comes directly from the patient, without interpretation of the patient‘s response by a clinician" [Hor09]. At the Dept. of Otorhinolaryngology, Head and Neck Surgery, University Medical Center, Leipzig, Germany, these PROs are collected electronically before the medical consultation and presented to the physician during consultation. The original presentation, however, had various limitations. For example, physicians were neither able to see the progress of the patient's condition over time nor the patient's condition in comparison to the whole cohort in order to predict the patient's future outcome based on the investigation of similar patients. Therefore, we developed an improved interactive visualization addressing the identified limitations and emphasizing problematic conditions in a concise manner (Fig. 1 [MZWOJ17, MZWOJ19, ZMW*20]). The visualization prototype is currently being integrated in the commercial software "OncoFunction" for clinical routine use at the Dept. of Otorhinolaryngology [ZMW*20].

7. Visual Assistance in Building Therapy Models

The systematic structuring and processing of clinical routine data offers new opportunities for the generation of decision support models. The large size and constant growth of available data enable the learning of models from data. However, within this process multiple complex challenges must be addressed such as mixed data types, high frequency of missing values and many, potentially correlated, redundant or irrelevant data variables. Therefore, an informed preselection of variables is required to improve the quality of the data-driven decision support model. In causal model learning, correlations among the variables within a data set may indicate potential causal relations and hence, assist in variables of interest identification. However, computing pair-wise correlations for many variables and observations is expensive and alternative approaches speeding up the identification of correlations, such as the dual analysis framework [TFH11], are just tailored to quantitative data. Hence, we developed an extension of the dual analysis approach for the integrated evaluation of quantitative and qualitative high-dimensional data (Fig. 1 [MGU*21]). By treating both, observations and variables, independently of their data type, as first order analysis objects, we are able to identify clusters, outliers, and possible correlations among the variables in a quick exploratory manner. These correlations may assist in data-driven causal BN generation and in hypothesis generation.

8. Summary and Outlook

We presented the decision-making workflow of cancer treatment within clinical routine and described several visual assistance solutions addressing the associated needs of physicians at multiple steps of this workflow. We conceptualized and implemented interactive solutions assisting physicians in tumor board preparation and implementation. For the latter, we developed a framework which supports physicians in understanding and justifying the process of treatment recommendation computation within a CDSS. Our solution allows for building trust in the computed recommendation and for its application within clinical routine as an additional objective decision-making opinion. Moreover, we developed tumor board dashboards summarizing the patients key findings, development over time, and applied treatments. A combination of the CDSS explanation and the dashboards would serve as a comprehensive visual assistance in tumor board implementation. For cancer aftercare, we designed improved PRO visualizations showing the progress of a patient, also in the context of a cohort of similar patients. Finally, we extended the dual analysis framework to support the identification of correlations in mixed data recorded within clinical routine and aftercare. Since correlations are indicators for causal relations, they form the basis for the data-driven development and validation of therapy models, which is the objective of our current research topic. These models can then be used within clinical routine as CDSS. By using familiar presentations and focusing on the interaction design, we decrease the required learning effort and improve acceptability for all applications.

In future work, we want to investigate the requirements on visualizations and interactions which would allow patients during clinician consultation to better understand the treatment recommendation of the tumor board. In this context, we have to identify the key information letting patients trust in the treatment recommendation as well as design abstracted visualizations and simple interactions usable for patients.

9. Acknowledgements

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