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Interactive visual guidance for automated stereotactic radiosurgery treatment planning

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ABSTRACT

The growing technology industry has led to the steady enhancement of expert systems, often at the cost of increased complexity for the systems' end users. Efforts to improve the prescriptive elements of systems, however, often prove unsuccessful, since the nature of complex and high-dimensional decision problems is difficult to capture precisely by models and algorithms. To rectify this deficiency, complementary softwares may be used to accept decision-making input from users. In this paper, we introduce a graphical interface-based multi-criteria decision support system for designing radiation therapy treatment plans. While many automated strategies for treatment plan generation exist in the literature, they often require a large amount of iteration and *a priori* decision-making in practice, so much of the planning is done manually. Our interface, morDiRECT (the Medical Operations Research Laboratory's Display for Ranking and Evaluating Customized Treatments) uses the variability associated with the planning parameters to generate diverse plan sets automatically, creating a comprehensive and visible decision space for users. We demonstrate morDiRECT's generation process, built-in analytical tooling and graphical display using four clinical case studies. In three cases, we find plans that fully dominate the benchmark forward plans, as well as additional plans that possess potentially desirable tradeoffs for all cases. Our results demonstrate that with relatively little upfront effort, users can pre-generate and choose from a diverse set of clinically acceptable plans, leading to reliable treatments for head-and-neck patients.

1. Introduction

Medical technology has advanced considerably over the past few decades, paving the way for a rapid evolution in radiation therapy treatment tools (Schimpff, 2014). As these tools grow in sophistication, the analytical complexity and resultant cognitive loading placed on their operators increases dramatically (Ruotsalainen, Boman, Miettinen, & Tervo, 2009). In order to alleviate some of this demand, we introduce a graphical user interface (GUI) called morDiRECT (the Medical Operations Research Laboratory's Display for Ranking and Evaluating Customized Treatments) to support expert users through the non-trivial tasks of radiation therapy treatment planning and selection.

The radiation therapy delivery process can be broken down into five key stages, depicted in Fig. 1. The majority of the tools designed to facilitate this process aim to support the more mechanical Stages 1 and 5 (21st Century Oncology, 2013; Elekta AB, 2013; General Electric Company, 2013; IBA, 2013; Philips, 2013). In contrast, the intermediate planning done in Stages 2–4, tends to be less supported, relying heavily on human operators (National Cancer Institute, 2014). Due to the complex nature of these planning stages, automated strategies such as inverse planning have become a prevalent source of discussion in the radiation therapy literature (Romeijn & Dempsey, 2008; Webb, 2014). The high versatility of inverse planning has also led to extensions to similar problems within the field, such as Leksell Gamma Knife® radiosurgery treatment (Ferris & Shepard, 2000; Ferris, Lim, & Shepard, 2002; Ferris, Lim, & Shepard, 2003; Ghobadi, Ghaffari, Aleman, Jaffray, & Ruschin, 2012; Ghobadi, 2014; Shepard, Yu, Murphy, Bussière, & Bova,2015; Shepard et al., 2015; Wu et al., 2003; Wu et al., 2004).

Inverse planning methodologies fall into a class of algorithms that specifically target Stage 3 of the delivery process. Stage 3 is difficult by nature as it is associated with a detailed understanding of the technology, as well as the case at hand. While carrying out this stage (either manually or with the help of traditional inverse

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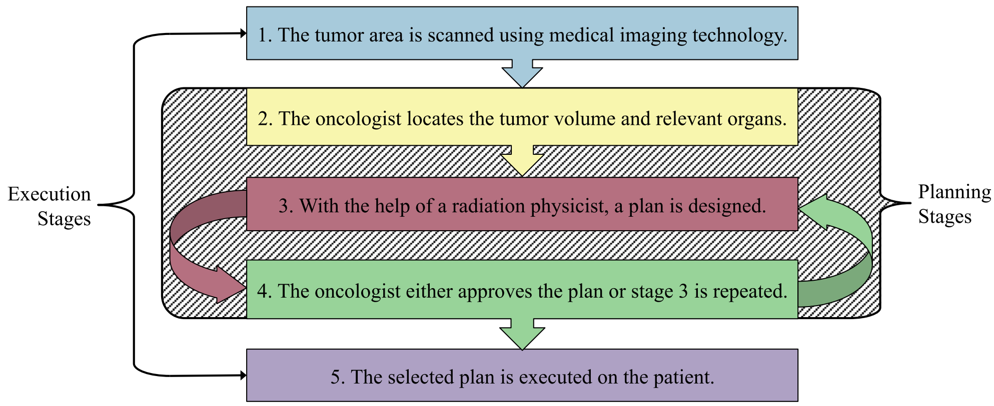

Fig. 1. Key stages in radiation therapy delivery.

planning software) the radiation physicist must use trial and error to balance a potentially large number of competing treatment objectives and complex machine specifications simultaneously. Failure to account for all the relevant objectives can be costly for both the patient and the hospital, as it may lead to the subsequent rejection of the proposed plan in Stage 4, and thus require further iterations. Proposals to remedy this issue typically employ either automatic or interface-based extensions to the existing inverse planning frameworks, in an effort to reduce the associated cognitive loading.

Among the automatic class of extensions are several multi-objective optimization techniques that have been broadened to incorporate expert preferences. These methods include hierarchical constraint tightening (or loosening) (Breedveld, Storchi, Keijzer, Heemink, & Heijmen, 2007), transformed statistical rankings (Lourenzutti & Krohling, 2014), decision theory-based rankings (Yu, 1997), stochastic analytical hierarchy processes (SAHP) (Cobuloglu & Büyüktahtakın, 2015) and lexicographic ordering (Long et al., 2012). A related form of automation is the case-based reasoning approach, which circumvents the need for concrete objectives in favour of choosing solutions based on similarities to past cases (Lolli, Ishizaka, Gamberini, Rimini, & Messori, 2015; Petrovic, Mishra, & Sundar, 2011). The major drawback of these algorithms is the rigidity that stems from an absence of human interference. While there is a potential gain in terms of speed and the reduction of human error, new errors are introduced by *a priori* decision-making that may not be universally acceptable. Additionally, each algorithm only outputs a single plan, meaning that in the case of a rejection, the burden for generating a subsequent plan is placed back on the radiation physicist.

In practice, treatment planning can involve a high degree of uncertainty (Romeijn & Dempsey, 2008) and even advanced algorithms tend to be quite specialized and are consequently no match for their human counterparts in terms of adaptability (Bonczek, Holsapple, & Whinston, 2014; Haight, 2010; Wickens, Lee, Liu, & Gordon-Becker, 2004). For this reason, successfully integrated decision support systems should provide a well-balanced allocation of tasks between experts and automation, motivating the interface-based class of extensions. Although interfaces are a well-established method to support human decision making (Grandjean & Kroemer, 1997; Korhonen & Wallenius, 1988; Lotov, Bushenkov, & Kamenev, 2004; Wickens et al., 2004), and have been more specifically addressed as useful in the field of medicine (Thyvalikakath et al., 2014; Aigner & Miksch, 2006; Gschwandtner, Aigner, Kaiser, Miksch, & Seyfang, 2011), they are still under-utilized in public health applications (Aigner & Miksch, 2006; Thyvalikakath et al., 2014; Yasnoff & Miller, 2014). Interfaces that are implemented frequently lack sophistication, making them less effective in their task of reducing the user's cognitive load (Wickens et al., 2004; Yasnoff & Miller, 2014).

Cotrutz and Xing (2002) present an interface concept for iterative radiotherapy plan improvement based on adjusting localized areas of a commonly used plan assessment plot called a dose volume histogram, though their methodology is only intended for fine tuning and their interface is not explicitly developed. Otto (2014) introduces a supervised approach for iterative dose design, along with a custom interface that uses a speedy approximation algorithm to ensure treatment plans are feasible. Since dosages must be designed before the computationally intensive optimization is run, plan characteristics such as the duration of the treatment will be unknown at the time of plan selection, and may consequently suffer in quality. Hence, while utilizing the planning system is simpler than unsupervised plan design, it is still a cognitively intensive task for clinicians.

Jain, Kahn, Drzymala, Emami, and Purdy (1993) also introduce a radiation therapy interface to support their plan ranking model, however, this fairly simple and tabular interface is only intended to support the selection process, not the plan generation. Hanne and Trinkaus (2003) present a fairly comprehensive spider plot interface called knowCube. While their interface does demonstrate a large range of functionality, their spider plot presentation modality makes it difficult to visualize multiple plan alternatives concurrently and their generation process is rigidly set to generate 1000 plan alternatives, rather than taking input from the planner. Lotov et al. (2004), Bortz et al. (2014) and Korhonen and Wallenius (1988) all discuss the design of Pareto front based interfaces, but do not deal with radiation therapy, while Craft, Halabi, Shih, and Bortfeld (2006) and Wang, Jin, Zhao, Peng, and Hu (2014) provide an analysis of Pareto tradeoffs in radiation therapy planning, but do not include an interface. Rosen, Liu, Childress, and Liao (2005), Ehrgott and Winz (2008) and Aubry, Beaulieu, Sévigny, Beaulieu, and Tremblay (2006), on the other hand, do use Pareto-optimality to generate radiation therapy interfaces. Rosen et al. (2005) introduce TPEx, a simplified dose volume histogram-based interface which allows experts to navigate through a number of allowable plans. The navigation, however, is performed strictly in terms of dose and volume properties and ultimately, the final plan is generated using a non-deterministic algorithm, leading to potential inconsistencies for the end user. Ehrgott and Winz (2008) and Aubry et al. (2006) both provide simpler interfaces, with basic filtering functionality for plan selection.

A prevailing issue with all the above-mentioned designs comes from the concept of choosing only Pareto optimal plans, while simultaneously limiting the number of objectives. By restricting the results to the Pareto front, plans with benefits that are unquantified in the objective function are discarded, obscuring potentially