33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Model Based User Interface Design for Predicting Lung Cancer Treatment Outcomes

Mingrui Zhang, Yingxu Liu, Yichen Jiang, Zhifu Sun and Ping Yang

Abstract— **We have developed a web-based tool to predict lung cancer patient's survival probability using previously developed survivability prediction software architecture. Four statistical models are included in this version, three for non-small cell lung cancer and one for limited-stage small cell lung cancer. To make the software tool more accessible and convenient for doctors and patients in a clinical setting, user interfaces are developed using a model based approach. Inputs common to prediction models are placed in interface which appears first, model specific inputs later. This design approach reduced both number of entries per interface and average number of interfaces a user needs to navigate.**

I. Introduction

In treating cancers, both physicians and patients require quantitative information on the expected benefits of a treatment for cancer in order to make appropriate treatment decisions. Such information may be provided by computer software. However, there exist barriers in adopting such a system; these include acquisition and implementation costs, slow and uncertain financial payoffs, and the lack of interoperability among different electronic health record systems [1]. As for the users of the system, physicians and patients often find available health information technology software frustrating due to its poor usability [2]. There is a need for tools to help physicians integrate prognostic information for cancer patients. Such tools might lead to greater accuracy and uniformity of prognostic estimates, and help clarify which treatments are worth pursuing during routine clinical practice.

Often, a computer tool is developed for a particular disease treatment model and is very difficult to modify or adapt for another model. To tackle the problem, we have developed a Survival Probability Prediction Architecture (SPPA) [3]. This architecture consists of a repository of statistical models uploaded by researchers on cancer treatments, and a web-based user interface for physicians and patients. A web-based software application would be developed within this architecture. It provides a coherent presentation for different treatment models, and allows a physician to select the most appropriate treatment(s) for the patient and explain the treatment options.

As more treatment models are added, inputs to user interface become cluttered and disordered. The situation becomes worse when software application is used on mobile device with small screen. Adaptive user interfaces may present a solution – user interfaces change their layouts and elements based on the needs of user or context. Researchers have debated the pros and cons of adaptive user interfaces, especially when flexible user interfaces require supports from additional facilities [4]. But, adaptive user interfaces apparently benefits users with disabilities. One recent study on the performance of ability-based user interfaces has shown that motor-impaired users would favor adaptive user interfaces and make 73% fewer errors [5].

In this paper, we describe a model based design of user interfaces for integrating four lung cancer treatment models into one web-based tool. The rest of the paper is organized as follows. We discuss three models in treating non-small cell lung cancer (NSCLC), and a model in limited-stage small cell lung cancer (LS-SCLC) in Section II. Then, we present a model based user interface design and its software implementation in Section III. We conclude in Section IV.

II. Lung cancer treatment models

Lung cancer has a dismal prognosis with only a 15% of five year survival rate. Though TNM (Tumor, Node, Metastasis) staging system is currently the most used guide for treatment and prognosis of lung cancer in clinical practice, other factors also contribute significantly to patient survival. These factors have been extensively researched on and used in models predicting cancer patient's survival.

A. Non-small Cell Lung Cancer

We have analyzed over 5,000 consecutively enrolled NSCLC patients and found the consistent role of histological grade of tumor in survival prediction of lung cancer. Two statistical models have been developed for predicting lung cancer patient survival (Table I). The first model predicts the patient's survival probability using patient's information available at the time of diagnosis and proven prognostic in our previous work, which includes age, gender, stage, cell type, and tumor grade. The second model uses additional information, including the treatment options and patient's smoking status.

In building these models, we examined the association of mentioned factors with patient's survival using the Kaplan-Meier method. A multivariable Cox proportional hazards model was applied to evaluate all above-mentioned variables

Manuscript received March 26, 2011.

M. Zhang is with the Computer Science Department, Winona State University, Winona, MN 55987, USA (phone: 507-457-2980; fax: 507-457-2464; e-mail: MZhang@winona.edu).

Y. Liu and Y. Jiang are with the Computer Science Department, Winona State University, Winona, MN 55987, USA.

Z. Sun is with Department of Health Science Research, Mayo Clinic College of Medicine, MN 55905, (e-mail: Sun.Zhifu@mayo.edu).

P. Yang is with Department of Health Science Research, Mayo Clinic College of Medicine, MN 55905, (e-mail: Yang.Ping@mayo.edu).

for their independent predictive value on patient's survival. Among the variables evaluated, only smoking status was not significantly associated with survival. Table I shows the predictors for two models with their hazard ratio (HR).

TABLE I NSCLC LUNG CANCER MODELS WITH OR REGARDLESS OF TREATMENT OPTIONS

	Regardless of Treatments			With Treatments		
Variables	**HR**	**95% CI**		**HR**	**95% CI**	
Age	1.02	1.02	1.03	1.02	1.01	1.02
Sex	1.18	1.09	1.29	1.24	1.14	1.35
Stage						
IB	1.18	0.95	1.46	1.08	0.87	1.35
IIA	1.45	0.99	2.11	1.37	0.94	1.99
IIB	2.13	1.70	2.67	1.91	1.52	2.39
IIIA	3.44	2.85	4.14	2.11	1.71	2.60
IIIB	4.69	3.90	5.64	2.42	1.96	2.99
IV	7.31	6.17	8.66	3.39	2.77	4.15
Cell Type						
Adeno	1.65	1.29	2.11	1.36	1.06	1.76
SQC	1.79	1.39	2.30	1.41	1.08	1.83
Large Cell	1.73	1.23	2.42	1.40	0.99	2.00
Other NSCLC	2.03	1.56	2.65	1.51	1.14	2.00
Grade						
Moderate	1.18	1.00	1.40	1.33	1.11	1.60
Poor	1.50	1.26	1.79	1.58	1.31	1.91
Treatment						
Chemo.				2.43	2.04	2.89
Radiation				3.43	2.86	4.12
Surgery & Radiation				1.37	1.07	1.74
Surgery & Chemo.				1.12	0.87	1.44
Chemo. & Radiation				2.21	1.87	2.61
Surgery & Radiation & Chemo.				1.30	1.04	1.61
Other				3.92	3.32	4.62
Smoking History						
Former				1.07	0.93	1.23
Current				1.10	0.95	1.27

Note: Adeno-adenocarcinoma; SQC-squamous cell carcinoma; large cell-large cell carcinoma; other NSCLC-other types of non-small cell carcinoma; HR-hazard ratio.

Both models were evaluated for their prediction accuracies on a test set of 1,518 patients. The evaluation was done by comparing the predicted and observed survivals. No statistic difference between the predicted and observed survivals was observed.

B. Limited-stage Small Cell Lung Cancer

Combined modality therapy is the standard care for limited stage-small cell lung cancer (LS-SCLC) and has led to a significant improvement in patients' survival. Chen, et al studied 284 patients with LS-SCLC diagnosed and prospectively followed from 1997 to 2008 at Mayo Clinic [6]. Their study demonstrated the negative impact of continued cigarette smoking on LS-SCLC survival. Patients who quit at or after diagnosis cut the risk of death by 45% (HR = 0.55, 95% CI 0.38–0.79) as compared to continued smokers. The study also showed that thoracic radiotherapy and platinum-based chemotherapy have significantly improved LS-SCLC survival. In predicting patient survival outcomes, a multivariate model has been built using variables including age, gender, smoking history, treatment options, tumor recurrence or progression and treatment (Table II). The model is coded in R program in our web-based tool.

TABLE II LS-SCLC MODEL WITH TREATMENT OPTIONS [6]

Variables	***P*-value**	**HR**	**95% CI**	
Age	<.01	1.03	1.02	1.05
Recurrence or progression	<.01	2.72	2.01	3.68
Quit years	<.01			
>1 years		0.72	0.52	1.00
at or after diagnosis		0.55	0.38	0.79
Treatment	< 0.01			
Surgery with/out chemo/radiation		0.60	0.38	0.94
Chemo or rad. only		2.55	1.79	3.63
No surgery/chemo/radiation		3.24	1.15	9.14

Prediction models described in this and the previous sections are developed based on lung cancer patient database collected between 1997 and 2008 at Mayo Clinic.

C. Prognostic Model for Resection

To test the flexibility of the SPPA and validate our model based approach for user interface design, we surveyed and abstracted a model from [7]. In a study of 766 patients underwent resection for primary non-small cell lung cancer, a prognostic model for survival with preoperative and postoperative mode is established (Table III). The factors associated with an impaired survival are male sex, age, chronic obstructive pulmonary disease (COPD), congestive heart failure, any prior tumor, moderate-to-severe renal disease, clinical tumor stage (preoperative mode), type of resection and pathological tumor stage (postoperative). The original model is translated into R program and included in our tool.

TABLE III PROGNOSTIC NSCLC MODEL [7]

	Preoperative			Postoperative		
Variables	**HR**	**95% CI**		**HR**	**95% CI**	
Male sex	1.1	0.9	1.4	1.2	0.9	1.5
Age	1.02	1.01	1.03	1.02	1.01	1.03
COPD	1.3	1.0	1.4	1.1	0.9	1.4
Congestive heart failure	1.1	0.9	1.4	1.2	0.9	1.4
Moderate/severe renal disease	1.6	1.0	2.8	2.1	1.2	3.5
Type of resection						
Wedge resection				1.5	0.9	2.6
Bilobectomy				1.3	1.0	1.7
Left-sided pneumonectomy				1.2	0.9	1.5
Right-sided pneumonectomy				1.6	1.2	2.0
Any prior tumor	1.3	1.0	1.6	1.2	1.0	1.5
Clinical, pathological stage						
IB	1.5	1.2	1.8	1.3	1.0	1.6
IIA	2.0	1.1	3.5	1.3	0.9	2.0
IIB	2.0	1.4	2.8	2.2	1.7	2.9
IIIA	1.8	1.2	2.7	2.7	1.9	3.7
IIIB	2.1	1.2	3.9	2.4	1.6	3.5
IV	15.9	6.3	39.7	10.7	5.9	19.3

III. SOFTWARE IMPLEMENTATION

To shorten the transition of medical research to clinical practice, a software support architecture has been developed [3]. It provides an environment that biomedical researchers can use to experiment with potential treatments without having to acquire expertise in a computer programming language and environment.

A. *Software Architecture*

The SPPA is based on the Model View Controller (MVC) architectural design pattern. This architecture consists of a repository of statistical models uploaded by researchers on cancer treatments, and a web-based user interface for physicians and patients. It provides a coherent presentation for different treatment models, and allows a physician to select the most appropriate treatment(s) for the patient and explain the treatment options [4].

The MVC is an object-oriented design pattern for separating the concerns of applications from user inputs. The model is the internal implementation of SPPA and interacts with cancer treatment models via the R programming environment (http://www.r-project.org). The view presents survival probability in forms of graph or table through the user interface to the user. The controller processes the input of the user into the system. While the web-based tool that delivers the cancer treatment model is hosted on an Apache Tomcat server (http://tomcat.apache.org), the patients' electronic records are stored on an SQL server (http://dev.mysql.com). Survival probability graphs are generated with Java and JavaScript programs. To integrate disparate software environments, extensible markup language (XML) is used to encapsulate the metadata about cancer treatment models.

In translating a cancer treatment model to a web-based tool, biomedical researchers need to upload their models to SPPA and edit the XML schema to enlist the variables to be used in their models. SPPA differs from other computer tools in that it allows a researcher to seamlessly plug in a new cancer treatment model and quickly turn it into a web-based application. Its user interface is designed for both desktop computers and mobile devices.

B. *User Interface*

Making a web-based application available on multiple types of devices, particularly on a mobile device, introduces several challenges. Among them is the small display size of the mobile device. The small display size on mobile devices poses a problem with displaying the information in a useful and effective manner. A mobile application typically needs to support several interface types of different devices, e.g. iPhone and Android. Each interface type has a different set of properties: the data entry method, the display size, etc. We cannot develop the "best" user interface for every type of mobile device and every type of interface. Even if we could, it would become obsolete once a new type of interface and device are available on the market.

In clinical setting, physicians and patients use the tool to discuss different cancer treatment options, their focus is on the treatment outcomes. A design should make all needed variable entries for a chosen prediction model visible without distracting the user with extraneous or redundant information. It should never overwhelm users with alternatives or confuse them with unneeded information [8]. The adaptive user interface design provides a potential solution to it. For example, SUPPLE system uses constrained decision-theoretic optimization to automatically generate user interfaces. In generating user interfaces, SUPPLE takes the device-specific constraints such as screen size [9].

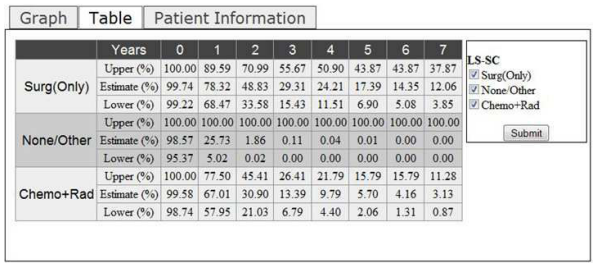

Fig. 1. Tabular view of prediction results from LS-SC model.

The main web page consists of three tabbed pages for the input of patient information, graphical and tabular views (Fig. 1) of prediction results. All entries in the patient information page are populated using the XML schema constructed on variables input to prediction models. The patient information page consists of sequence of interfaces for user entries. The design of the user interfaces puts related entries together and separates unrelated entries (Fig. 2). Specific model would be picked by the underlining SPPA based on user inputs.

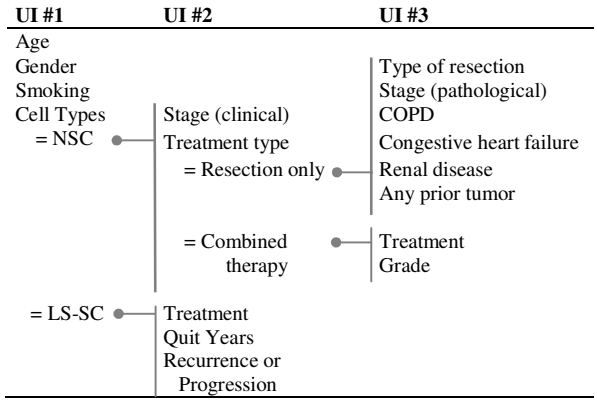

Fig. 2. Distribution of variables entries on user interfaces

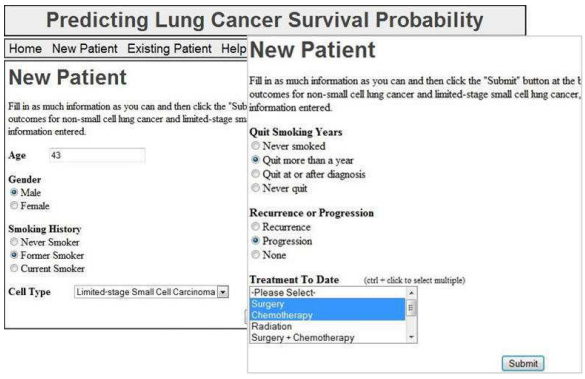

Fig. 3. User interfaces for patient informatin entry form.

Before a prediction model is invoked by the system, a sequence of user interfaces would be presented to user. Variable entries common to prediction models are placed on interface that displays first, model specific entries later (Fig. 3). For instance, user inputs on his/her age at diagnosis, gender, smoking status and cancer cell types are placed on

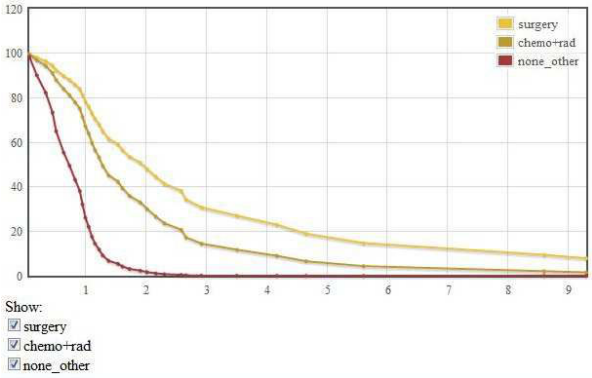

Fig. 4. Graph view of prediction results from LS-SC model.

the first user interface, they are needed by most models. If user selects limited-stage small cell (LS-SC) for cell types, the next interface is generated with three entries, recurrence or progression, treatment and quit years. The LS-SCLC model would be used in predicting patient's survival probability in tabular (Fig. 1) or graph (Fig. 4) views. As such, we are able to limit number of inputs per screen and still minimize the number of interactions the mobile users have with the application.

To make the comparison of cancer treatments more convenient, checkboxes are used with the graph view of prediction results. Based on feedback from physicians, annotation is added to the graph view to help users interpret the survival probability accurately. As the user moves the cursor (or his/her finger tip on an iPhone) over the prediction graph, the survival probability is displayed as an annotation over the curve (Fig. 4).

C. *Usability Study*

Our usability tests were conducted on two versions of the web-based tool. The first version has a single web interface with all needed inputs; the second version has separate interface for each model. Participants were divided into two groups, one group started with the first version, and the other started with the second version. In addition to measuring user's preference in likert scales, we attempted to quantify the usability in terms of task completion time and the accuracy of user's interpretation of survival probability.

Thirty participants were asked to find the survival probability of three patients in 3.5 years on survival prediction charts. Information provided to participants included the patient's age, gender, lung cancer stage, cell type, grade, smoking history, and the treatment(s) received by the patient. In estimating survival probabilities, participants had to interpolate the probabilities since there is no direct output (or annotation) available for survival time at 3.5 years.

All participants have successfully finished their tasks and wrote down the survival possibilities they found on the curves. We measured the time each participant took from creating a patient record to finding the survival possibility. Results show all participants had a shorter finishing time with the second version of web-based tool. Therefore, in real medical situations, doctors would tend to save more time when using the user interface designed on models to be used. Furthermore, over 90% of the participants claimed it was easier to accomplish tasks on the second version.

With model-based user interface design, we are able to minimize both data input for user interaction, and the number of navigations from one interaction to the next throughout the application. Annotation helps to improve the accuracy of user's interpretation of survival probability. Moving a cursor on probability curves, the user can find probabilities predicted at adjacent survival times, and interpolate to the survival time where direct prediction is not available.

IV. DISCUSSION

As more treatment models are made available and incorporated into a web-based tool in predicting cancer treatment outcomes, input entries on user interface become cluttered and disordered. This situation becomes worse when the tool is used on mobile device with small screen. In this paper, we discussed a model based user interface design for integrating multiple statistical models into one software tool. We have successfully implemented four predictions models of lung cancer treatments. With additional cursor annotation, accuracy of user's estimates on survival probabilities is also improved.

REFERENCES

[1] R. Miller and I. Sim, "Physicians' Use of Electronic Medical Records: Barriers and Solutions," *HEALTH AFFAIRS,* vol. 23, pp. 116–126, 2004.

[2] C. Weimar, "Electronic Health Care Advances, Physician Frustration Grows," *Physician Executive Journal,* vol. March/April, 2009.

[3] M. Zhang, S. Olson, J. Francioni*, et al.*, "Integrating R Models with Web Technologies," in *International Conference on Health Informatics*, Porto, Portugal, 2009.

[4] B. Shneiderman and P. Maes, "direct manipulation vs. interface agents," *Interactions,* vol. 4, pp. 42-61, 1997.

[5] K. Z. Gajos, J. O. Wobbrock, and D. S. Weld, "Improving the performance of motor-impaired users with automatically-generated, ability-based interfaces," in *The twenty-sixth annual SIGCHI conference on Human factors in computing systems*, 2008, pp. 1257-1266.

[6] J. Chen, R. Jiang, Y. I. Garces*, et al.*, "Prognostic factors for limited-stage small cell lung cancer: A study of 284 patients," *Lung Cancer,* vol. 67, pp. 221-226, 2010.

[7] Ö. Birim, A. P. Kappetein, M. Waleboer*, et al.*, "Long-term survival after non-small cell lung cancer surgery: Development and validation of a prognostic model with a preoperative and postoperative mode," *The Journal of Thoracic and Cardiovascular Surgery,* vol. 132, pp. 491-498, 2006.

[8] Nielson, *Usability Engineering (Interactive Technologies)*, 1st ed.: Morgan Kaufmann, 1993.

[9] K. Z. Gajos, D. S. Weld, and J. O. Wobbrock, "Automatically generating personalized user interfaces with Supple," *Artificial Intelligence,* vol. 174, pp. 910-950, 2010.