Leveraging Social Supports for Improving Personal Expertise on ACL Reconstruction and Rehabilitation

Jinye Peng, Naiquan (Nigel) Zheng, and Jianping Fan

***Abstract*—In this paper, a social health support system is developed to assist both anterior cruciate ligament (ACL) patients and clinicians on making better decisions and choices for ACL reconstruction and rehabilitation. By providing a good platform to enable more effective sharing of personal expertise and ACL treatments, our social health support system can allow: 1) ACL patients to identify the best matching social groups and locate the most suitable expertise for personal health management; and 2) clinicians to easily locate the best matching ACL patients and learn from well-done treatments, so that they can make better decisions for new ACL patients (who have similar ACL injuries and close social principles with those best matching ACL patients) and prescribe safer and more effective knee rehabilitation treatments.**

***Index Terms*—ACL reconstruction and rehabilitation, hierarchical patient clustering, patient-specific knee joint model, personalized expertise recommendation, social health support system.**

I. Introduction

The anterior cruciate ligament (ACL) plays an important role in controlling the stability of human knee joint, not only by limiting tibia anterior translation but also by controlling knee axial rotation and various movement [1], [2]. If the ACL is injured, the stability of human knee joint and the load-bearing patterns between the contact joint surfaces will be altered, which will further result in abnormal loadings on the cartilage during functional activities [3]. The changes of motion patterns will associate with cartilage degeneration and progressive development of knee joint osteoarthritis [4]. According to the Center for Disease Control and Prevention, ACL injury is the leading cause of disability and it happens to more than 250,000 adults annually, which results in millions of dollars in health-care cost each year. By year 2020, more than 60 million American adults will suffer from ACL injury disease and knee joint osteoarthritis, where more than one-third of them will have activity limitations. It is worth noting that most population of ACL patients are young adults (high school and college students) and the expenditure on subsequent joint disease and disability is rising for the rest of their life. Thus, it is very important to develop new tools and leverage new sources for reducing national and personal health-care costs by allowing ACL patients to make better decisions and choices on ACL reconstruction and rehabilitation.

The rapid growth in the popularity of online health support communities (e.g., forums, chat rooms, listservs, message boards, wikis, blogs, online support groups) has opened a new channel for ACL patients to seek cost-free social supports and deal with their health situations more effectively [5]–[12]. By sharing their personal health situations, treatments, and experiences on managing personal exercise, ACL patients can learn from others' expertise on ACL reconstruction and rehabilitation. As the online health support communities grow [13]–[20], patient expertise is of tremendous value for individuals with ACL injuries to recover from knee injury or surgery: 1) exchange of their opinions and experiences of drugs and treatments can help ACL patients understand and learn to cope with their ACL injuries and rehabilitation; 2) expression of their feelings (such as anxiety, concern, empathy, or reassurance) will bolster interpersonal connectedness and self-esteem as well as reduce distress.

The patient expertise significantly differs from the expertise of clinicians because it emphasizes the management of personal, rather than medical aspects of health. Because many ACL patients are managing similar health situations, they can be the best matching specialists for personal aspects of ACL rehabilitation, which are distinct from clinicians who are specialized in the medical management and treatment of the ACL injury and subsequent joint disease. Thus, it is a valuable research to create online social communities for assisting ACL patients to locate peers with the best matching expertise. Some online health support communities (e.g., www.patientslikeme.com) offer people finders to locate the community members with similar diagnosis profiles, but having similar diagnosis profiles is not necessary to have the best matching patient expertise, e.g., the effectiveness of their personal ACL rehabilitation treatments depends on both their injury levels and their social principles such as jobs, hobbies, etc.

As suggested in Manhattan Research study [21], 60% of U.S. clinicians use or plan to use social networks to exchange the latest in medical advances. Online health support system could also be very attractive to medical professionals, such as physical therapists, clinicians, and trainers, for the following reasons: 1) They may deal with the same challenging issue (prescribing

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safer and more effective knee rehabilitation treatments to their ACL patients); 2) They may want to learn from other clinicians about their successful treatments.

Based on these observations, a social health support system is developed to empower individuals' abilities on locating the best matching patient expertise for improving their practical strategies on daily ACL rehabilitation. The rest of this paper is organized as follows. Section II reviews related work briefly. Section III introduces our work on patient recruitment and medical data collection; Section IV presents our algorithm for patient-specific knee joint model generation; Section V introduces our hierarchical patient clustering algorithm for automatic patient assignment; Section VI presents our work on constructing a social health support system to leverage social supports for ACL reconstruction and rehabilitation; Section VII describes our work on system evaluation; We conclude in Section VIII.

II. Related Work

ACL reconstruction surgery is typically recommended to restore the knee joint stability and function. Employing exercise therapy during ACL rehabilitation has demonstrated beneficial and positive in pain severity and functional disability [22]. Moreover, the quality of ACL rehabilitation is paramount in determining the health and wellbeing of ACL patients and achieving a faster return to the knee joint functions [23]. Although the ACL rehabilitation after knee injury or surgery can be a long and arduous process, the use of appropriate exercises can improve this process by decreasing the rehabilitation time and improving the knee joint function [24]. The use of weight bearing exercises has shown to be effective, both in short and long term outcomes, in decreasing anterior knee pain and enhancing functional performance [25], [26]. Clinicians use various types of exercises to minimize anterior knee pain and muscle loss, strengthen hip and thigh musculature, enhance balance and stability, and minimize the risk of future injuries [23].

Zheng and his team have done extensive studies on the effectiveness of various exercises on ACL reconstruction and rehabilitation [27]–[29], where large-scale medical data are used for generating patient-specific knee joint models for motion pattern characterization. Human gait (i.e., manner of walking) [30], [31], which contains information about the patient's physical situation and even about his/her psychological state, can also be used for patient representation (i.e., motion patterns of ACL patients).

Online health support communities have recently received enough attentions by integrating smart technologies and personal expertise for health-care applications [5]–[20]. Civan *et al.* [5], [6] have designed a social software (locater) to support patient expertise sharing. Semantic Web technologies and social networks have been used to promote medical information sharing among massive numbers of patients [7]–[12]. E-health, which can seamlessly integrate patients, medical records, and treatments in an electronic format for easy sharing and transmission, is also very attractive for supporting better medical services [13]–[20].

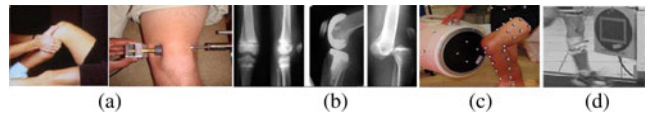

Fig. 1. Tools for ACL diagnose and medical data collection: (a) physical exam; (b) X-rays; (c) fluoroscopy; (d) MRI.

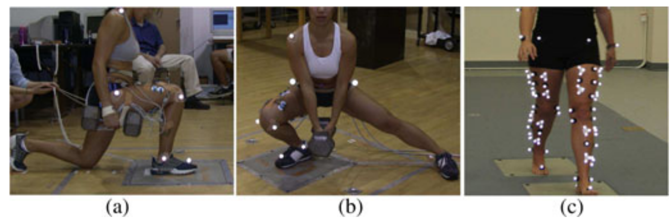

Fig. 2. Weight bearing exercises for ACL diagnose and medical data collection: (a) forward lunge; (b) side lunge; (c) weight-carrying walking.

III. Patient Recruitment and Medical Data Collection

Large-scale medical data are collected from a large number of ACL patients: 1) 1,000 ACL patients in our local area (Charlotte city, NC) are recruited from Carolinas Medical Center for medical data collection [27]–[29]; 1) American Sports Medical Institute has shared their large-scale medical data collections for more than 15,000 ACL patients [32].

According to our prior research work of ACL patients [27]–[29], they tend to have strong motivation to contribute their personal expertise to assist others for the following reasons: 1) They may seek for health advice, e.g., many ACL patients may have strong needs to obtain new expertise and daily exercise skills to deal with their ACL injuries, and they may like to gain advice from other ACL patients (with similar ACL injuries and close social principles) on selecting safer and more effective treatments and exercises on ACL reconstruction and rehabilitation; 2) They may seek for community support, e.g., they may have strong motivation to make and socialize with more friends by sharing their expertise, and they could like to contribute back to the ACL disease community and get recognized by others for their community contribution; 3) They may want to balance their medical bills with rehabilitation progress, e.g., ACL patients may want to reduce their personal health-care cost by getting cost-free assistants from other ACL patients.

As shown in Fig. 1, most ACL patients have to go through the following diagnoses: (a) physical exam; (b) X-rays; (c) fluoroscopy; (d) MRI. To assess their ACL injury levels, some ACL patients have to perform three weight bearing exercises (weight-carrying walking, forward lunge, and side lunge) as shown in Fig. 2, and most ACL patients have to perform five common daily activities (walking, stair climbing, stair descending, step turn, spin turn) as shown in Fig. 3. A marker set is usually used for collecting the motion patterns of human knee joints of our ACL patients as shown in Fig. 4 [27]–[29]. All these medical data (e.g., medical records from physical exams, CT, X-rays, and MRI images, knee joint motion data) are stored in our data bank, which are further used for generating high-quality patient-specific knee joint models to characterize knee joint motion patterns accurately.

Fig. 3. Common daily activities for ACL diagnose and medical data collection: (a) walking; (b) stair climbing; (c) stair descending; (d) step turn; (e) spin turn.

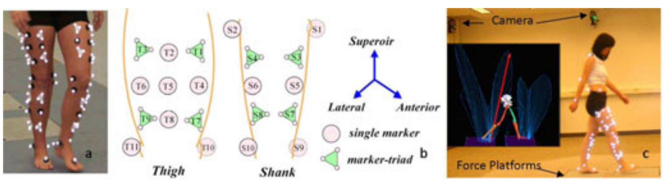

Fig. 4. Point cluster marker set and cameras for motion pattern capturing: (a) a subject with reflective markers; (b) placement of marker set; (c) subject during level walking.

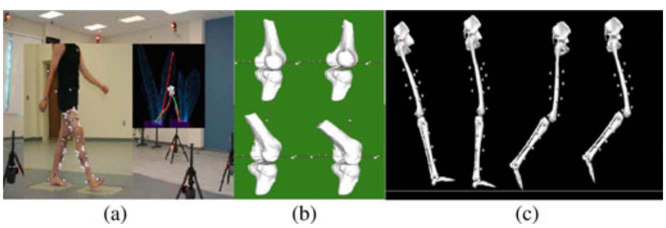

Fig. 5. Patient-specific knee joint model generation: (a) a subject during level walking; (b) base knee joint model; (c) patient-specific keen joint motion models for level walking.

IV. Patient-Specific Knee Joint Model Generation

As shown in Fig. 5(b), a human knee consists of three bones (femur, tibia, and patella), a tibiofemoral joint, a patellofemoral joint, and soft tissues (e.g., ligaments and a joint capsule). The ligaments and joint capsule guide the joint movement and provide the stability to the joints. Muscles provide dynamic stabilization to the joints, and injuries to the knee joint soft tissues may alter the joint motion and loading patterns. It is worth noting that patients may suffer from ACL injuries at different levels and such differences on their ACL injuries may significantly influence their motion patterns and the effectiveness of their rehabilitation treatments [1]–[4], [22], [27]–[29]. Thus, it is very attractive to develop low-cost approach to generate high-quality patient-specific knee joint models, e.g., integrating patient-specific medical data (such as X-rays, MRI, and CT images for diagnosis purposes) with base knee joint model [as shown in Fig. 5(b)] for patient-specific knee joint model generation to achieve more accurate characterization of both the motion patterns of their knee joints and their individual injury levels.

The patient-specific knee joint models should follow some general structures and consist of the key components of human knee joint, and the base knee joint model can provide general structural information of human knee joint including detailed joint surfaces, insertions, and origins of ligaments and tendons as shown in Fig. 5(b). Thus, the base knee joint model can provide a good starting point for generating high-quality knee joint motion models. On the other hand, the degrees of ACL injuries often vary with the patients, thus the knee joint motion models should be patient specific.

Our patient-specific knee joint model generation algorithm consists of the following key components: 1) an interactive image segmentation algorithm for extracting more suitable features such as the shape of a joint surface from medical images; 2) an incremental learning algorithm by integrating the patient-specific medical data to rescale and reshape the base knee joint model for generating high-quality patient-specific knee joint models; 3) an automatic alignment algorithm for integrating the motion data with the patient-specific knee joint models, so that we can generate high-quality patient-specific knee joint motion models for predicting the changes of motion patterns and the functions of human knee joint after ACL injury and reconstruction; and 4) an interactive model assessment algorithm for evaluating the accuracy of our patient-specific knee joint motion models and leveraging human guidance for model improvement.

Because the patient-specific medical data are only used to rescale and reshape the base knee joint model, our algorithm can require less patient-specific medical data for generating high-quality patient-specific knee joint models. Requiring less patient-specific medical data can significantly reduce the computational cost for knee joint motion model generation and result in low health-care cost for medical data capturing. By using patient-specific medical data to rescale and reshape the base knee joint model [as shown in Fig. 5(b)], our algorithm can generate high-quality patient-specific knee joint models accurately and a set of results (patient-specific knee joint motion models) for level walking are shown in Fig. 5(c). With the patient-specific knee joint motion models, we can examine the effects of ACL deficiency and reconstruction on 3-D knee joint kinematics during daily and sports activities, which can allow us to assess the effectiveness of various treatments for ACL reconstruction and rehabilitation.

V. Hierarchical Patient Clustering and Assignment

Our patient-specific knee joint models can provide an effective platform for patient representation, e.g., representing their ACL injuries according to their motion patterns and the functions of human knee joint during daily and sports activities. As a social creature, each ACL patient should also be described by other social principles such as his/her jobs, hobbies, etc. The patients' social principles (such as their jobs and hobby activities) may significantly influence the effectiveness of their treatments for ACL reconstruction and rehabilitation. Thus, the ACL patients can learn from others' expertise for recovering from knee injury or surgery when they have similar ACL injuries and close social principles. Based on these observations, it is very attractive to organize massive numbers of ACL patients according to both their ACL injuries (which can be characterized accurately by their patient-specific knee joint motion models) and their social principles.

A. Model Properties for Patient Representation

Our patient-specific knee joint motion models are able to characterize both the changes of motion patterns and the changes of human knee joint functions precisely. Thus, a set of local features are extracted from the range images for characterizing the local histograms of the surface locations of 3-D knee joint models. The range images of 3-D knee joint models, which can provide detailed information about the shape for 3-D knee joint models, may have different properties, thus a set of local features are extracted for capturing different aspects of model shapes. The basic requirements for these local features are: easy to calculate, robust to viewpoint changes, and containing sufficient discrimination information.

In this paper, three shape-specific local features are extracted from 3- knee joint models: pixel depths, surface normals, and curvatures. The histogram of pixel depths is invariant against the translations and the image plane rotations, thus it is very good for measuring the visual similarity contexts between the 3-D knee joint models. The surface normals can be calculated easily from the first derivatives of the range images of 3-D knee joint models. The surface curvature can be calculated either directly from the first and second derivatives, or indirectly as the rate of the change of normal orientations in a certain local context region of the range images of 3-D knee joint models. To reduce the computational cost, curve-skeleton is used to represent the 3-D shape of 3-D knee joint models. These three local features are invariant to the translations and rotations.

Motion patterns can provide the changes of patient-specific knee joint motion models, thus they are critical for characterizing both the changes of motion patterns and the changes of human knee joint functions. As a result, matching between the patient-specific knee joint motion models can significantly be different from the traditional issue of 3-D object recognition [33]–[43], and the motion patterns play a critical role in determining the visual similarity contexts between the patient-specific knee joint motion models, e.g., the changes of motion patterns of human knee joints are critical for characterizing the similarity between the injury levels of ACL patients.

Based on these observations, the model properties for patient representation (i.e., patients' ACL injury levels) consist of: 1) a set of local features for characterizing the visual properties of 3-D knee joint models or a small part of 3-D knee joint models; 2) the motion patterns of 3-D knee joint models. A kernel-based approach is further used to characterize the similarity relationships between the patients' ACL injuries according to the visual similarity contexts between their patient-specific knee joint motion models (3-D knee joint models and their motion patterns).

B. Social Principles for Patient Representation

Social matching is another criterion for identifying the best matching ACL patients and their expertise and treatments for ACL reconstruction and rehabilitation. For each ACL patient, a patient-specific social profile is generated for describing his/her social principles: 1) job and job-related activities; 2) hobbies and hobby-related activities; 3) weight and height and body mass index (BMI); 4) daily diet and exercises and the balance between diet and exercise; 5) diagnosis and treatment prescribed by clinicians; 6) daily activities and life styles; 7) exercise instruments; 8) gender; 9) muscle condition and strength; 10) patient self-evaluations of their knee joint functions; and 11) leg-dominance (left leg-dominant patients are different from right leg-dominant patients).

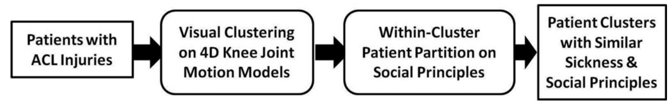

Fig. 6. Flowchart for hierarchical ACL patient clustering and indexing.

All these social principles can significantly influence the effectiveness and speed for ACL reconstruction and rehabilitation. As a result, supporting social matching can allow ACL patients to locate the best matching peers (who have similar ACL injuries and close social principles) and make extensive use of their expertise for managing daily efforts associated with ACL reconstruction and rehabilitation.

C. Hierarchical Patient Clustering

To achieve more accurate patient clustering and assignment, multiple base kernels are constructed for characterizing the diverse similarity relationships between the ACL patients under different feature subsets: 1) intensity kernel for the histograms of pixel depths of 3-D knee joint models; 2) surface kernel for the surface normals of 3-D knee joint models; 3) curvature kernel for the shapes of 3-D knee joint models; 4) motion kernel for the motion patterns of 3-D knee joint models; 5) semantic kernel for the diagnosis profiles; 6) meta kernel for the numerical data such as weights, heights, and BMI; 7) supporting matching kernel for the knee supporting entities such as muscle condition and strength; and 8) social kernel for other social principles. Each of these base kernels focuses on characterizing one certain type of the similarity contexts between the ACL patients under one particular feature subset.

In this paper, a hierarchical approach is developed for patient clustering and its major components are shown in Fig. 6: 1) ACL patients are first assigned into multiple clusters according to the similarity contexts between their ACL injuries, e.g., the visual similarity contexts between their patient-specific knee joint models; and 2) ACL patients in the same cluster (which have similar levels of ACL injuries) are further assigned into multiple smaller groups according to the social similarity contexts between their social principles.

A mixture-of-kernels approach is used to achieve more accurate approximation of the visual similarity contexts between the patient-specific knee joint motion models by combining the relevant base kernels [32], [44], [45]

$$\kappa_{\text{visual}}(x,y) = \sum_{l=1}^{4} \alpha_l \kappa_l(x,y), \qquad \sum_{l=1}^{4} \alpha_l = 1 \tag{1}$$

where different base kernels play different roles on characterizing the visual similarity contexts between two patient-specific knee joint motion models x and y, $\alpha_l \geq 0$ is the importance factor (weight) for the lth base kernel $\kappa_l(x, y)$ [32], [44], [45], and 4 is the number of base kernels (i.e., intensity kernel, surface kernel, curvature kernel, and motion kernel) for characterizing the visual similarity contexts between two patient-specific knee joint motion models x and y.

The affinity propagation algorithm [46] is used to achieve more precise patient clustering, where a patient similarity graph is first constructed to organize all the ACL patients according to their visual similarity contexts $\kappa_{\text{visual}}(\cdot, \cdot)$ [47]. In the patient similarity graph, each node is one particular ACL patient (which is represented by his/her patient-specific knee joint motion model), and an edge between two nodes is used to characterize the visual similarity context between two ACL patients (i.e., two patient-specific knee joint motion models).

For visual-based patient clustering, the AP clustering algorithm [46] transfers two types of messages among the nodes of ACL patients: 1) *Responsibility* $r(i, k)$, which is passed from the ACL patient (which is represented by his/her patient-specific knee joint motion model) i to the exemplar k, indicates the preference of the ACL patient i to select the ACL patient k as its exemplar; 2) *Availability* $a(i, k)$, which is a feedback from the exemplar k to the ACL patient i, shows what degree does the ACL patient k fit to be a cluster center for the ACL patient i.

The responsibility $r(i, k)$ is calculated as

$$r(i, k) = \kappa_{\text{visual}}(i, k) - \max_{k' \neq k}\{a(i, k') + \kappa_{\text{visual}}(i, k')\} \quad (2)$$

where $\kappa_{\text{visual}}(i, k)$ is the kernel-based visual similarity context between two ACL patients i and k (i.e., two patient-specific knee joint motion models) as defined in (1).

The availability, for $i \neq k$, are updated as

$$a(i, k) = \min\left\{0, c(k) + r(k, k) + \sum_{i' \notin \{i, k\}} \max\{0, \kappa_{\text{visual}}(i', k)\}\right\} \quad (3)$$

and self-availabilities indicate preferences

$$a(k, k) = c(k) + \sum_{i' \neq k} \max\{0, r(i', k)\}. \quad (4)$$

The AP clustering algorithm iteratively updates the responsibilities $r(\cdot, \cdot)$ and the availabilities $a(\cdot, \cdot)$ until convergence. The exemplar that is associated with the ACL patient i is determined by

$$f(i) = \arg\max_k \{r(i, k) + a(i, k)\}. \quad (5)$$

By passing the message between the nodes on the patient similarity graph through affinity propagation, all these ACL patients are then assigned into multiple clusters with similar ACL injuries (i.e., with similar visual properties of their patient-specific knee joint motion models).

The patients with similar ACL injuries are assigned into the same cluster and they can further be separated into multiple groups with similar social principles. The social similarity context between two ACL patients with the social principles X and Y is defined as

$$\rho_{\text{social}}(X, Y) = \sum_{m=1}^{4} \beta_m \rho_m(X, Y), \qquad \sum_{m=1}^{4} \beta_m = 1 \quad (6)$$

where different base kernels play different roles on characterizing the social similarity contexts between two ACL patients with the social principles X and Y, $\beta_m \geq 0$ is the importance factor (weight) for the lth base kernel $\rho_m(X, Y)$, and 4 is the number of base kernels (i.e., semantic kernel, meta kernel, supporting matching kernel, and social kernel) for characterizing the social similarity contexts between the ACL patients according their social principles. The affinity propagation algorithm [46] is further used to achieve more precise patient clustering according to their social similarity contexts $\rho_{\text{social}}(\cdot, \cdot)$.

Our hierarchical patient clustering algorithm has provided a good environment for organizing large groups of ACL patients according to both their ACL injury levels and social principles. The patients with similar ACL injuries and close social principles can be assigned into the same social group, so that they can easily locate the best matching peers and share their specialized expertise on ACL reconstruction and rehabilitation. The ACL patients in the same social group may share similar personal health needs, thus health communication among these ACL patients in the same group will be more effective because such communication strongly relates to their social or life contexts. Based on these observations, our patient assignment and social setting approach can significantly increase social interactions and communications among the ACL patients and foster close collaboration on managing their personal health situations more effectively.

VI. Social Health Support System for Personal Expertise Sharing

By constructing a social health support system, the Internet can provide a good environment for harnessing collective intelligence of massive numbers of patients on ACL reconstruction and rehabilitation. To enhance the involvement of ACL patients in our social health support system, it is very important to study: 1) dynamics of social networks; 2) collective behaviors of ACL patients; and 3) patient involvement.

A. Dynamical Social Network Analytics

Our social health support system can provide a computer-mediated environment for massive numbers of ACL patients to interact with each other by sharing their personal health needs and expertise. Thus, our social health support system can provide a good platform for us to collect large-scale cyberspace behavior data by capturing message exchange flows among ACL patients.

A "macro" social network is constructed for our social health support system through analyzing the message exchange flows among the massive numbers of ACL patients. The "macro" social network may change dramatically over time as shown in Fig. 7 because: 1) ACL patients may change their social groups over time for seeking more specialized expertise; 2) Some new

Fig. 7. Evolution of social networks over time, where each circle represents a social group and the overlapped circles with same background color represent multiple social groups with strong information exchange flows or even contain some common participants.

ACL patients may join our social health support system along the time; and 3) Some ACL patients may withdraw from our social health support system when the specialized expertise for the corresponding social groups cannot match their specific health needs.

It is worth noting that interpersonal interactions in the same social group may happen more frequently and have significant influences on the performance at both the individual level and level group level because ACL patients may pay more attentions to the specialized expertise (i.e., which is the best matching with their personal ACL injuries and social principles). Instead of directly modeling the cyberspace behaviors of all the ACL patients in our social health support system, we will first partition the "macro" social network for whole social health support system into many small pieces ("micro" social networks).

As shown in Fig. 7, each piece is a "micro" social network for one certain social group. The ACL patients in the same social group may interact and communicate more frequently. Their communications and interactions may be associated with high performance at both the individual level and the group level, thus focusing on such "micro" social network can allow us to achieve more accurate modeling and characterization of collective behaviors of ACL patients. Virtual teams are becoming a common strategic work unit in many organizations, thus performing cyberspace behavior modeling and prediction on such a "micro" social network (social group or virtual team) may allow us to gain new knowledge about what are the key factors to make groups and individuals to be productive. By analyzing the evolution of "macro" social network and the dynamics and cohesiveness of "micro" social network, we can also identify the cohesive social groups within the "macro" social network.

As shown in Fig. 7, some social groups may shrink or even dissolve over time, some new social groups may emerge, some big social groups may split into multiple small ones, and some social groups may grow. Combining all these "micro" social networks and their dynamics can provide a mixing view of the evolution of "macro" social network over time. In order to model both the evolution of "macro" social network and the dynamics of "micro" social networks jointly, a unified approach is developed for modeling both the social groups and their evolutions simultaneously, where a transition parameter is used to explicitly indicate the dynamics (changes) of social groups ("micro" social networks) over time. *Markov Random Field Chain* is used to model both the evolution of "macro" social network and the dynamics of "micro" social networks jointly, and the probability for the assignments of all the social groups over T time steps can be defined as

$$P(\Omega_T, Z_T|\tau, \Psi, \Phi)$$
$$= \sum_{Z_t \in Z_T, \Omega_t \in \Omega_T} P(\Omega_t|Z_t, \Psi) \prod_{t=2}^{T} P(Z_t|Z_{t-1}, \Phi) P(Z_1|\tau) \quad (7)$$

where $P(\Omega_t|Z_t, \Psi)$ is the emission probability and $P(Z_t|Z_{t-1}, \Phi)$ is the transition probability, $Z_T = \{Z_1, \ldots, Z_t\}$ is used to denote the collection of all the assignments for all the social groups over T time steps, $\Omega_T = \{\Omega_1, \ldots, \Omega_t\}$ is used to denote the collection of all the "micro" social networks of a given "macro" social network over T discrete time steps, Φ is a transition matrix to denote the intergroup transition probability, Ψ is the intergroup link matrix, $P(Z_1|\tau)$ is used to denote the assignment probability at the first time that is initiated by our hierarchical patient assignment algorithm.

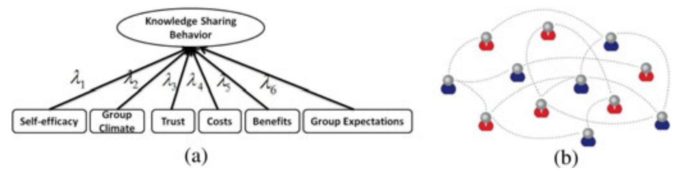

Fig. 8. (a) Key factors for knowledge sharing behavior modeling; (b) Structure of a "micro" social network for collective behavior modeling.

To learn the Markov random field chain model for dynamical social network analytics, the maximum likelihood criterion can be used as the objective function to determine the model parameters. The estimation of the maximum likelihood can usually be achieved by using a traditional electromagnetic (EM) algorithm and its recent variants [48]–[50]. Instead of using traditional EM algorithm and its recent variants, Monte Carlo statistical methods with reversible jumps [51]–[53] are used in this paper to determine the model parameters in our Markov random field chain model as defined in (7). The training samples for model parameter estimation are selected from large-scale cyberspace patient behavior data, which are captured from the message exchange flows among massive numbers of ACL patients in our social health support system.

By modeling both the evolution of "macro" social network and the dynamics of "micro" social networks jointly, our Markov random field chain model can: 1) capture the dynamics of social groups (e.g., emerge, dissolve, split, grow, and shrink) more faithfully; 2) reveal more insights of the evolution of the "macro" social network; and 3) achieve more accurate detection of the growth patterns of social groups or even the whole social community.

VII. Collective Behavior Modeling

We have also evaluated multiple factors to determine the key factors that may significantly influence collective behaviors of ACL patients (e.g., which can support or hinder ACL patients to share their expertise). As shown in Fig. 8(a), six factors are examined from both personal and environmental (social group) perspectives: 1) self-efficacy; 2) group climate (interpersonal social relationships); 3) trust; 4) costs for knowledge sharing; 5) benefits for knowledge sharing (making friends, pleasure, reputation, and cooperation, etc.); and 6) group expectations. Thus, the probability $P(S|X)$ for a given cyberspace behavior on knowledge sharing is defined as

$$P(S|X) = \sum_{j=1}^{6} \lambda_j P(S|X_j) \tag{8}$$

where $P(S|X_j)$ is the contribution of the jth key factor X_j on supporting or hindering the knowledge sharing behavior S, λ_j is the importance of the jth key factor X_j and its value could be negative or positive.

As shown in Fig. 8(b), Markov random field chain is integrated to take into account the structure of a "micro" social network for collective behavior modeling, where a social group of ACL patients is treated as a set of dynamic states linked by a Markov chain and a transition parameter is used to explicitly indicate the strength of interpersonal social relationships. Thus, the probability $P(\mathrm{GS}|\Theta)$ for a given collective behavior GS is defined as

$$\begin{aligned} &P(\mathrm{GS}|\Theta) \\ &= \sum_{X_n, X_l \in \Theta} P(S|X_n) \prod_{l=1}^{n-1} P(S|X_l) P(X_l \to X_{l+1}) P(S|X_0) \end{aligned} \tag{9}$$

where $P(S|X_n)$ and $P(S|X_l)$ are the probabilities for the nth ACL patient and lth ACL patient in the given social group Θ, $P(X_l \to X_{l+1})$ is the social influence from the lth ACL patient to the $(l+1)$th ACL patient to perform the collective behavior GS, all these pairwise social influence $P(X_l \to X_{l+1}) \neq 0$ together can represent both the structure of a "micro" social network and the strength of interpersonal social relationships, $P(S|X_0)$ is the initial influence.

Bayesian approach [51], which can simultaneously determine both the model structures and the model parameters through a posterior distribution over the training samples, is used to estimate the model parameters for our Markov random field chain model as defined in (9). The training samples for model parameter estimation are gathered from large-scale patient self-assessment data, which are collected by interviewing groups of ACL patients and inviting ACL patients for online survey. When the models for both individual behaviors and group-based collective behaviors are available for all the social groups, we can observe a mixing view of various behavior patterns for different social groups. By integrating such a mixing view of various collective behavior patterns for different social groups with their performances, we can determine what kinds of social factors and social settings are more important to make a social health support system to be successful.

A. Patient Involvement Modeling

It is worth noting that patient involvement is different from patient participation, and multiple factors are used for achieving

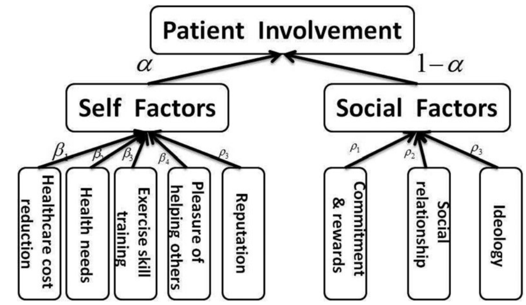

Fig. 9. Social and self-factors for the patient involvement modeling.

more accurate modeling of the involvement of massive numbers of ACL patients. The ACL patients can be motivated by both their self-factors and social factors to join our online health support community and share their personal expertise. In this study, five self-factors are considered: 1) *health needs*: ACL patients may have strong motivation to locate the best matching peers and expertises to deal with their health needs more effectively; 2) *health-care cost reduction*: ACL patients may have strong motivation to locate the best matching peers and learn from their expertises for improving daily exercises and reducing personal health-care cost; 3) *exercise skill training*: ACL patients can be motivated by locating the best matching peers and learning their daily exercise skills on ACL reconstruction and rehabilitation; 4) *pleasure of helping others*: ACL patients can be motivated by the pleasure of helping others and making more friends; and 5) *social reputation*: ACL patients may want to be recognized by others or even the whole social health support system because of their contributions on providing their specialized expertises.

Three social factors, which may motivate ACL patients to join our social health support system and share their personal expertises, are considered: 1) *commitment and rewards*: good commitment among group members and social rewards may play very important role in enhancing the involvement of massive numbers of ACL patients; 2) *social relationships*: it is well known that interpersonal communication, interaction, relationships, and trust significantly affect the involvements of group members, and good social relationships may result in better collaboration among the group members; and 3) *ideology*: when people have similar attitudes, beliefs, and values, they may keep in touch and work together, such ideology may influence group members' sense of belonging and their views and commitment of the importance of their collaborations.

As shown in Fig. 9, a new approach is developed to quantitatively model the causal relationship between the involvement of an individual and the self and social factors. The personal involvement is modeled as

$$\begin{aligned} &P(I, X_l|Y_{\mathrm{self}}, Y_{\mathrm{social}}) \\ &\quad = \alpha \sum_{i=1}^{5} \beta_i P(I, X_l|Y_{\mathrm{self}}^i) P(Y_{\mathrm{self}}^i) \\ &\qquad + (1-\alpha) \sum_{j=1}^{3} \rho_j P(I, X_l|Y_{\mathrm{social}}^j) P(Y_{\mathrm{social}}^j) \end{aligned} \tag{10}$$

where Y_{self}^i is the ith self factor and Y_{social}^j is the jth social factor, $P(I, X_l|Y_{\text{self}}^i)$ and $P(I, X_l|Y_{\text{social}}^j)$ are the contributions of the ith self-factor and the jth social factor on the involvement of the given ACL patient X_l, α, β, and ρ are the importance factors that can be estimated automatically from cyberspace behavior data. By modeling the personal involvement, we can gain more knowledge about the key factors for enhancing patient involvement, so that we can expand new sources to promote the involvement of ACL patients and make our social health support system to be successful.

After the personal involvement model is available, Markov random field chain is integrated to take into account the structure of a "micro" social network for collective involvement modeling at the group level. The collective involvement $P(CI|\Theta)$ for a given social group Θ is defined as

$$P(CI|\Theta) = \sum_{X_n, X_j \in \Theta} P(I, X_n|Y_{\text{self}}, Y_{\text{social}}) \times \prod_{j=1}^{n-1} P(I, X_j|Y_{\text{self}}, Y_{\text{social}}) P(X_l \to X_{l+1}) P(I|X_0) \tag{11}$$

where $P(I, X_n|Y_{\text{self}}, Y_{\text{social}})$ and $P(I, X_j|Y_{\text{self}}, Y_{\text{social}})$ are the personal involvement for the nth and jth ACL patient in the given social group Θ, $P(X_l \to X_{l+1})$ is the social influence from the lth ACL patient to the $(l+1)$th ACL patient on their involvement, all these pairwise social influence $P(X_l \to X_{l+1}) \neq 0$ together can represent both the structure of a "micro" social network and the strength of interpersonal social relationships, $P(I|X_0)$ is the initial personal involvement.

By using the marginal likelihood as the objective function, Bayesian approach [51] is performed over the micro social network (indirected graphical model) to determine the model parameters for our Markov random field chain model as defined in (11). By optimizing a lower boundary approximation to the marginal likelihood in a procedure similar to the standard EM algorithm [48]–[50], Bayesian approach can determine both the model structures and the model parameters accurately. The training samples for model parameter estimation are gathered from large-scale patient self-assessment data, which are collected by interviewing groups of ACL patients and inviting ACL patients for online survey. When the collective involvement models are available for all the social groups in our social health support system, we can observe a mixing view of the involvement for different social groups. By integrating such a mixing view of various collective involvement for different social groups with their performances, we can easily determine which social and self-factors and what kinds of social settings are more important to promote the involvement of massive numbers of ACL patients.

VIII. Algorithm and System Evaluation

Our experimental studies are carried on large-scale patient self-assessment data. Two approaches are incorporated for collecting large-scale patient self-assessment data by *interviewing groups of ACL patients* and *inviting ACL patients for online survey*. Our large-scale patient self-assessment data are used to evaluate: 1) whether personal expertise from other ACL patients can improve individuals' abilities on recovering from knee injury or surgery; 2) whether joining our social health support system can allow individuals to obtain unique social supports for improving their relationships with family and friends; 3) whether our social health support system can provide the opportunity for individuals to help others by sharing their personal expertise; 4) whether our personalized expertise recommendation framework can allow individuals to easily and accurately locate the best matching patients and their expertise; and 5) whether ACL patients trust the expertise from others.

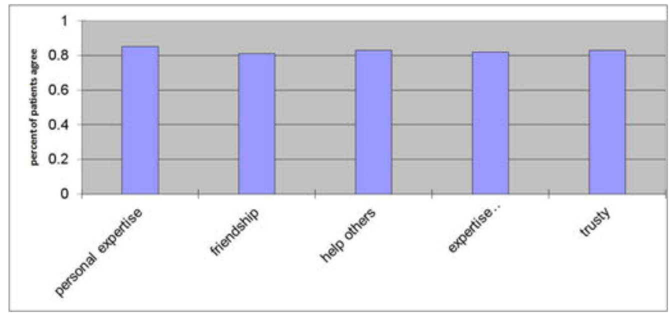

Fig. 10. Effectiveness of various factors on improving the patients' experiences on ACL reconstruction and rehabilitation: (a) personal expertise; (b) friendship; (c) help others; (d) expertise recommendation; (e) trusty.

As shown in Fig. 10, one can observe that most ACL patients (over 80%) agree that our social health support system can significantly improve their personal experiences on ACL reconstruction and rehabilitation by allowing them to easily learn from the best matching peers. Many ACL patients (which share similar ACL injury levels and social principles) are managing similar health situations, they can be the best matching specialists to consult their personal experiences for ACL rehabilitation. Our social health support system can allow ACL patients to easily identify the best matching specialists and expertises, which can provide a wonderful platform for leveraging social supports for ACL reconstruction and rehabilitation.

Patient involvement reflects their beliefs about their social groups, e.g., patient involvement can reflects whether our patient assignment and social groups can assist them on: 1) reducing health-care cost by leveraging social supports for ACL reconstruction and rehabilitation; 2) finding their health needs by locating the best matching peers and their specific expertises; 3) training their skills on personal health management; 4) obtaining reputations from others by sharing their personal expertises; and 5) feeling better by helping others. All these self-factors have seamlessly been integrated in our patient involvement model, thus it is very attractive to evaluate their importance for patient involvement modeling. As shown in Fig. 11, one can observe that health-cost reduction, health needs, and exercise skill training are the most important self-factors as compared with other factors such as pleasure of helping others and reputation. Many ACL patients participate our social health support system because they want to reduce their health-care cost by

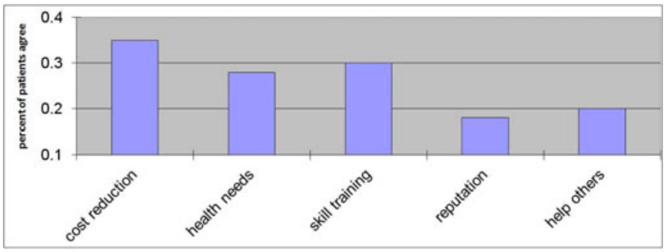

Fig. 11. Importance of multiple self-factors for patient involvement modeling, where ACL patients score five factors and summation of their five scores is equal to 1 (100%).

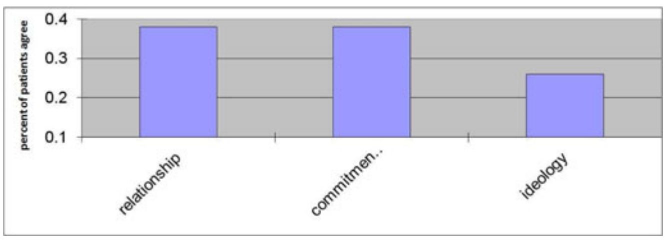

Fig. 12. Importance of multiple social factors for patient involvement modeling, where ACL patients score three factors and summation of their three scores is equal to 1 (100%).

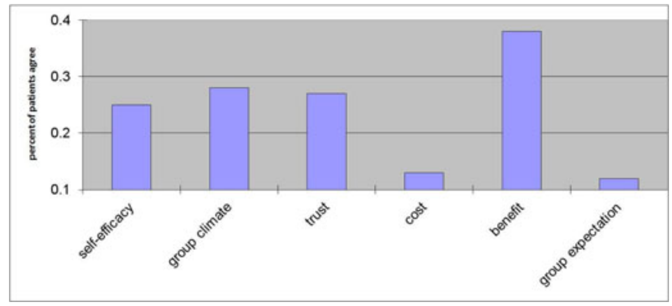

Fig. 13. Importance of multiple key factors for collective behavior modeling, where ACL patients score six factors and summation of their six scores is equal to 1 (100%).

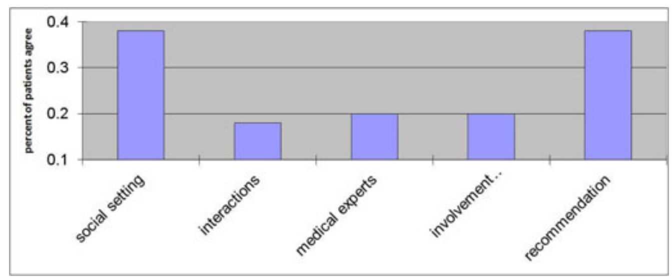

Fig. 14. Improvement of patients' involvements for various enhancement tools, where ACL patients score five factors and summation of their five scores is equal to 1 (100%).

seeking expertises from others and getting training of their exercise skills for ACL function recovery. This is the reason why some self-factors (such as health-cost reduction, health needs, and exercise skill training) are more important than others.

Another primary source of factors for patient involvement modeling is the social factors, e.g., the community characteristics can influence the behaviors of ACL patients on expertise sharing. In this paper, three social factors are integrated for patient involvement modeling: 1) social relationships among ACL patients; 2) commitment among group members; and 3) ideology for collaboration. We have evaluated the importance of these three social factors for patient involvement modeling. As shown in Fig. 12, one can observe that social relationship and commitment play more important role in patient involvement modeling than ideology. Many ACL patients participate our social health support system because they want to seek social supports from the best matching peers and establish good relationships with others for sharing their opinions, feelings, and experiences. This the reason why some social factors (such as social relationship and commitment) are more important than others.

Collaboration and competition among many ACL patients in the same social group or even from different but inter-related social groups may have strong influence on their cyberspace behaviors and may emerge some collective behaviors on dealing with the challenging issue of ACL reconstruction and rehabilitation. In this paper, six factors have been integrated for collective behavior modeling. We have also evaluated the importance of all these six factors for collective behavior modeling. As shown in Fig. 13, one can observe that benefits, trust, group climate, and self-efficacy are more important than costs and group expectations. Many ACL patients participate our social health support system because they want to seek benefits (social supports) from the best matching peers, socialize with trusty group members, and be associated with social groups with good relationships. This is the reason why some factors (such as benefits, trust, group climate, and self-efficacy) are more important than others.

It is worth noting that the patients' involvement plays an important role in the success of our social health support system, and we have incorporated multiple approaches to enhance the patients' involvement: 1) hierarchical patient assignment and social setting; 2) supporting multimodal communications and interactions; 3) involving medical professionals; 4) patient involvement modeling; and 5) supporting personalized expertise recommendation. To evaluate the effectiveness of these approaches on enhancing patients' involvement, we have compared the patients' involvement before and after such patient involvement enhancement approaches are performed in our social health support system, and the improvement of patients' involvement is then used to measure the effectiveness of our patient involvement enhancement tools. As shown in Fig. 14, our research has shown that: 1) our patient involvement enhancement tools can significantly enhance the involvement of ACL patients; and 2) social setting and personalized expertise recommendation are most important for enhancing patients' involvement.

Generating more accurate patient-specific knee joint models play a critical role in achieving more effective clustering and assignment of large amounts of ACL patients. In this paper, we have seamlessly integrated base knee joint model with patient-specific medical data to generate high-quality patient-specific knee joint models. Thus, it is very attractive to validate the effectiveness of our model generation algorithm (integrating

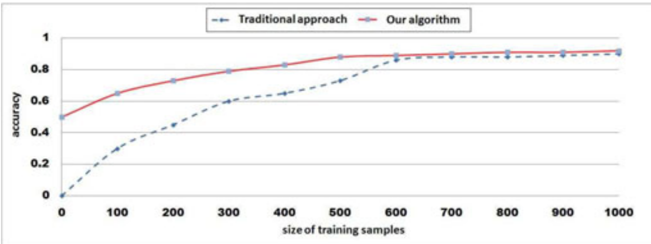

Fig. 15. Comparison on the accuracy rates for patient-specific knee joint model generation by using our algorithm and traditional approach.

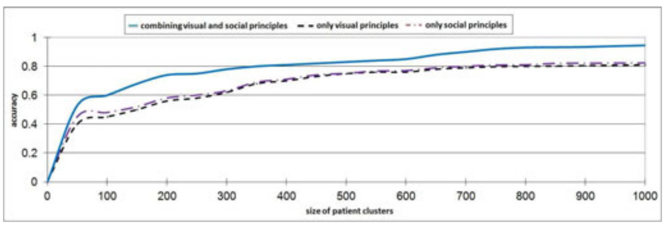

Fig. 16. Comparison results on the accuracy rates of our hierarchical patient clustering algorithm by combining different feature subsets.

patient-specific medical data with base knee joint model) with traditional model generation algorithms [27]–[29] (only using patient-specific medical data). As shown in Fig. 15, one can observe that integrating base knee joint model for generating patient-specific knee joint models can significantly reduce the size of patient-specific medical data, which can dramatically reduce the health-care cost for medical data capturing.

Different feature subsets (model properties of patient-specific knee joint models and social principles of ACL patients) may play different roles on patient similarity characterization and decision making for patient clustering and assignment. By combining different feature subsets for patient clustering and assignment, we have also compared the performance difference of our hierarchical patient clustering algorithm, which may provide good evidences to assess the effectiveness of various feature subsets. As shown in Fig. 16, one can observe that integrating model properties of patient-specific knee joint models with social principles of ACL patients can achieve more precise clustering and assignment of massive numbers of ACL patients.

IX. Conclusion

In this paper, a social health support system is developed to assist both ACL patients and clinicians on making better decisions and choices for ACL (reconstruction and rehabilitation. Our hierarchical patient clustering and assignment algorithm can provide a good environment for supporting personalized expertise recommendation, so that each ACL patient can easily locate his/her best matching ACL patients and learn from their personal expertise for recovering from knee injury or surgery. Our social health support system can also allow us to identify appropriate social and computational technologies with desirable properties and values for leveraging patient expertise to empower individuals' abilities on recovering from ACL injury or surgery.

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