B2-3. 質管理・ガイドライン（口演） 14：00-15：00

座長：上塚　芳郎（東京女子医科大学医学部　医療・病院管理学）
山内　慶太（慶應義塾大学看護医療学部・大学院健康マネジメント研究科）

B2-3-1　多職種チームによる慢性呼吸不全を対象とした統合型診療ユニット（IPU）の試み
土畠　智幸（医療法人　手稲渓仁会病院　小児在宅医療・人工呼吸器センター）

B2-3-2　ICD 分類作業ガイドラインの実効性の検証
佐藤　恵（筑波大学大学院　ビジネス科学研究科　企業科学専攻）

B2-3-3　病院機能評価更新受審病院を対象にアンケートを実施して
川本　一男（一般社団法人　愛知県医療法人協会）

B2-3-4　地域医療機関の DPC 関連データを集約化してできること
— 静岡県 Nakama Project の分析報告から —
小林　利彦（浜松医科大学　医学部　附属病院　医療福祉支援センター）

B2-3-5　イギリスにおけるケアのアウトカム指標 — 研究の知見と政策動向を中心に
長澤紀美子（高知県立大学　社会福祉学部　社会福祉学科）

B2-4. 訪問看護・在宅ケア（口演） 15：15-16：25

座長：杉山みち子（神奈川県立保健福祉大学　保健福祉学部　栄養学科）
緒方　泰子（東京医科歯科大学大学院保健衛生学研究科）

B2-4-1　訪問看護ステーションにおける連携戦略の実態と課題
磯山　優（埼玉学園大学　経営学部　経営学科）

B2-4-2　一般病床からの自宅退院要介護高齢者に対する退院支援プロセスの現状と課題
— 複数地区での検証 —
川越　雅弘（国立社会保障・人口問題研究所）

B2-4-3　訪問看護ステーションにおける情報活用の実態に関する研究
王　麗華（東京工科大学　医療保健学部　看護学科）

B2-4-4　脳血管障害者に対する居宅系リハビリテーションの効果に関する検討
金川　仁子（東北大学大学院　医学系研究科　医療管理学分野）

B2-4-5　在宅高齢者の「食べること」を支援するための栄養ケアチーム研修とその評価
野地　有子（千葉大学）

B2-4-6　管理職以外の病棟看護職におけるバーンアウトと看護職特性および看護実践環境との関連
緒方　泰子（東京医科歯科大学大学院保健衛生学研究科）

10月19日（金）　C 会場

C2-1. 医療情報 1（口演） 9：30-10：18

座長：梅里　良正（日本大学医学部社会医学系　医療管理学分野）
岡田美保子（川崎医療福祉大学　医療福祉マネジメント学部　医療情報学科）

C2-1-1　院内がん登録データを用いた診療圏の検討 — 乳がん症例 —
村上　玄樹（広島大学　医学部　公衆衛生学講座）

B2-3-4

地域医療機関のDPC関連データを集約化してできること
—静岡県Nakama Projectの分析報告から—

小林　利彦

浜松医科大学　医学部　附属病院　医療福祉支援センター

【背景】2011年7月以降，静岡県西部地域の医療機関を中心に，DPC関連データの集約化事業（Nakama Project）を展開している。これまでに，県内のDPC病院の約半数の関連データを一元化収集した。今回，本プロジェクトの中で，結腸手術症例について分析を行ったので報告する。

【対象と方法】静岡県内のDPC病院22施設（基礎係数1群：1施設，2群：3施設，3群：19施設）を対象とした。平成23年度のDPC関連データの中から，結腸がん（MDC：060035）患者を抽出し，開腹手術症例（Kコード：7191, 7192, 7193）と腹腔鏡下手術症例（Kコード：719-21, 719-22, 719-3）に分けて比較検討を行った。分析ソフトはgirasolを使用し，検討項目としては一般的診療情報のほか，周術期のアプロセスとアウトカムに注目した分析を行った。

【結果】平成23年度における22施設の退院患者総数は173,3565人であり，060035コード（結腸悪性腫瘍）は2,651人，その中で，開腹手術（O群）症例は691人（1施設平均31.9人），腹腔鏡下手術（L群）症例は303人（1施設平均14.4人）であった。平均年齢はO群63.9歳，L群66.9歳，性別（M：F）はO群351：340，L群182：121であり，術前日数が2日以内の症例がO群34.1%，L群73.4%，平均在院日数ならびに術後入院期間はO群が29.0日と19.1日，L群は17.5日と12.7日であった。術前日数が2日以内の患者において，中心静脈注射の実施率はO群20.3%，L群15.2%であり，手術後の食事開始が2日以内の患者はO群25.6%，L群38.9%であった。周術期の注射抗菌薬使用に関して，術後3日目以降および7日目以降の投与例はO群が57.4%と28.4%，L群が41.9%と13.9%であり，7日目以降の抗菌薬使用患者の在院日数は各々43.9日，33.2日と長期化していた。手術後8日目以降にドレーン管理が行われていた患者比率は，O群36.7%，L群10.9%であった。腫瘍のステージとして1：2：3：4：不明は，O群で79（11.9%）：213（32.1%）：241（36.3%）：125（18.9%）：5（0.8%），L群で105（38.5%）：80（29.3%）：68（24.9%）：14（5.1%）：6（2.2%）であった。なお，死亡退院例はO群で5例（0.7%）見られたがL群にはなかった。

【まとめ】腹腔鏡下手術は開腹手術の半数近く選択され，比較的低いステージの高齢症例で行われていたが，クリニカルパス症例も多い可能性が示唆された。また，腹腔鏡下手術症例における周術期の抗菌薬使用は少なく，食事開始も早めでドレーン管理期間も短いことなどから，術後入院期間や平均在院日数は短い傾向にあった。本来，この種の多施設間比較検討はパス大会等で可能であるが，地域におけるDPC関連データを一元化・集約化することで，スクリーニング的な分析は可能となり，協力病院への貴重な情報還元につながると考える。

19日 B2

キーワード：DPC，クリニカルパス，地域医療

8. 小林利彦:
DPC データを利用したクリティカルパス分析
-腹腔鏡下胆嚢摘出術-.
第 32 回医療情報学連合大会論文集,
医療情報学 32-Suppl., 756-757, 2012.

DPCデータを利用したクリティカルパス分析 －腹腔鏡下胆嚢摘出術－

小林 利彦
浜松医科大学医学部附属病院　医療福祉支援センター

Criticalpath analysis for laparoscopic cholecystectomy cases, using DPC data

Kobayashi Toshihiko
Healthcare-Welfare Support Center, Hamamatsu Medical University Hospital

DPC data analysis of 23 hospitals in Shizuoka was done for laparoscopic cholecystectomy cases. The cases defined as criticalpath were 847 (1-109 cases of each facilities / year), and the average length of hospital stay was 7.4 days. Preventive antibiotic injection was used during two days on the average, and intraoperative cholangiography was done in 7.8%, the average time of anesthesia was two hours and 46 minutes, the oral intake on first postoperative day was begun by 90%. Postoperative infectious event was supposedly occurred in 2.6%. These analytic approaches for DPC data were relatively useful.

Keywords: criticalpath,DPC,laparoscopic cholecystectomy

1. はじめに

DPC(Diagnosis Procedure Combination)データを用いた各種分析手法として、これまで様々なものが提案されてきた。当初は、DPC-出来高差額や診断群分類別の費用分析といった診療報酬に直結したものが多かったが、Clinical Indicator (CI)やQuality Indicator (QI)が注目されて以来、診療の質に着目したDPC分析が多く行われるようになった。実際、DPC時代となり、多くの診療科で標準化が推進される過程において、他施設とのタスク内容の比較分析は重要な作業と考える。特に、クリティカルパスの活用が当然とされるような典型的症例では、その傾向が強いと思われる。従前、多施設のスタッフを一堂に集め各施設とのタスク比較を行う「パス大会」は、ある意味その役割を担ってはきたが、DPCデータを一元化・集約化さえできれば、その作業も容易になるかと思われる。
今回、静岡県内23施設のDPCデータを一元化・集約化する機会を得たので、クリティカルパスとして典型事例である「腹腔鏡下胆嚢摘出術」症例でのバーチャル・パス大会を試みた。

2. 対象と方法

静岡県中東遠地域医療支援センター事業（通称、Nakama Project）を通して、静岡県DPC対象病院の約半数（23施設）との契約のもと、DPC関連データを一元化・集約化することができた。
今回、平成23年4月～平成24年3月の入院患者の中で、MDC6が060330(胆嚢疾患[胆嚢結石など]), 060335(胆嚢水腫・胆嚢炎等)、手術コードとしてK672-2:腹腔鏡下胆嚢摘出術が行われた症例を抽出し、そのうち術前日数が1日のものを「パス症例」と仮定した。
各施設の患者数や平均在院日数といった基本情報のほかに、レセプト項目から周術期のタスクを拾い上げ、多施設間の比較分析を行った。おもな分析項目としては、周術期の抗菌薬の使用実態、術中胆道造影の有無、麻酔時間、第1病日のルーチン血液検査の状況、経口摂取の開始時期、術後感染症の発生状況などに注目した。

3. 結果

静岡県内23施設の年間患者総数は182,019件であり、その中でMDC06：060330,060335＋K672-2の患者は1,198人、さらに手術前日入院の患者（＝パス症例）は847人（男422, 女425, 平均年齢59.2歳）であった。
各施設における年間のパス症例数は1-109例（平均36.8例）と幅広く、その平均在院日数は7.4日であった（図1）。

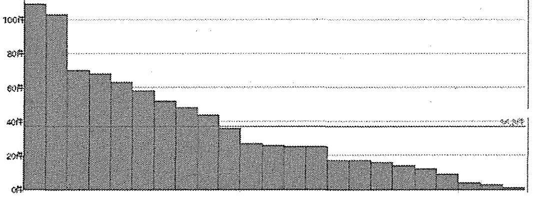

図1　腹腔鏡下胆嚢摘出術のパス症例数
術前日数が1日のものをパス症例と仮定した。施設によってパス症例数は1-109例とバラつきがある。

術中の予防的注射抗菌薬は99.3％で使用され、薬剤の種類としては、セフメタゾール(1g)、フルマリン(1g)、セファメジンα(1g)などが上位を占めた。予防的注射抗菌薬の使用回数は平均4.2回であり、術後2日目以降の施設毎の実施率は平均28.8％であった（図2）。

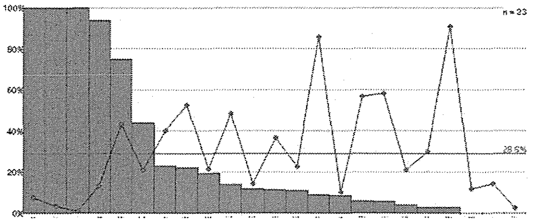

図2 術後2日目以降の予防的抗菌薬の使用率
各施設の術後2日目以降の注射抗菌薬使用率は平均28.8%であった。折れ線グラフは各施設の症例数を示す。

術中胆道造影は66例(7.8%)で行われており、麻酔時間は53-493分(平均2時間46分)であった。
全体の90.6%の患者では第1病日に食事が開始されていたが、2施設では絶食となっていた。第1病日の血液検査は83.5%の症例で行われ、CRP測定は39.0%、TP測定は59.4 %の実施率であった。術後感染症発生の目安として、第5病日以降の注射抗菌薬使用率を調べると、2.6%と低値ではあるものの、それらの患者の平均在院日数は17.2日と延長していた(図3)。

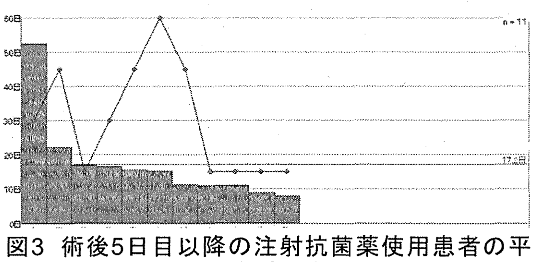

図3 術後5日目以降の注射抗菌薬使用患者の平均在院日数
術後5日目以降の注射抗菌薬使用は術後感染症の発生を示唆するが、該当患者の平均在院日数は17.2日と延長していた。折れ線グラフは各施設の症例数を示す。

4. 考察

DPCデータを利用した分析手法として、従前、医事課や経営企画室などが中心となり、DPC-出来高差額や診断群分類別の費用分析等が行われてきた。診療の標準化を進める上で一定の成果はあったと思われるが、分析の視点や評価指標はあくまで金銭的なものであり、診療サイドからすると、それらの議論に積極的に参画するモチベーションは乏しい状況にあった。その後、CIやQIが登場したことで、事務サイドから医療者へのコミュニケーション強化が期待されたが、結果として、欧米の既存指標を多く引用したことや、DPCデータから簡便に計算できる指標ばかりが流用されたこともあって、医師の賛同や興味は思ったほど得られなかった感がある。
DPCシステムが本邦で動き出す以前から、診療の標準化はクリティカルパスの活用という流れで広がっていた。全国学会や地域の集まりにおいて、お互いの診療スタイルを見せ合い、比較分析する「パス大会」としての議論が多くなされ、その中で自院の診療スタイルを改善してきた経緯がある。DPCが導入されてから、DPC-出来高差額を最大にするような「DPC適応型パス」という言葉が広まったが、本来は本末転倒だと考える。全国の医療者がガイドライン等を準拠して自院の診療プロセスを構築し、その全国平均あるいは地域での平均プロセスが当面のベストプラクティスとなり、そのプロセスに対して診療報酬が反映されるべきだと考える。
とは言え、日々の診療で忙しい地域の医療者は、常々、自分のやり方が正しいのか?全国的にみて平均的なプロセスであるのか?といった疑問を抱いている。また、診療プロセスには地域性が大きく影響し、全国のブランド病院のスタイルをそのまま借用することは困難な場合が少なくない。
そのような面でも、今回、一都道府県の約半数の診療データ(DPCデータ)を一元化・集約化できた意義は大きいと考える。また、医事課的発想でなく、全国的に良く見る既存指標でもなく、むしろ、現場感覚に近い臨床指標を提案できたことで、現場医師にも興味を持ってはもらえるのではないかと考える。また、ガイドライン等に記載がある抗菌薬の選択や使用日数に関して、どれほど遵守されているのか?名前しか知らない遠方のブランド病院のプロセスよりも、近隣病院の実態を知りたいのが本音であろう。「当院のパスは前日入院で術後4日目に帰ります」とパス大会で論じても、実際の入院日数は、病棟看護師長がベッドコントロールしつつ調整するといった現実は案外多い。そのような実態を相互に知ることで、自院のプロセスを振り返りながら競争力を高めていくことが、最終的な質向上につながるものと考える。
なお、DPCやレセプトデータの分析おいて、病名グルーピングの不正確性がよく議論となる。医療資源が最も投入された病名=主病名や、いわゆるレセプト病名などはその典型である。この問題の解決は、直ぐには困難であり、当面は手術術式や処置名などを活用してタスク抽出を基本に分析するのが有効と考える。実際、MDC6:060330,060335+K672-2に含まれない「腹腔鏡下胆嚢摘出術パス症例」が少なからずあると思われる。術後の比較的軽い合併症で別コードに分類された事例等に関して、ミスコーディングの議論をすることは本報告の主意ではない。分析対象として適切な患者抽出を、如何に精度高く効率的に拾い上げられるか、そのロジックを組み立てることにより対応すべき課題かと考えている。

5. 結論

今回、静岡県西部地区23施設のDPC対象病院の入院データを一元化・集約化し、その中で、クリティカルパス事例として典型的な腹腔鏡下胆嚢摘出術症例のタスク分析(バーチャルパス大会)を行った。該当症例をもれなく抽出する分析手法ではなく、DPCデータの特殊性から限界もあるが、地域における診療プロセスのスクリーニング的な比較分析には有効な方法論だと考える。

9. 小林利彦:

バーチャルクリニカルパス大会の試み

-乳がん手術症例-.

第13回日本クリニカルパス学会学術集会

抄録集 425, 2012.

日本クリニカルパス学会誌

Journal of Japanese Society for Clinical Pathway

Vol.14 No.4 2012

第13回日本クリニカルパス学会学術集会抄録集

CLINICAL
PATHWAY

口演（2-B-01～2-B-04）　14:00～14:48　B会場（1F イベントホール）

座長：今田　光一（黒部市民病院）

クリニカルパスの新たな活用法

2-B-01（紹介）　電子カルテ時代の患者と医療者のパスを通した情報共有

熊本機能病院　今屋　将美

2-B-02（研究）　パスを用いた術前経口補水療法の前向き比較検討

盛岡市立病院　沢内 節子

2-B-03（パス）　長期クリニカルパスによるGISTの外来グリベック治療マネジメント

神奈川県立がんセンター　長　晴彦

2-B-04（研究）　バーチャル・クリニカルパス大会の試み －乳がん手術症例－

浜松医科大学医学部附属病院　小林　利彦

口演（2-D-01～2-D-05）　10:35～11:35　D会場（3F 301会議室）

座長：安東　立正（前橋赤十字病院）

がん関連

2-D-01（研究）　クリニカルパスを用いたS1/CDDP療法における腎障害の検討

古賀総合病院　猪野　真基

2-D-02（パス）　前立腺強度変調放射線治療パスの作成

渋川総合病院　酒井　毅

2-D-03（研究）　幽門側胃切除術後における全粥開始パスの検討

横須賀共済病院　三宅謙太郎

2-D-04（研究）　泌尿器科GC療法バリアンス分析および有害事象の検討

前橋赤十字病院　矢島　俊介

2-D-05（研究）　化学療法を受ける患者の意向をふまえたクリニカルパスの作成

川崎医科大学附属病院　大藤加奈子

口演（2-D-06～2-D-12）　13:50～15:14　D会場（3F 301会議室）

座長：佐藤　博（新潟大学医歯学総合病院）

チーム医療1

2-D-06（紹介）　感染対策室との連携によるクリニカルパスで使用の抗菌薬の見直し

北摂総合病院　和田　恭子

2-B-01(紹介)

電子カルテ時代の患者と医療者のパスを通した情報共有

[1]熊本機能病院 総合リハビリテーション部、
[2]同 診療部 循環器内科、[3]同 診療部 整形外科、[4]同 総合管理局 情報システム課
今屋 将美(いまや まさみ)[1]、原田 栄作[2]、清田 克彦[3]、相馬 章人[4]

【はじめに】クリニカルパス(以下、パス)は医療の標準化、工程管理、チーム医療、PDCAサイクル、質向上を可能とするものである。パスは患者と医療者のタスクや達成目標を共有できるツールでもある。しかしながら、パスは患者用と医療者用とが厳密には分かれており、患者が検査結果や目標達成度を知るには、医師からの情報提供が原則であり、患者と医療者とでは情報量とタイミングに差がある。そこで、患者と医療者との情報量とタイミングの差をなくすことは、患者満足度向上にも通じ、今の電子カルテ時代だからこそパスが貢献できることがあると考える。
【提案】キーワードは「患者と医療者のパスを通した情報共有」として具体的に考えてみたい。
1.電子タブレットの貸与
2.個人IDとパスワード管理のもと、患者は自身の情報に限り全ての情報を閲覧できる
3.患者が医療者と同じレベルで自身の経過プロセス、今後の工程を知ることができるわかり易いオーバービューパス画面
4.検査結果、目標達成の医療者による評価などは、入力と同時に新着情報として患者も知ることができる
【考察】カルテ開示や情報共有に取り組んだ研究は過去にも行なわれており、患者の積極的な治療参加が得られ、医療者に対する信頼が高まるなどその効果は大きい。本提案のシステム構築は、さらに患者と医療者との情報量とタイミングの差をなくすことができ、患者の治療選択、決定、協力などの患者満足度向上に貢献できるのではないかと考える。
【まとめ】今回提示した将来像はパスの理想のひとつである。電子カルテをベースにした「患者と医療者のパスを通した情報共有」は、今後の方向性と考える。

2-B-02(研究)

パスを用いた術前経口補水療法の前向き比較検討

[1]盛岡市立病院 外科 看護部、[2]同 外科
沢内 節子(さわうち せつこ)[1]、須藤 隆之[2]

【目的】近年、術前経口補水療法が注目されている。今回、パスを用いて腹腔鏡下胆嚢摘出術における術前経口補水療法の有用性についてRandomized Controlled Studyにて検討を行った。
【方法】2012年3月より2012年8月までに腹腔鏡下胆嚢摘出術を行った40例を対象とし(緊急手術、嚥下障害を有する症例は除外)、点滴群と補水群の2種類のパスを作成し、周術期管理を行った。点滴群は、術当日絶飲食として点滴を行い、補水群は、術当日OS-1(大塚製薬)1000mlを内服とし点滴を行わなかった。全例胃管は挿入せず、気腹下で3ポートにて手術を行った。さらに術後、患者満足度アンケートを行った。
【結果】点滴群(20例)、補水群(20例)の平均年齢は、58.9±13.5歳、54.6±12.5歳(p=0.18)、両群とも男性14例、女性6例で、両群間の背景因子に有意差はなかった。点滴群、補水群いずれも、麻酔導入時の嘔吐などのトラブル無く、術中胃管挿入、ポートの追加等は無かった。在院日数は、4.4±1.47日、4.6±1.8日(p=0.82)、手術時間は、84.7±24.6分、72.3±17.6分(p=0.08)、出血量は、12.5±12.0cc、22.3±29.8cc(p=0.85)でいずれも有意差はなかった。補水群は、90%がOS-1全量内服可能であった。アンケート結果は、補水群で手術前の口渇感が少なかった。また、次に手術を受ける事があれば、次回も補水療法を希望するという回答が多かった。
【考察】術前経口補水療法は、麻酔、手術操作、在院日数に影響を及ぼさなかった。アンケート調査から、患者の満足度が高かった。
【結論】腹腔鏡下胆嚢摘出術における術前経口補水療法は、安全性・患者満足度ともに高く、有用性のある方法である。

2-B-03(パス)

長期クリニカルパスによる GISTの外来グリベック治療マネジメント

[1]神奈川県立がんセンター 消化器外科、[2]同 看護科
長 晴彦(ちょう はるひこ)[1]、上遠野 千夏[2]

消化管間質腫瘍(以下GIST)はまれな悪性疾患であり、地域の主幹病院でも年間新規症例数は数例程度である。さらにグリベック治療の対象となる進行・再発GISTはその一部であり、1人の医師が短期間に経験値を積み、治療の傾向を把握することは困難である。一方、分子標的治療薬であるグリベックは長期間安定した服用を続けることで腫瘍の制御が可能となるが、投与初期の副作用管理に失敗し、治療継続に支障をきたしているケースが多くみられる。今回われわれはグリベック治療を標準化する目的で、外来長期クリニカルパスを作成したので報告する。パスは進行再発例に対するlife-long(until PD)投与と、根治切除後のadjuvant投与(海外エビデンスは3年間)がともに使用できる共通パスとした。期間は耐性獲得期間とadjuvant期間を考慮して3年間とした。発生頻度が比較的高く、日常生活に支障をきたす有害事象(悪心嘔吐、浮腫、皮疹、下痢)については、患者さん自身が自己観察用紙に記入し、来院時に医療者用パスに転記する形式とした。医療者用パスには休薬・減量基準を附し、患者用パスには副作用マネジメントとして、自身でも行える支持療法を記載した。コンプライアンスや有害事象の確認は外来看護師が行い、必要に応じて薬剤説明は薬剤師が、栄養管理は栄養科が介入することも、パスを介して行えるようにした。当日はパス導入までの経緯と、実際の運用経験について報告する。

2-B-04(研究)

バーチャル・クリニカルパス大会の試み－乳がん手術症例－

[1]浜松医科大学医学部附属病院 医療福祉支援センター
小林 利彦(こばやし としひこ)[1]

【目的】地域のDPC関連データを集約化して分析することで、多施設の医療関係者が集まることなく、クリニカルパス大会のシミュレーションを行うことを目的とした。
【方法】静岡県西部地区を中心に、23施設のDPC関連データを集約化した。平成23年度データでMDC6が090010(乳房の悪性腫)かつ乳腺悪性腫瘍手術(K4761-K4767)が行われた患者を抽出し、術前日数2日以内をクリニカルパス症例と仮定した。同症例群に関して、周術期タスクや管理指標、診療報酬指標等について比較分析した。
【結果】23施設の全患者件数は182,019件で、今回定義した乳腺悪性腫瘍手術のパス症例は1365例(平均年齢58.4歳)であった。各施設の年間手術件数は1-257件(平均62件、9施設が週1件以上)であり、予防的抗菌薬はセフェム第一世代の術中使用がほとんどで、第1病日の投与は34%であった。胃カテーテル使用率53%、創部ドレーン留置率68%、感染関連指標：術後8日目以降の抗菌薬使用は3.9%であった。腋窩廓清(-)乳房部分切除術(559例)の全身麻酔時間は平均179分、センチネルリンパ節生検の実施率は80%、術後在院日数は平均4.6日、1入院当たりの診療報酬請求額は63.9(29.5-78.2)万円であった。
【考察と結論】本手法では、病名やステージなどデータ入力精度の問題は残るが、多施設の医療関係者が一同に集まることなく、診療プロセス等のスクリーニング的な比較分析が可能となる。よく行われているClinical Indicatorの多施設比較では、遠方の病院との比較分析が多く、本手法のように身近な病院の診療プロセスが知れるメリットは大きいものと思われた。

10. Rudy Raymond, Naoki Nakashima, Yasunobu Nohara, Sozo Inoue: Sensor Data Analytics to Complement Sparse and Incomplete Medical Records for Diabetes Disease Management, Proceeding of International Workshop on Pattern Recognition for Healthcare Analytics, 5-8, 2012.

Sensor Data Analytics to Complement Sparse and Incomplete Medical Records for Diabetes Disease Management

Rudy Raymond
IBM Research – Tokyo
raymond@jp.ibm.com

Naoki Nakashima, Yasunobu Nohara
Kyushu Univ. Hospital
{nnaoki,y-nohara}@info.med.kyushu-u.ac.jp

Sozo Inoue
Kyushu Institute of Technology
sozo@mns.kyutech.ac.jp

Abstract

Diabetes mellitus is considered one of the main chronic diseases, and uncontrolled diabetes can lead to various complications that trigger other chronic diseases. Disease management for diabetes is therefore important to reduce the total healthcare cost. Unfortunately, managing diabetic patients is often difficult due to their sparse and incomplete medical records. Many patients drop out during treatment, and each patient might require different treatment. On the other hand, the widespread use of mobile devices with various sensors and instant communication capability has enabled healthcare providers to collect and monitor patients' condition. In this paper, we study the role of sensor data analytics to complement sparse and incomplete medical records for diabetes disease management. We test various machine-learning techniques on real-world datasets of diabetic patients, and show that sensor datasets can be used to improve the precision of methods identifying high-risk patients.

1. Introduction

Many developed countries are faced with aging population that brings a serious problem with the increase of chronic diseases. It is expected that in Japan more than 40% of the workforce will be over 60 year in 2050, while the figures in US, China, and EU countries range from 30% to 40% by 2025. Chronic diseases that are often prolonged in duration and rarely completely cured, occupy more than 75% of the total healthcare cost. Diabetes is considered one of the main chronic diseases in aging population, and uncontrolled diabetes can lead to various complications of other chronic diseases, such as, heart diseases, strokes, nerve damages, blindness, and kidney failures. Disease management for diabetes, especially to identify high-risk patients, is therefore important to reduce the total healthcare cost since hemodialysis for the advanced stage of diabetic patient requires $50K per year per patient.

Disease management for diabetes is aimed to prevent such advanced stage of diabetic complication that can also significantly decrease patients' quality of life. Important steps for managing chronic diabetes include providing periodical medical checkup, identifying high-risk persons, inferring patients' condition from their medical records, and monitoring patient condition to prevent complication. Unfortunately, in practice these steps are often difficult to perform due to sparse and incomplete medical records. Obtaining periodical medical condition of diabetic patients is difficult since many of them drop out during treatment, and each patient might require different measurement which results in sparse and incomplete health measurement data. On the other hand, the widespread use of mobile devices with various sensors and instant communication capability has enabled healthcare providers to collect and monitor patients' condition, such as blood pressures, weights, and blood sugar levels, and activities, with minimal interruption to patients' daily activities.

In this paper, we study the role of sensor data analytics to complement sparse and incomplete medical records for diabetes disease management. We tested various machine-learning techniques on real-world datasets of diabetic patients, and found that sensor datasets can be used to improve the precision of identifying high-risk patients. On a set of patients who performed up to four times of medical check-up, we found patients that were classified as having worse fast plasma glucose (FPG) value or having worse HbA1c value at the last medical check-up could be predicted using the results of their first-time medical check-up and the values of their sensor datasets. The prediction accuracies were better with more sensor data, and hence showing the importance of monitoring patients with sensors for diabetic disease management. We also found evidences that monitored patients tend to have lower FPG than unmonitored patients. We believe that our study is the first to show the plausibility of sensor data sets in disease management that enhance many previous work on predicting patients' future health state, such as, [3] and [2].

2. Methods

We describe methods used for exploiting electronic medical records of patients along with their sensor data for diabetes disease management.

2.1. Problems and Data Sets

The problems that are considered in this paper include two types of prediction outcomes. The first type is to predict the future (real) values of HbA1c (also called glycohemoglobin) and Fast Plasma Glucose (FPG). The HbA1c values reflect the average plasma glucose concentration over prolonged periods of time (two or three months), while the FPG values reflect the amount of glucose in the blood 12 hours after eating. A patient with HbA1c higher than 6.5 is considered to have diabetes, while the values of FPG is used for monitoring the state of disease management of patients with diabetes. The second type is to predict the binary values of the state of patients after treatment: having worse HbA1c or FPG values, or not (better, or roughly the same). More formally, the problems are:

Input: Patients' electronic medical records at the first medical check-up and their temporal sensor data on their weights, blood pressures, blood sugar values, and activities.

Output: Patients' values of HbA1c, FPG, and the states of the values of HbA1c and FPG at the final medical check-up compared to the initial ones (worse, or normal/same).

The electronic medical records and temporal sensor data sets in this paper are obtained from anonymous patients' records collected from around November, 2008 to January, 2009. The medical records consist of observation data sets (such as, age, sex, height, weight, types and number of chronic diseases, and so on), and measurement data sets (taken during medical check-ups at hospitals, such as, cholesterol, blood pressures, blood sugar, and so on). The temporal sensor data sets are gathered from sensor devices that were distributed to a selected set of patients. The sensor devices collect patients' weight, blood pressure and sugar values, as well as patients' activities (walking, running, etc).

2.2. Label

For determining the states of patients, their values of HbA1c and FPG at the final check-up are compared against those at the first check-up. Each patient performed at least two and at most four medical check-ups during the period of data collection. A patient state is called *worse* if his values of HbA1c or FPG were higher than the initial values by several percents, provided that his HbA1c or FPG values satisfied the condition of diabetic patients[1].

2.3. Performance Evaluation

The predicted real values of HbA1c and FPG for each patient are evaluated against their true values (from the last medical check-up) using the Mean Squared Error (MSE). We performed Leave-One-Out Cross Validation and computed the MSE of all patients for each predictive model described in the next subsection. For the binary prediction (worse or normal/same values of HbA1c or FPG), the predicted values are compared against their true values to obtain the area under the receiver operating characteristic curve (AUC) using Leave-One-Out Cross Validation. The AUC value for the binary classification is the same as 1 − MSE.

2.4. Predictive Model

In this paper, we use the framework of generalized linear model (GLM) to predict the values of HbA1c and FPG. In GLM, the predicted value y_i of patient i is obtained from a linear combination of his input data (medical records and temporal sensor data), $\mathbf{x_i} = (x_{i1}, ..., x_{in})$, where n is the length of inputs. Namely, $y_i = w_0 + \sum_{j=1}^{n} w_j x_{ij}$. One of the advantages of GLM is that we can obtain the values of weight vector elements and interpret their signs as their positive or negative contribution to the predicted values. The magnitude of their absolute values can also be used to find significant factors to the predicted values.

Several methods are used to obtain the weight vector $\mathbf{w} = (w_0, w_1, ..., w_n)$. We used Linear Regression (*LR*), Ridge Regression (*RR*), Lasso (*Las*), and Bayesian Ridge Regression (*BRR*). *LR* finds a weight vector w that minimizes the sum of squared differences of predicted values and true values. *RR* is similar to *LR* but puts a penalty to the sum of square of the weight vector element. *Las* can produce sparse weight vector by assigning a penalty to the sum of absolute value of the weight vector element. *BRR* is similar to *RR*, but it assumes the Gaussian distribution of the weight vector element. For binary prediction, we employed Logistic Regression (*LogitR*). Readers are directed to standard

[1]See, e.g., Executive Summary: Standard of Medical Care in Diabetes – 2011

textbooks in machine learning, such as, [1] for detailed discussions of those methods.

3. Experimental Results

To perform experimental results using predictive methods described in the previous section, we first prepared medical records and temporal sensor data sets by: (1) preprocessing data, (2) interpolating missing values, and (3) building feature vectors. Once we obtained a feature vector $\mathbf{x}_i$ for each patient i, it is straightforward to apply the aforementioned predictive models.

The preprocessing of medical records is essential since some elements of records are categorical (i.e., sex, stages of complication, etc.), or different patients can have different elements of records due to different treatments they received. We employed interpolation of missing element values by using the median of record values from other patients, as suggested in [3].

We experimented with 68 patients: 35 patients without and 33 ones with intervention of sensor devices. From 35 patients without intervention, there were only observation and measurement data sets. Prior to preprocessing, each patient of this set had 35 fields of observation records, and 89 fields of measurement records. After preprocessing, those numbers became 13 and 50, respectively. The fields of observation records include age, sex, weight, height, and stages of diabetic complication, while those of measurement records include blood sugar levels when fasting and after meals, blood pressure, glycoalbumin, HbA1c, FPG, and other lab test data.

From 33 patients with intervention, besides observation and measurement data sets, there were also temporal sensor data sets that recorded weight, blood pressure, blood sugar, and activities. The activities contain types and their frequencies which were determined by acceleration sensor devices developed by Bycen Co. Ltd. For each type of activities, we created a field of feature vector whose element denoted the averaged frequencies of each activity per day. For other sensor values, we created elements of feature vectors from their mean and standard deviation, which is quite standard in the literature (see, e.g., [4]). After preprocessing, the number of fields in the measurement data sets is 35, which is 30% less than that of patients without intervention.

On the patients without intervention, we labeled them with worse diabetic state if their HbA1c or FPG values at the final check-up were higher by at least 6% from those at their initial check-up. On the patients with intervention, we labeled them with worse diabetic state if their corresponding values of HbA1c or FPG were worse by at least 5%. From this labeling, we obtained 15 patients (out of 35 patients) without intervention whose final states were worse, while there were 16 patients (out of 33 patients) with intervention whose final states were worse.

Table 1 shows the values of MSE (the lower the better) of each predictive method for HbA1c and FPG on patients without intervention. We can see that *RR* (Ridge Regression) produces the best prediction for HbA1c, while *Las* (Lasso) produces the best prediction for FPG.

Table 3 shows the values of MSE of each predictive method for HbA1c and FPG on patients with intervention. Notice that on those patients, there were less number of features from measurement records, and more features from temporal sensor devices. We can observe that *Las* (Lasso) gives the best prediction for both HbA1c and FPG.

Table 2 shows the variation of the MSE values when only a fraction of sensor data sets is used in *Las*. We can observe that the MSE values are very much the same for predicting the values of HbA1c and FPG on patients with intervention.

With regards to binary prediction on the state of patients, we found that by using Logistic Regression, the

Method	HbA1c	FPG
LR	2.28 (4.47)	17907.23 (27564.32)
RR	**0.46** (0.95)	13929.64 (22108.35)
Las	0.69 (1.73)	**5343.62 (12337.31)**
BRR	0.48 (0.98)	7412.27 (15375.31)

Table 1: The MSE (and its variance) of predictive methods for HbA1c and FPG of patients without intervention.

Method	HbA1c	FPG
Las+0.25-sensor	1.10	2019.16
Las+0.50-sensor	1.14	2018.79
Las+0.75-sensor	1.19	2015.24

Table 2: The MSE of Lasso for HbA1c and FPG of patients with intervention. The variances for HbA1c and FPG are 5.0, and 5500, respectively.

Method	HbA1c	FPG
LR	2.16 (3.06)	3349.82 (4413.9)
RR	1.93 (2.81)	3208.54 (4228.0)
Las	**1.19 (2.68)**	**2015.24 (3893.53)**
BRR	1.59 (4.38)	2624.78 (4229.73)

Table 3: The MSE (and its variance) of predictive methods for HbA1c and FPG of patients with intervention.

Method	AUC
LogitR+0.25-sensor	0.45
LogitR+0.50-sensor	0.66
LogitR+0.75-sensor	0.70

Table 4: The changes in prediction accuracy (AUC) of Logistic Regression when using a quarter, half, and three quarters of sensor data sets.

value of AUC (the higher, the better) is ≈ 0.69 on patients without intervention. On the other hand, on patients with intervention, the value of AUC is ≈ 0.70.

On Table 4, we can observe the effect of temporal sensor data sets on the prediction quality of *LogitR* (Logistic Regression). When we only used up to the first quarter of sensor data sets, the prediction is not better than random quessing (LogitR + 0.25-sensor in the table). When we use up to half of the sensor data sets, the AUC becomes 0.66, and by using up to three quarters of them, the AUC is the same (0.70) as using the whole sensor data sets.

4. Discussion

We have seen in the previous section that Lasso (*Las*) gives the best accuracy for predicting FPG on patients without intervention, and for both HbA1c and FPG on patients with intervention. For HbA1c on patients without intervention, Ridge Regression (*RR*) gives the best one but the value is not that far from that of Lasso.

One of the advantages of Lasso compared to other generalized linear models is the ability to derive simple but important features that are highly correlated to the predicted values. This is due to the sparsity of coefficients of weight vectors produced by the method. On patients without intervention, Lasso showed that for predicting future values of HbA1c, the previous values of HbA1c, FPG, in-urine protein quantity, intraoral examination, coronary heart disease, and visits to diabetologist/urologist are important features. On the other hand, for predicting future values of FPG, those features are the previous values of FPG, HbA1c, intraoral examination, in-urine protein quantity, and age. Similary, those features can also be derived from Lasso on patients with intervention with several types of activities having effects of reducing the values of HbA1c.

From the experiments, we also observed that the sensor data sets did not give significant improvement for predicting the real values of HbA1c and FPG. However, the sensor data sets could improve the prediction quality of Logistic Regression for identiying patients whose HbA1c or FPG values were worse by 5% to 6% from their initial values.

We also compared the model learned from patients without intervention against patients with intervention to see the effects of monitoring patients with sensor devices. We found that there were 22 common features of measurement records of patients with and without intervention. Building predictive models on those features, we found that Lasso model that was constructed on patients without intervention could be used to predict HbA1c of patients with intervention with roughly the same quality on those without intervention. However, we found that the FPGs of patients with intervention were predicted higher than actual ones by models learned on patients without intervention.

It also seems that the Logistic Regression on patients without intervention could not be used on those with intervention, since the quality was worse than random quessing (ACU was less than 0.5). This might imply the importance of monitoring patients with sensor devices to identify high-risk patients, i.e., those whose HbA1c or FPG could be worse after some period of treatment.

5. Conclusion

We found that temporal sensor data sets that recorded variation of weight, blood pressure, blood glucose, and activities of diabetic patients could be used to improve the quality of prediction of the changes of their HbA1c and FPG values. The more sensor data sets, the better was the quality of the prediction. We presented experiments on various regression methods that hinted the possibility of sensor devices to identify high-risk patients without burdening them to have regular medical check-ups. We found that the data sets from the first medical check-up combined with the sensor data sets were sufficient to predict the future states of patients.

There are obviously many future work to pursue. For example, how to improve the prediction accuracy by methods such as SVM, or how to better interpolate missing values which are common in medical records.

References

[1] C. M. Bishop. Pattern recognition and machine learning, 2006.

[2] J. Davis, E. Lantz, D. Page, J. Struyf, P. Peissig, H. Vidaillet, and M. Caldwell. Machine learning for personalized medicine: Will this drug give me a heart attack? In *ICML'08*, 2008.

[3] H. Neuvirth, M. Ozery-Flato, J. Laserson, M. Rosen-Zvi, J. Hu, M. S. Kohn, and S. Ebadollahi. Toward personalized care management of patients at risk – the diabetes case study. In *KDD'11*, 2011.

[4] X. Sun, H. Kashima, R. Tomioka, and N. Ueda. Large scale real-life action recognition using conditional random fields with stochastic training. In *PAKDD'11*, 2011.

11. Yasunobu Nohara, Sozo Inoue,
Naoki Nakashima, Naonori Ueda,
Masaru Kitsuregawa:
Large-scale Sensor Dataset in a Hospital,
Proceeding of International Workshop on
Pattern Recognition for Healthcare Analytics,
9-12, 2012.

Large-scale Sensor Dataset in a Hospital

Yasunobu NOHARA
Kyushu University Hospital
y-nohara@info.med.kyushu-u.ac.jp

Sozo INOUE
Kyushu Institute of Technology
sozo@mns.kyutech.ac.jp

Naoki NAKASHIMA
Kyushu University Hospital
nnaoki@info.med.kyushu-u.ac.jp

Naonori UEDA
NTT CS-Labs
ueda.naonori@lab.ntt.co.jp

Masaru KITSUREGAWA
University of Tokyo
kitsure@tkl.iis.u-tokyo.ac.jp

Abstract

In this paper, we describe a sensor dataset, which was collected in a hospital, to be used for pattern recognition and/or data mining for medical purposes. The dataset includes those of patients and nursing care in a cardiovascular center in a hospital. The experiment was applied for hospitalized patients who caught such as an acute cardiac infraction or angina (pre-infarction), applied PCI (Percutaneous Coronary Intervention) or CABG (Coronary Artery Bypass Graft), and who have consented to the experiment. The patients provided vital sensor data such as monitoring cardiogram, bed sensor to measure heart rate and breath, accelerometer, environmental sensor, and also medical information which were recorded in the electronic clinical pathways and indirectly in patients' sensor data. At the same time, we also gathered accelerometer data of real nursing in the hospital. As far as we know, these data are the 'biggest data' of sensors which were used in a real hospital in real situations.

1 Introduction

In this paper, we describe a sensor dataset, which was collected in a hospital, to be used for pattern recognition and/or data mining for medical purposes. The dataset includes those of patients and nursing care in a cardiovascular center in a hospital. The experiment was applied for hospitalized patients who caught such as an acute cardiac infraction or angina (pre-infarction), applied PCI (Percutaneous Coronary Intervention) or CABG (Coronary Artery Bypass Graft), and who have consented to the experiment. The patients provided vital sensor data such as monitoring cardiogram, bed sensor to measure heart rate and breath, accelerometer, environmental sensor, and also medical information which were recorded in the electronic clinical pathways and indirectly in patients' sensor data.

At the same time, we also gathered accelerometer data of real nursing in the hospital. We asked nurses to bring smart devices (iPod touches), which have accelerometers, into their breast pockets with a roughly fixed direction. Moreover, they attached small 2 accelerometer devices on their right wrists and the back waists. We collected 100 hours data of 5964 activities which was labeled with 41 nursing activity classes and 7400 hours data of real nursing activities. As far as we know, these data are the 'biggest data' of sensors which were used in a real hospital in real situations.

Moreover, we analyze the correlations among multiple sensors. In order to see mutual effects among sensors including time lags, we calculate cross-correlation values between every pair of sensor data for each patient.

2 Plan for data collection

Clinical pathways, also known as critical pathways, are one of the main tools used to manage the quality in healthcare concerning the standardization of care processes. Clinical pathways reduce the variability in clinical practice and improves outcomes such as medical care cost and hospitalization period. A main objective of this research is finding factors that affect pathway outcomes by exploratory analysis[1]. There exists two types of affecting factors: one is caused by patients and the other is caused by medical staffs such as doctors and nurses. Therefore, we plan two experiments : one is for patients and the other is for medical staffs.

In the experiment for patients, we collect patients' various information including sensor data and their outcome in order to discover important patients' data that affect pathway outcomes. If we notice patients' variance before some hours, we may keep standard care process by appropriate cares and improve outcomes.

In the experiment for medical staffs, we collect nursing care information — when and what kinds of cares are done by nurses for patients. We invastigate what are important care factors — kinds of cares, work speed, care interval, years of experience of nurses etc.

3 Collected dataset

From April 2011 to March 2012, we have 70 patients who consent to this experiment. In this section, we describes the collected dataset.

3.1 Patient data

An electrocardiogram (ECG) is attached to the chest of the patients to collect the patients' vital data during the period from after the surgery to discharge. ECGs send vital data via wireless connection to an ECG monitor placed in a nursing station, and the ECG monitor centralizes these vital data. The vital data, which includes heartbeat, type of arrhythmia and ST level is stored on a PC connected to the ECG monitor. We have collected total 3900 hours of cardiogram data.

We use a bed sensor system in which a thin, air-sealed cushion is placed under the bed mattress of the patient[2]. The system measures heartbeat, respiration and body movement of the patient non-invasively by detecting the changes of air pressure of the cushion caused by their heartbeat etc. We have collected total 2500 hours of bed sensors.

The patients wear a 3-axis accelerometer on their wrist to measere the patients' movement. Accelerometers detect turn over in patients' sleep and measure the depth of their sleep. Moreover, accelerometers detects the position of the patients and help recognizing nurses' care for the patients by integrating the nurses' accelerometers data described in Section 3.3.

We also gather medical record of the patients — age, sex, height, weight, body temperature, blood pressure, diagnosis, medical cost and hospitalization period etc.

Figure 1. Nurses with three accelerometers

3.2 Environment data

In order to check the effect of patients' environment on their prognosis, three environment data loggers are placed on the patients' room and record four types of data — temperature/humidity, illuminance and loudness. Temperature and humidity are recorded every 5 seconds and the others are recorded every second. We have collected 5600 hours of environmental sensors' data.

3.3 Nurses data

Nurses who care the patients bring smart devices (iPod touches), which have accelerometers, into their breast pockets with a roughly fixed direction[3]. Moreover, they attached small two accelerometers on their wrist and waist(See Figure 1). These three accelerometers are used for recognizing when and what kinds of activities are done by the nurses. The nurses also carry an RFID tag and an RFID reader is installed on the entrance of each of the patients' rooms. RFID enables to detect nurses' entering and leaving of the rooms, i.e. when and for which patients nurses care. Therefore, we recognize when and what kinds of cares are done by the nurses for the patients. We have collected total 7400 hours of real nursing activities and 4600 hours of RFID data.

We also collect accelerometers data which is categorized by activities for supervised learning, which enables to predict nursing care using accelerometers data. These data is collected through a simulated nursing, in which the real nurses care for simulated patients (See

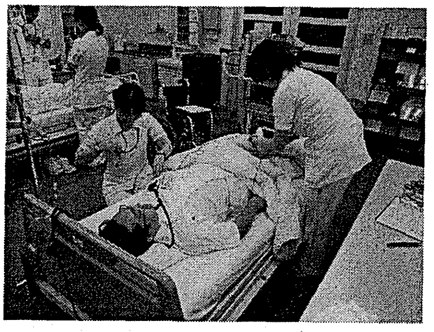

Figure 2. Simulated nursing for supervised learning

Figure 2). In the simulated nursing care, we collected 100 hours data of 5964 activities which are categorized 41 activity classes.

4 Preliminary analysis

In this section, we analyze the correlations among multiple sensors. One factor on the site may affect one or more sensors, or one sensor value may affect another. Moreover, such a mutual effect might have a time lag between sensors, since the effect might appear with latency. Therefore, to see mutual effects among sensors including time lags, we calculate cross-correlation values between every pair of sensor data for each patient.

By knowing cross-correlations among sensors, we can apply the result to higher-level pattern recognitions or data mining tasks, such as:

- To estimate the value of a sensor from another sensor, and alert if there are abnormal values by outlier detection.
- If there is strong correlations between sensors at a particular time lag, future-value prediction of a sensor form the/another sensor would be possible.
- To know the necessity of omitting independency among sensor values when they are used for pattern recognition inputs.
- To find optimum time lags of the sensors as an input variable to recognize a static values of the patient, or the care.

The procedure of the analysis is as follows: For each patient,

1. Take the median values of 1 minutes for each sensor value. Exceptionally, take number of entering the room from the RFID logs.
2. Divide them to 3 hours.
3. For every pair of sensors of 3 hours, calculate cross-correlation values with time lags of ± 60 minutes at maximum.

Utilized sensors are:

- (ECG monitor): from the ECG monitors which are placed in the nursing station, we extracted heart rates values and ST levels.
- (Bed sensor): from the bed sensors, heart rates, breath rates, and body movement rates were extracted.
- (RFID tags): from the RFID which identifies the entries of nurses, we counted the number of nurses' entries.
- (Environment sensors): the illuminance sensor, temperature/humidity sensor, and the loudness sensor data.

In the following, we show typical cross-correlations we obtained.

Figure 3 shows the cross-correlations between body movement and loudness for all patients, which is represented by box-and-wisker plot to show distributions among patients. Moreover, Figure 4 shows the cross-correlations between ECG heart rates and loudness for all patients. These figures show that loudness has correlations with body movement and ECG heart rates around 0 minutes. This implies that patients tend to move and the heart rates tends to be higher when there is noise. Using a bed sensor or ital sensors and such an environment sensor, we can know in which environmental condition patients states become active.

Figure 5 shows the cross-correlations between the number of nurse entries and illuminance for all patients. Moreover, Figure 6 shows those between nurse entries and loudness for all patients. If we look at the quantile values, we can see that nurse entries have positive correlations with illuminance and loudness around 0 minutes. Using a RFID and such environment sensors, we can know the relationship between nurses' entry and environment changes.

As shown in this section, by looking at the correlations between sensors, we can find which sensor value may affect another sensor. Moreover, since it seems that there exist stronger correlations if we see each sample,

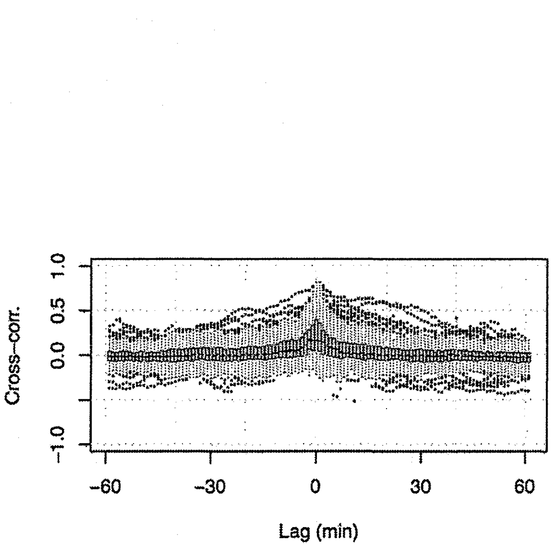

Figure 3. Cross-correlation between body movement and loudness for all patients.

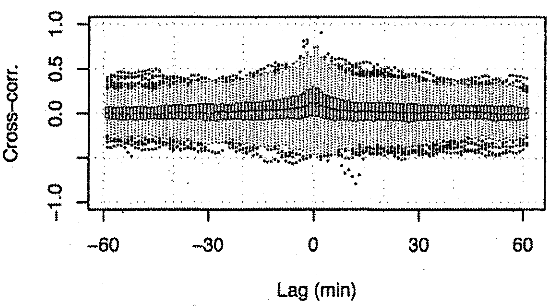

Figure 4. Cross-correlation between ECG heart rates and loudness for all patients.

we could find more effective correlations with personalized approach. Clustering patient to several categories of correlation natures and utilizing them for higher-level mining tasks are our future work.

5 Conclusion

In this paper, we described a sensor dataset, which was collected in a hospital, to be used for pattern recognition and/or data mining for medical purposes. The dataset includes those of patients and nursing care in a hospital. For analyzing nursing activities, we collected 100 hours data of 5964 activities which was labeled with 41 nursing activity classes and 7400 hours data of real nursing activities.

Moreover, we analyzed the correlations among multiple sensors. In order to see mutual effects among sensors including time lags, we calculated cross-correlation values between every pair of sensor data for each patient.

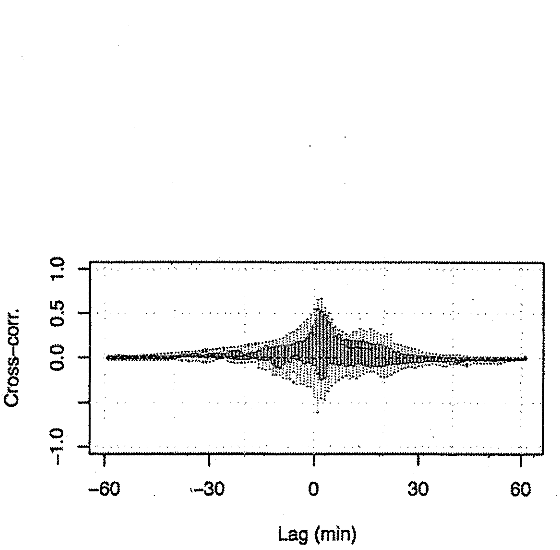

Figure 5. Cross-correlation between nurse entries and light sensors for all patients.

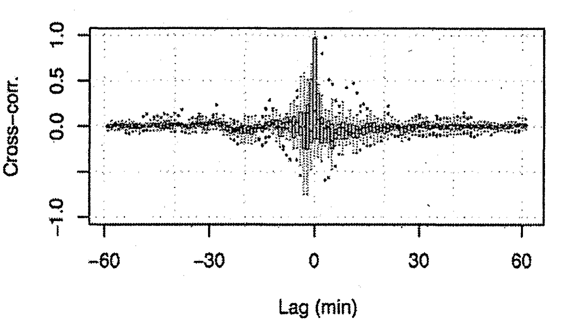

Figure 6. Cross-correlation between nurse entries and loudness for all patients.

References

[1] N. Naoki et al., "Exploratory Data Analysis to Extract Critical Indicators by Outcome Oriented Electronic Clinical Pathways and Body Area Sensors (in Japanese)", Japan Association for Medical Informatics Spring Conference 2012, Jun. 2012.

[2] K. Watanabe et al., "Noninvasive measurement of heartbeat, respiration, snoring and body movements of a subject in bed via a pneumatic method", Biomedical Engineering, IEEE Transactions on , vol.52, no.12, pp.2100-2107, Dec. 2005

[3] Y. Hattori and S. Inoue,"A Large Scale Gathering System for Activity Data using Mobile Devices", Journal of Information Processing, Vol. 20, No. 1, pp. 177-184, Sep. 2011

12. 中島直樹，若田好史，野原康伸，井上創造，
小妻幸男，副島秀久，田中雅夫:
アウトカム志向型電子パスと生体センサを用いた
探索的なクリティカルインディケータ抽出，
第 16 回日本医療情報学会春季学術大会
シンポジウム 2012 in 函館，
プログラム・抄録集，84-85，2012.