Developing a Framework of Biomedical Data Classification Methodologies for Telehealthcare Applications

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2013/07/17
Outline

✓ Research background
  • Home telehealth
  • Different categories of biomedical data in telehealthcare
✓ Research purpose
✓ Research methods
  • Four categories of biomedical data in telehealthcare
  • Example of each category
✓ Discussion & future work
RESEARCH BACKGROUND
Home telehealth

- Home has become the centerpiece of health delivery system today. Intensive monitoring of health parameters in the home environment is necessary for health care and management. [Office of Health and Information Highway, 1998]

- Home telehealth allows the patient the dignity of remaining in their own home for as long as possible and by providing care that is equal to or superior than approaches that rely solely on health providers coming into the home for scheduled visits. [American Telemedicine Association, 2007]
Home telehealth vs. telemedicine

✓ Home telehealth systems can provide access to the users’ monitored data for users themselves, contributing to health self-management and reduction in in-person home visits. [Bensink, M. et al., 2006; Finkelstein, S. M. et al., 2006]

✓ Home telehealth differs from telemedicine in the sense that people who transmit and receive medical information are not necessarily medical doctors but the patients themselves and their families, nurses, care-givers, home helpers and medical technical experts, etc. [Tsuji, M., 2002]
Main technical functions of a home telehealth system

✓ To collect biomedical data measured at home, to classify these data, and to generate real-time alerts for further actions.

This research focus on

Data collection

Classification

Alerts and actions
Different categories of biomedical data (I)

1. **Single-valued vital sign measurements**: blood pressure, heart rate, blood glucose, body temperate, body weight, etc.

2. **Vital sign time series**: the vital sign measurement with continuous values, such as ECG time series.
3. **Human motions & behaviors**: the measurement of body motions (such as gaits data, body movements during sleep, etc.) and recording of activities (such as activity of daily living, medication compliance, etc.).
Different categories of biomedical data (III)

4. **Subjective observations of symptom data**: the symptom data from observations & perceptions, such as pain, swollen and wound fluid.
RESEARCH PURPOSE
Research purpose (I)

✓ The purpose of this research is to **develop a framework for biomedical data classification for telehealthcare applications.**

✓ **Classifications of various biomedical data** measured in home telehealth applications are studied.

✓ **One data classification example is constructed** for each category.
Research purpose (II)

- A framework that can guide the development of methodologies for classifying different categories of biomedical data.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Telehealthcare</th>
</tr>
</thead>
<tbody>
<tr>
<td>Category</td>
<td></td>
</tr>
<tr>
<td>Single-valued vital sign measurement</td>
<td>Vital sign time series</td>
</tr>
<tr>
<td>Blood pressure, blood glucose</td>
<td>Heart beats</td>
</tr>
<tr>
<td>Rule-based expert system - TES</td>
<td>AIIA method</td>
</tr>
</tbody>
</table>
RESEARCH METHODS

Four categories of biomedical data in telehealthcare
Single-valued vital sign measurements (I)

✓ Needs

• **Real-time alerts**: method cannot be too complicated
• Classification rules are **composed by boundaries / thresholds** of the vital sign measurement
• **Customizations** of the rules **based on individual clinical history**
• **Detection of the compliance of vital sign measurements**
• **Detection of the malfunction of hardware devices** (vital sign meters and home gateway)
Single-valued vital sign measurements (II)

✓ Approach

• Using the **rule-based expert system** to classify single-valued vital sign measurements (e.g. blood pressure, blood glucose)

Vital sign time series

✓ Needs

- Algorithms to **extract features** representing **the characteristic of the time series**
- Classification is based on the comparison of **extracted features of disease groups with that of healthy groups**

✓ Approach

- Using the **adaptive feature analysis method** to classify vital sign time series (e.g. heartbeats time series)
Human motion & behaviors

✓ Needs

• Algorithms to **extract indices** representing **the characteristic of the data**
• Classification is based on comparing indices with **long-term data** or a big volume of samples

✓ Approach

• Using **statistical estimation method** for constructing the threshold
Subjective observations

√ Needs

• To derive clinical suggestions from subjective observation
• Classification based on human heuristics and machine learning

√ Approach

• Using the clinical decision support system to provide clinical indication from symptoms (e.g. pain, swollen, wound fluid) and clinical histories
RESEARCH METHODS

Example of single-valued vital sign measurements

Development and practice of a Telehealthcare Expert System - TES
Analysis

✓ **Category**: Single-valued vital sign measurement

✓ **Measured by**: vital sign meters (e.g. blood pressure)

✓ **Subjects**: patients with chronic diseases
  (e.g. hypertension, diabetes)

✓ **Method**: rule-based expert system - TES

✓ **Classification**: rules with boundaries / thresholds by doctors

✓ **Validation**: compare with vital sign measurement standards
  (e.g. AHA, ADA, WHO)

✓ **Further actions**: telehealthcare service provider receive alerts
  with urgent degrees

※ TES, telehealthcase expert system; AHA, American Heart Association;
ADA, American Diabetes Association; WHO, World Health Organization.
Method

✓ TES is designed to detect three different types of events:

1. Abnormality of vital signs
2. Violation of vital sign measurement prescriptions
3. Malfunction of hardware devices
Results (I)

- 2009~2011: **19,182** patients served by TES in M.S. Hospital
- Each patient is assigned 34.6 rules for abnormality of vital signs in average
- There were 23,455 measurement prescriptions given by doctors
- 41,755 events detected by TES

![Pie chart]

- **75.2%** violation of measurement prescription
- **22.9%** abnormality of vital signs
- **1.9%** malfunction of devices
Results (II)

✓ TES detects three types of events for the telehealthcare.
✓ TES not only detects the events of vital sign abnormality but also take care about users’ compliance of measurement prescription and malfunction of devices.
✓ TES also provides the mechanism to customize for each patient to provide the personalized care in the telehealthcare practice.
RESEARCH METHODS

Example of vital sign time series

Using n-gram analysis to cluster heartbeat signals
Analysis

✓ **Category**: vital sign time series
✓ **Measured by**: vital sign instruments (e.g. ECG/EKG)
✓ **Subjects**: 72 patients with heart diseases (apnea: 20 patients) from PhysioBank
✓ **Method**: adaptive feature analysis method - AIIA
✓ **Classification**: classic classifiers (e.g. Bayesian Network)
✓ **Validation**: compare with the data of 40 healthy subjects from PhysioBank
✓ **Further actions**: telehealthcare service provider receive heart disease alerts

※ AIIA, Adaptive Interbeat Interval Analysis; ECG/EKG, Electrocardiography.
※ PhysioBank is a large and growing archive of well-characterized digital recordings of physiologic signals and related data for use by the biomedical research community.
Method (I)

✓ This research presents the “Adaptive Interbeat Interval Analysis (AIIA)” method.

✓ The AIIA method uses the Simple K-Means algorithm for symbolization, which offers a new way to represent subtle variations between two interbeat intervals without human intervention.

Interbeat intervals

Data clustering for symbolization
Method (II)

✓ After symbolization, it uses the **n-gram analysis** to **analyze features** of each **symbolic sequence**.

✓ Finally, the symbolic sequences are **categorized by classic classifiers** (e.g. Bayesian Network, Support Vector Machine).

※ P, Probability of occurrence.
Results

✓ AIIA method achieved 91% (3-gram, 26 clusters) accuracy in successfully classifying between the patients with Atrial Fibrillation (AF), Congestive Heart Failure (CHF) and healthy people.

✓ It also achieved 87% (3-gram, 26 clusters) accuracy in classifying the patients with apnea.

✓ The two experiments demonstrated that AIIA method can categorize different heart diseases.

✓ Both experiments acquired the best category results when using the Bayesian Network classifier.
RESEARCH METHODS

Example of human motions & behaviors

Assessing Abnormal Gaits of Parkinson Disease Patients Using a Wearable Motion Detector
Analysis

✓ **Category**: human motion & behaviors (e.g. gait cycle parameters)

✓ **Measured by**: wearable motion detector (WMD)

✓ **Subjects**: 5 patients with Parkinson’s disease

✓ **Method**: statistical estimation – lower confidence limit

✓ **Classification**: thresholds at different confidence level

✓ **Validation**: compare with the data of 25 health subjects from recruitment

✓ **Further actions**: telehealthcare service provider receive abnormal gaits alerts
Method (I)

✓ Gait cycle parameters \((D_1, D_2, S)\) are derived from the measured trunk accelerations by autocorrelation procedure:

- **Step regularity** \((D_1)\): defined as the regularity of each step
- **Stride regularity** \((D_2)\): defined as the regularity of two steps
- **Step symmetry** \((S)\): defined as the symmetry between two steps of both legs
Method (II)

✓ This research attempts to assess abnormal gaits of Parkinson disease (PD) patients based on the gait cycle parameters derived in real-time from an accelerometry-based wearable motion detector.

✓ Five PD patients diagnosed as Hoehn & Yahr stage I to II were recruited.

✓ It is difficult to collect data of abnormal gaits of the PD patients; therefore, ranges of the gait cycle parameters of abnormal gaits of PD patients were estimated statistically based on the “lower confidence limit” of the gait cycle parameters of their normal gaits.
Results

- If a PD patient is walking normally and then develop an abnormal gait, **a warning signal can be issued in real-time** to remind the patient to adjust his or her stride.

<table>
<thead>
<tr>
<th>Type I error $\alpha$</th>
<th>Confidence level $100 \times (1-\alpha)%$</th>
<th>Gait cycle parameters $D_1$</th>
<th>$D_2$</th>
<th>$S$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>90%</td>
<td>0.4797</td>
<td>0.5059</td>
<td>0.8317</td>
</tr>
<tr>
<td>0.05</td>
<td>95%</td>
<td>0.4712</td>
<td>0.4974</td>
<td>0.8214</td>
</tr>
<tr>
<td>0.025</td>
<td>97.5%</td>
<td>0.4636</td>
<td>0.4897</td>
<td>0.8121</td>
</tr>
<tr>
<td>0.01</td>
<td>99%</td>
<td>0.4543</td>
<td>0.4802</td>
<td>0.8007</td>
</tr>
</tbody>
</table>

Table 4-5. The lower confidence limits of gait cycle parameters of normal gaits of PD patients
Results

- If a PD patient is walking normally and then develop an abnormal gait, **a warning signal can be issued in real-time** to remind the patient to adjust his or her stride.
RESEARCH METHODS

Example of subjective observations of symptom data

Development of a telehealthcare decision support system for patients discharged from hospital
Analysis

✓ **Category**: subjective observations
  (e.g. pain, swollen, wound fluid)

✓ **Measured by**: patient themselves observations and perceptions of their body

✓ **Subjects**: 1,467 patients discharged from hospital

✓ **Method**: telehealthcare decision support system (TDSS)

✓ **Classification**: predictive model
  (generated by machine learning algorithm)

✓ **Validation**: validate with the 1,467 clinical histories

✓ **Further actions**: nursing team receive indication of the need of revisiting a doctor
Method (I)

The application scenario of TDSS

Patients → Phone calls → Symptoms → Call center

Parameters input → Indication

Predictive model → Machine learning algorithm

Telehealthcare decision support system (TDSS)

Clinical histories

Clinical records → Hospital Information Systems (HIS)

Doctors → Revisit the doctor regularly

Nurses
Method (II)

The flow chart of TDSS
Method (III)

✓ This research is focus on the design of TDSS for providing the indication of the need of revisiting a doctor for patients discharged from hospital in telehealthcare.

✓ TDSS collects 49 parameters (e.g. pain, swollen and wound fluid symptoms) from patients and hospital information system and provides 1 indication (e.g. patient need to return to the hospital immediately, patient need to make appointment with doctor in 3 days) to nurses in telehealthcare.
TDSS uses **machine learning** algorithms such like Bayesian Network, Logistic, Neural Networks and Support Vector Machine to generate and update a **predictive model** from **real patient cases’ parameters (symptom) input and clinical histories** to provide the indication of the need of revisiting doctor.
Results (I)

✓ **TDSS was used to collect 1,467 patients** discharged from Min-Sheng General Hospital.

✓ For most of the patients, the indication for a need to revisit a doctor is validated as “Tracking needed in one week” with a degree of urgency of 3 (67.6%).

<table>
<thead>
<tr>
<th>No.</th>
<th>Urgency degree</th>
<th>Indication of revisiting doctor</th>
<th>Patients</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>No need for advanced tracking</td>
<td>289</td>
<td>19.7%</td>
</tr>
<tr>
<td>2</td>
<td>3</td>
<td>Tracking needed in one week</td>
<td>992</td>
<td>67.6%</td>
</tr>
<tr>
<td>3</td>
<td>5</td>
<td>Tracking needed in three days</td>
<td>71</td>
<td>4.8%</td>
</tr>
<tr>
<td>4</td>
<td>7</td>
<td>Suggest that an appointment be made with doctor in three days and tracking needed again in three days</td>
<td>100</td>
<td>6.8%</td>
</tr>
<tr>
<td>5</td>
<td>9</td>
<td>Suggest that patient visit doctor or return to hospital immediately and tracking needed again in 24 hrs</td>
<td>15</td>
<td>1%</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Total</strong></td>
<td><strong>1,467</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>
The best performance of classifiers is the **Tree J-48 algorithm**.

- It correctly classified 1,166 instances in 1,467 patients, and the precision **under the 10-fold cross validation is 79.5%**.

### Table 5-10. Performance comparison among machine learning algorithms

<table>
<thead>
<tr>
<th>Machine learning algorithm</th>
<th>Correctly classified</th>
<th>Incorrectly classified</th>
<th>Performance (10 C.V.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tree J-48</td>
<td>1,166</td>
<td>301</td>
<td>79.5%</td>
</tr>
<tr>
<td>Bayesian Network</td>
<td>1,163</td>
<td>304</td>
<td>79.3%</td>
</tr>
<tr>
<td>Support Vector Machine (SVM)</td>
<td>1,147</td>
<td>320</td>
<td>78.2%</td>
</tr>
<tr>
<td>Neural Networks</td>
<td>1,142</td>
<td>325</td>
<td>77.9%</td>
</tr>
<tr>
<td>Logistic</td>
<td>1,142</td>
<td>325</td>
<td>77.9%</td>
</tr>
</tbody>
</table>

※ 10 C.V., 10-fold cross-validation.
The performance of the nursing team (clinical personnel) is also evaluated and compared with TDSS.

Table 5-12. The performance evaluation and comparison among TDSS and nursing team

<table>
<thead>
<tr>
<th>Performance evaluation item</th>
<th>Calculation</th>
<th>TDSS</th>
<th>Nurses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>TP / (TP + FN)</td>
<td>0.63</td>
<td>0.68</td>
</tr>
<tr>
<td>Specificity</td>
<td>TN / (TN + FP)</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>PPV</td>
<td>TP / (TP + FP)</td>
<td>0.39</td>
<td>0.3</td>
</tr>
<tr>
<td>NPV</td>
<td>TN / (TN + FN)</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td>FPR</td>
<td>FP / (FP + TN)</td>
<td>0.05</td>
<td>0.057</td>
</tr>
<tr>
<td>FNR</td>
<td>FN / (FN + TP)</td>
<td>0.37</td>
<td>0.32</td>
</tr>
<tr>
<td>LR+</td>
<td>Sensitivity - (1 - Specificity)</td>
<td>0.58</td>
<td>0.62</td>
</tr>
<tr>
<td>LR-</td>
<td>(1 - Sensitivity) / Specificity</td>
<td>0.39</td>
<td>0.34</td>
</tr>
<tr>
<td>Pre-test probability (Prevalence)</td>
<td>(TP + FN) / (TP + FP + FN + TN)</td>
<td>0.049</td>
<td>0.034</td>
</tr>
<tr>
<td>Pre-test odds</td>
<td>Prevalence / (1 - Prevalence)</td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td>Post-test odds</td>
<td>Pre-test odds x Likelihood ratio</td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td>Post-test probability</td>
<td>Post-test odds / (Post-test odds + 1)</td>
<td>0.047</td>
<td>0.03</td>
</tr>
</tbody>
</table>

TP, true positive; TN, true negative; FP, false positive; FN, false negative; PPV, positive predictive value; NPV, negative predictive value; FPR, false positive rate; FNR, false negative rate; LR+, positive likelihood ratio; LR-, negative likelihood ratio
DISCUSSION & FUTURE WORK
Discussion & future work (I)

✓ This research is focus on the **developing a framework of biomedical data classification methodologies** for telehealthcare applications.

✓ **Four categories of biomedical data are demonstrated** with corresponding example methods to provide classification results for further actions in telehealthcare.
Discussion & future work (I)

✓ Data and methods which are demonstrated in this research **are not one and only method for each category.**

✓ **More other cases of biomedical data** (e.g. ADL, sleep, etc.), **methods, related literatures and approaches** can be collected and developed for completing this framework and this research in the future.
Thank you

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