Towards Simulation of Patient Data for Evaluation of E-Health Platform and Services

O.Lo, L. Fan, W. Buchanan, C. Thuemmler and A. Lawson
Faculty of Engineering, Computing & Creative Industries
Edinburgh Napier University, Edinburgh, UK
O.Lo@napier.ac.uk

***Abstract*—This paper presents the design and implementation of the Patient Simulator, a software application used for the simulation of patient data. The simulator aims to evaluate e-Health platforms and services in regards to efficiency, reliability, security and scalability without the need to use real patient data. Using discrete event based simulation in conjunction with random normal distribution techniques, preliminary prototyping of the Patient Simulator shows that it is capable of generating five vital physiological signs including heart rate, blood pressure, body temperature, oxygen levels and respiration rate. Offline performance evaluation of the software shows that it is capable of simulating up to 10,000 patients with average CPU utilisation of 57.53% and memory usage of 159.30 MB. Future work aims to validate the accuracy of data simulated along with integrating the simulator with existing e-Health technologies to evaluate the capabilities of this software in an online environment.**

Keywords: Patient Simulation; e-Health Evaluation; Patient Modelling; Discrete Event Simulation; Normal Distribution; Vital Physiological Sign Simulation

I. Introduction

E-Health brings about an ease of communication for the health care industry as a whole [1]. However, there is also an increased risk of patient privacy being violated in the case of using electronic systems. A prime example of this occurred in 2009, when the English National Health Service (NHS) lost thousands of medical records [2] due to a lack of security in their computer systems. More recently in July 2011, the NHS was once again put under the spotlight when computer criminals attempted to gain access to their systems which held patient medical records [3]. Although this recent attack was unsuccessful, one could easily justify that patients may still feel rather uneasy about medical facilities storing their personal data in an e-Health environment.

To alleviate unease, and to validate the capabilities of e-Health, evaluation of this technology is essential. Key attributes which should be considered during evaluation include scalability, efficiency and functionality of the e-Health implementation. One method of evaluating e-Health technologies is to conduct a live clinical trial. Recent research including [4], [5], [6] have achieved this goal. However, many legal [7] and ethical [8] barriers exist in performing live clinical trials since real patient data will be manipulated and stored. The risk and consequences of patient data being compromised in any manner would reflect badly on both the clinical organisation participating in the live trial and the developers of the e-Health implementation.

To enable rapid and safe evaluation of e-Health technologies to take place, this paper proposes the concept of using simulated patient data in place of real world patient data. The software application, named the Patient Simulator, generates patient data based on models of patients rather than the use of real-world data. Simulation of patient data enables extensive testing and validation of e-Health implementations to be take place whilst mitigating both legal and ethical barriers faced in live clinical trials. The primary contribution this paper makes is in presenting the design and implementation of the Patient Simulator. Furthermore, this paper presents an offline performance evaluation of the simulator to demonstrate the capabilities of this software application.

The remainder of this paper is organised as follows. Section II sets context for this research by providing background on e-Health technologies and patient simulation. Section III shows related work in the field of healthcare simulation and how this research differs. Next, Section IV discusses the design of the Patient Simulator, including the modelling of a virtual patient and the methodology applied during simulation. Implementation and performance evaluation carried out on the Patient Simulator are outlined in Section V. Finally, Section VI provides a conclusion and discussion of future work.

II. Background

A. E-Health Technologies

In essence, E-Health is the concept of using digital technologies for communication and storage of patient data. E-Health encompasses a wide variety of technologies therefore, to provide definition in the context of this paper, we consider two primary categories of e-Health: platform and services.

E-Health platforms can be considered the primary infrastructure which enables the storage and management of patient data. Current existing e-Health platforms include Microsoft HealthVault [9], DACAR Platform [10], DOSSIA [11] and World Medical Card [12]. E-Health platforms are generally managed on standard hosting technologies such as private servers, web based servers (e.g. Microsoft HealthVault) or cloud based servers (e.g. DACAR Platform). In comparison, as the name implies, e-Health services are services which offer improved patient health care to take place. E-Health services range from simple mobile applications [13] which enable

the retrieval and logging of patient data to more complex technologies such as clinical risk assessment services (for use in monitoring a patient's health status).

Both e-Health platform and services interact primarily with patient data. In order to test and validate these technologies, patient data is essential. In order to mitigate the difficult process of carrying out live clinical trials (due to legal and ethical barriers), this paper proposes simulation of patient data rather than the use of real-world patient data. The next subsection provides background to the concept of patient simulation.

B. Patient Simulation

The term Simulated Patients (SP) often refers to the practice of using trained professionals, i.e. actors, to interact with health workers, e.g. medical students or nurses in training. Scenarios are re-enacted between the SP and health workers to allow the trainee to develop his or her skills, such as history taking, physical examination and counseling [14]. This form of role play allows a health worker to grow accustomed to interacting with patients in their day-to-day work along with assessing how effective their skills as a medical professional are [15].

The Patient Simulator (not to be confused with Simulated Patients) borrows some of the concepts of SPs but with the goal of modelling and simulating patients for evaluation of e-Health platform and services. The Patient Simulator models both the physical, i.e. vital physiological signs, and non-physical, e.g. patient id, name, and address, attributes of a patient. The aim of the Patient Simulator is to generate all aspects of patient data, which can be used in the testing and validation of e-Health platforms and services.

The current implementation of the Patient Simulator is capable of simulating five of the vital physiological signs of a patient, namely Heart Rate (HR), Blood Pressure (BP), Body Temperature (Temp), Oxygen Levels (SpO2) and Respiratory Rate (RR). This paper presents simulation of these vital physiological signs which are considered within the range of "normal". However, simulating "abnormal" vital physiological signs, i.e. vital signs which deviate from the norm, is a future requirement as this brings about the possibility to test and validate e-Health services in terms of their capability to handle anomalous data.

To avoid ambiguity, it should be clarified that the Patient Simulator is not a Human Patient Simulator (HPS) but a completely virtual patient. The disambiguation between HPS and the Patient Simulator is discussed in the related works section which follows.

III. Related Works

Laerdal presents SimMan®, a full-scale robotic mannequin [16] which is capable of simulating the physical attributes of a patient. Dedicated software, which can either be run on a personal computer or a replicated patient monitor, allows for the simulation of vital physiological signs of the mannequin. Although evaluations carried out on SimMan®have generally been favorable [17], [18], it is classified as a HPS whereby the main aim of such simulation is for the purpose of educating medical personnel for training purposes by providing a physical representation of a human body (i.e. a mannequin) [19]. This paper differs from the work of SimMan®, since it aims to provide a completely virtual patient (VP), one which is catered towards the e-Health environment rather than provide training for medical personnel.

Hwang et al. proposes the integration of both HPS and VP to provide a physical simulation of a patient and a virtual simulation of the clinical environment [20]. The HPS component of their work is a mannequin which models the clinical signs, e.g. heart rate, blood pressure, body temperature, of a patient using scripts whilst the VP component acts as a interactive clinical environment allowing users to "control" the mannequin with predefined commands. One novel feature of this work is the ability of the HPS to react to speech commands via the VP system. Similar to this paper's work, the work of Hwang et al. allows for the simulation of vital physiological signs however, it is again catered towards a educational learning environment and does not aim to provide a complete virtual representation of a patient and the data they produce.

With focus on work towards vital physiological sign simulation, Agar et al. presents a simulation system which is capable of simulating blood glucose and insulin levels of both healthy patients and patients with Type 1 diabetes [21]. The model they present is focused on the physiological compartments which relate specifically to blood glucose and insulin levels including the heart, brain, liver and kidney as examples.

The virtual reality world Second Life [22] has been a domain in which health care simulation systems have been popular. The work of Beard et al. identified five main categories of health care simulations found in this virtual world including education and awareness, support, training, marketing and promotion of health services and research [23]. As Second Life is, in essence, a user-driven interactive world with the main goal of providing entertainment, it was found that most health care simulation was simply to provide users with information rather than employing any techniques to simulate actual patients.

In regards to discrete event based simulation, both Meng et al. and Kolb et al. have proposed to apply this technique to the modelling of emergency hospital environments [24], [25]. Both works are quite similar in which they propose the concept of applying discrete event based simulation to research overcrowding and waiting and processing times in emergency departments of hospitals. This paper presents the simulation of patients entities rather than the traffic flow produced by them.

IV. Simulation Design

A. Patient Modelling

A variety of ontologies have been proposed by researchers in defining a model of a patient including [26], [27], [28]. The Patient Simulator adopts a simplified ontology, whereby two main categories of attributes are considered: non-medical

attributes and medical attributes. Within the subclass of medical attributes, these may be further split into dynamic medical attributes and static medical attributes.

This model features a "plug-and-play" architecture which allows for the ability to easily add further attributes so long as they fall under either non-medical attribute or medical attribute.

Non-medical attributes refer to attributes which, though important, do not have significance when applied to a health care environment. In other words, medical staff will not take these attributes into consideration when it comes to diagnosing a patient's health. Examples of non-medical attributes are:

- *Patient Identification* - A unique ID which is given to each patient
- *Forename(s)* - The first given name of a patient along with any middle names
- *Surname* - The last given name of a patient
- *Home Address* - Patients address of residence

Medical attributes are split into two subcategories: static and dynamic attributes. Static attributes are defined as such since they will not generally change regardless of a patient's health status. Examples of the static medical attributes are as follows:

- *Blood Type* -Blood type of patient (ie. A, B, AB or O)
- *Gender* - Male or Female
- *DoB* - Date of Birth of a patient

Finally, dynamic medical attributes relate to a patient's vital physiological signs, which have the characteristics of discrete change throughout a patient's stay in a health care facility. Examples of the dynamic medical attributes include:

- *HR* - The heart rate of a patient, measured in the unit of beats per minute (BPM)
- *BP* - The systolic blood pressure of a patient, measured in mmHg (millimeters of mercury)
- *Temp* - Temperature of a patient's body, measured in degree celcius (°C)
- *SpO2* - Oxygen level of a patient, measured in percentage (%)
- *RR* - Respiratory rate of patient, measured in Breathing Frequency (BF) per minute

B. Simulation Methodology

For the simulation of vital physiological signs, a Discrete Event-based Simulation (DES) method is employed. A vital sign value is generated periodically using random normal distribution techniques. **DES** refers to a simulation system in which variables only change at specific points in time (known as the time interval). As a comparison, the opposite of DES system would be a Continuous Event-based Simulation (CES) system which - as the name implies - will have variables which change continuously throughout the simulation period [29].

The choice of simulation method depends entirely on the goal of simulation. For instance, since DES models variables which only change at specific points in time, it is well suited to simulating the events taking place on a factory production line. However, since CES will model events continuously, this method is better suited to simulating systems which will have constant changes, such as a stock market [30]. In the implementation of the Patient Simulator, a DES approach has been taken since there is only a need to model a variable, i.e. vital signs, at certain intervals. The use of DES best reflects scenario's which take place such in real life clinical environments, e.g. when a patient is in the Intensive-Care Unit (ICU) monitoring devices will only log his or her data at periodic intervals. The use of CES would not be suited for this simulation since it would produce too much variation within any given time scale, and thus result in unrealistic vital signs being generated.

C. Generation of Vital Physiological Signs

The probability statistics concept of **Normal Distribution** has been applied for the generation of vital physiological sign values. Alternatively known as Gaussian Distribution [31], normal distribution is the theory that by generating a set of random values, and applying the mean (average) and standard deviation (variance), the values will tend to cluster around the mean [32], [33].

To provide an example, consider the vital physiological sign of a patient's heart rate. The work of Fox et al. state that the average heart rate of a normal healthy adult person will fall under the range of 75 to 85 beats per minute (BPM) [34]. Given this fact, for the purpose of generating a heart rate using normal distribution, it can be stated that the mean value is equal to 80. In applying the arbitrary value of 1.5 for standard deviation, a random number of X samples will provide variables which will resemble a bell-curved chart as shown in Figure 1. In using this technique for the generation of vital physiological signs at each time interval, i.e. the discrete event, the concept of "controlled randomness" is produced, yet the simulation retains realism in the variables due to the fact that the values will always be catered towards a mean. In other words, the vital physiological signs which simulated will never deviate too far from what is considered abnormal, e.g. a heart rate of 300 BPM at time interval 1 and then a heart rate of 10 BPM at time interval 2 would never occur.

Defining a mean value for each vital physiological sign is outlined later on in this section but, unfortunately, determining the standard deviation proves to be a lot more difficult. In determining the standard deviation which would be applied to heart rate, as an example, one must consider the heart rate variance (HRV) of a patient. The HRV is the change in a person's heart rate from each time interval. A number of factors contribute to the HRV of a patient, including the gender and age of a patient, the lifestyle choices they make, e.g. smoking and alcohol consumption [35] and any diseases they may have such as diabetes [36].

Due to such complexities in defining a variation for heart rate (and the other four vital physiological signs), by default, the Patient Simulator applies a arbitrary standard deviation for each of the vital signs. The default standard deviation value

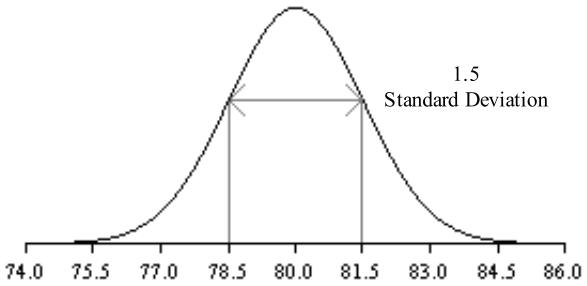

Figure 1. Normal Distribution of Heart Rate

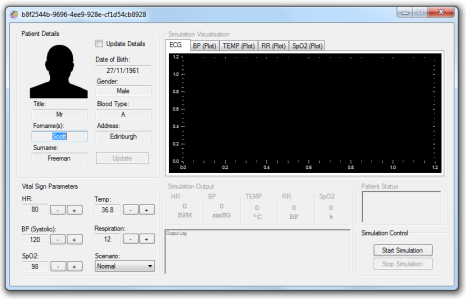

Figure 2. Patient Simulator GUI

used for each vital sign is relatively small, with heart rate (as an example) using the value of 1.5.

Table I presents the default mean and arbitrary standard deviation applied to all five vital physiological signs which are simulated in a patient by default. The mean value of blood pressure is based on the work of Pesola et al. in which they state that a normal systolic blood pressure is found to be 112 mmHg [37]. From studies carried out by both Mackowiak et al. and Shoemaker the result of 36.8 °C [38], [39] is applied for the mean body temperature. O'Driscoll et al. defines normal Spo2 as 96-98% [40], hence the average value of 97% is used. Finally, both Sherwood and Tortora et al. agree that the mean respiration rate is found to be 12 breaths per minute [41], [42].

V. Implementation and Evaluation

A. Patient Simulator Prototype

The Patient Simulator was implemented using Microsoft .NET C#. A simple GUI interface was developed for the software to allow for ease of use (Figure 2). The built-in timer component provided by the .NET framework is used in the implementation of the discrete event simulation technique discussed in Section IV-B. At each "tick" interval, the simulation of the five vital physiological signs will take place. The default time interval is one second however, this can easily be adjusted by the user. For the generation of the vital physiological signs, a modified version of the Random Number Generator class library [44] was used.

Within the class library, five classes are implemented, one for each vital physiological sign. An object-oriented programming approach was taken, whereby all five vital sign classes inherit from the abstract class "VitalSign". Using this approach, a instance of each vital sign can be created and calling the *Generate* method enables the generation of a vital sign. The *Generate* method requires the passing of two variables, the mean and standard deviation. The method then carries out the normal distribution calculations and returns a value, i.e. the vital physiological sign.

Table I
Mean and Standard Deviation of Vital Signs

Vital Sign	Mean	Standard Deviation
Heart Rate	80 BPM	1.5
Blood Pressure	112 mmHg	2
Body Temperature	36.8°C	0.2
SpO2	97%	0.5
Respiration Rate	12 breaths per min	1

B. Offline Performance Evaluation

The primary aim of this evaluation was to determine the maximum amount of patients which can be simulated on a single machine along with assessing the performance load which *N* number of patients would entail. Thus, the metrics monitored in this performance evaluation included the two primary attributes of a system which are CPU utilisation and memory usage. This experiment attempts to evaluate the performance of the core simulation engine code in regards to resource management, scalability and functionality - the GUI performance of the implementation is not considered. For the scope of this experiment, the patient simulator runs in standalone mode. No interaction to any e-Health platform or service takes place. The simulated data is simply output to the console to validate that the process of simulation is taking place. The specification of the machine used in this experiment is detailed in Table II.

To monitor the metrics of CPU utilisation and memory usage the inbuilt Windows monitoring tool, named Perfmon, is used. Concise documentation of this tool can be found in in [45]. In the case of this experiment, two counters were configured using Perfmon:

- **Process(<Process Name>)\%Processor Time**
- **Process(<Process Name>)\Private Bytes**.

<*Process Name*> is the process to be monitored (the patient simulator application in this case). *%Processor Time* provides detail on the percentage of CPU utilised by the application whilst *Private Bytes* provides details on the total amount of memory requested by the application.

In each instance of running this experiment, *N* number of patients would simulate all five vital physiological signs at every 1 second interval. Each simulated patient was configured

Table II
Specifications of Experiment Machine

OS:	Windows 7 Professional 64 bit Edition
CPU:	Intel Dual Core i3 540 4.39GHz
Memory:	4GB DDR3
Storage:	465 GB HDD

to simulate 500 samples of data. One sample of data consists of all five vital physiological signs. The total duration of each experiment was approximately 8 minutes and 25 seconds (1 second interval * 500 samples of data).

Perfmon was configured to monitor CPU and memory usage at every 1 second interval and output to a log file. Up to 10,000 patients were simulated concurrently. The results are presented in the next section.

C. Evaluation Results & Discussion

Figure 3 and Figure 4 shows the average CPU utilisation and memory usage from groups of 100, 1000 and 10,000 patients which were successfully simulated to completion.

In the case of simulating 100 patients, the average CPU utilisation was found to be 2.33%. Average CPU Utilisation of 1000 and 10,000 patients was 22.71% and 57.53% respectively. It can be stated that increased number of patients simulated result in higher CPU utilisation. However, with an average value of less than 60% CPU utilisation, it can also be stated that the Patient Simulator does not consume much CPU even with high volumes of patients simulated concurrently.

For memory usage, 100 patients produced an average of 43.79 MB whilst 1000 and 10,000 patients produced 27.72 MB and 159.30 MB respectively. The maximum memory usage was 281.33 MB which occurred during the simulation of 10,000 patients. In regards to this metric, the first point which can be stated is that the Patient Simulator does not use much memory. With 4 GB of RAM installed on the machine used for these experiments, the simulator places very little stress on this particular resource. This can be further attributed to the fact that the patient simulator requires very little resource to be stored in memory to begin with.

However, although overall memory usage was quite low, an interesting anomaly of results was produced during the gathering of this metric. Unlike CPU utilisation, memory usage did not grow in such a straight forward manner in comparison with CPU utilisation. From the memory usage graph (Figure 4), it can be seen that 1000 patients apparently used less memory than 100 patients. This is attributed to the fact that the Perfmon metric **Process(<Process Name>)\Private Bytes** can only show how much memory is requested by a process rather than the how much memory is consumed at any given instance in time. Thus, in the case of simulating 100 patients, the software requested more memory than was actually necessary. Possibilities for optimisation of code exist to ensure the simulator does not request more memory that it actually consumes.

VI. Conclusion & Future Work

This paper presents work carried out on the design, implementation and offline performance evaluation of a software application called the Patient Simulator. The Patient Simulator aims to simulate the key attributes of patient data which are otherwise known as vital physiological signs. It's proposed that the use of the Patient Simulator enables rapid testing of e-Health platform and services to take place without the need to use real-world patient data hence mitigating both legal and ethical barriers imposed by live clinical trials. The results obtained in conducting an offline evaluation of the Patient Simulator show that it is capable of simulating up to 10,000 patients concurrently without stressing either CPU utilisation or memory usage to any great extent.

However, although the performance evaluation results are positive, multiple areas of future work need to be conducted. Firstly, both quantitative and qualitative validation techniques will be looked at in order to compare and contrast the simulated patient data against real-world patient data. This is an essential part of this research to ensure the accuracy of the simulated patient data. It is especially important in the case of using the Patient Simulator to test and validate e-Health services such as clinical risk assessment systems.

The second area of future work involves deploying the Patient Simulator in a online environment whereby interaction and uploading of patient data will take place between the software and an e-Health technology. With network overhead implications, live interaction with an e-Health technology will produce more accurate results on how well the Patient Simulator performs in comparison with an offline evaluation.

The third area of future work is to define evaluation metrics which can be obtained from an e-Health platform or service

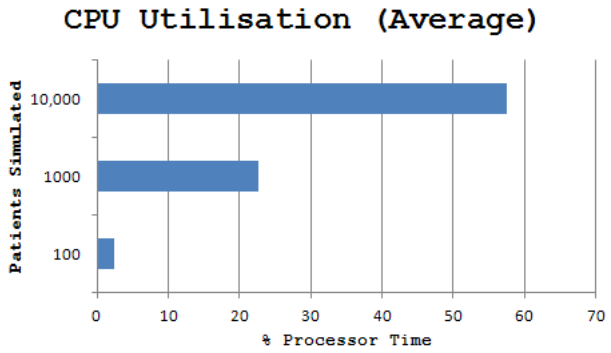

Figure 3. CPU Utilisation Results

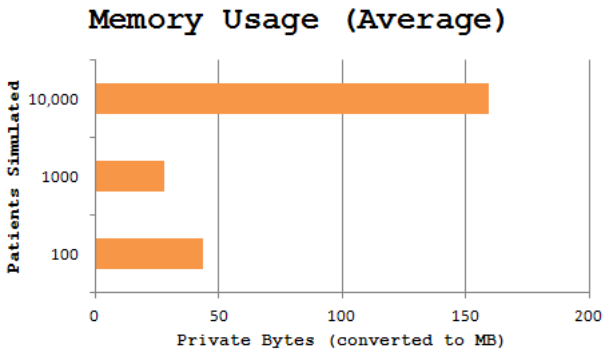

Figure 4. Memory Usage Results

via the Patient Simulator. Example of evaluation metrics include the response time, scalability, security, performance and network usage of an e-Health technology. The end goal of this research is to show that meaningful evaluation of e-Health platform and services may take place without the need to conduct a live clinical trial or use real world patient data.

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