Intelligent Determination for Readmission of Postoperative Patients in Ambulatory Surgery

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Abstract—The present paper presents an intelligent system which determines the need for readmission in postoperative patients of ambulatory surgery, after being discharged. The decision made by the system depends on the answers given to a follow-up questionnaire, which includes questions related to the recovery state of the patient, and information about his/her medical records stored in a database. In order to carry out the system, Artificial Neural Networks (ANNs) were implemented to model clinical decision-making, by using different configurations of ANN, to select the one that presented the highest success rate in the decision.

Index Terms—Follow-up questionnaire, intelligent decision maker, neural network, patient monitoring.

I. INTRODUCTION

Patients of ambulatory surgery, who are discharged in the first days after the procedure, generally receive medical instructions about the proper care they should have during that period. On occasions, when their organisms present unexpected changes, some patients ignore what may be negative reactions and self medicate inappropriately, while others get disturbed by changes that may be normal. The medical personnel, unaware of the condition of patients after surgery, do not proceed immediately to cases of complications, or occupy their time with patients who do not need any special care. According to [1], the percentage of patients who really need medical assistance after discharging is about 0.8%, for a sample of 250 patients.

Different solutions have been proposed for monitoring patients in their homes, for instance, regularly scheduled nurses’ home visits [2]; nurse-led telephone questionnaires [1]; follow-up by sending mobile-phone images of surgically treated areas [3]; monitoring by sending videos and vital signs information with medical devices [4]; follow-up through mailed questionnaires [5]; monitoring using wireless sensor networks to examine patients mobility [6], among others. However, one or more limitations can be found in the previous solutions, including:

1) They require medical staff availability, either to design and examine the questionnaires, or by directly monitoring patients.
2) The motion and biomedical sensors are characterized by high complexity in their development and/or with high-associated costs.
3) They implement technological tools that can be complicated for patients with limited computer knowledge.

Monitoring patients during this period not only would improve the hospital services quality, but also anticipate cases of possible complications or avoid overcrowding medical centers with false alarm cases. Furthermore, a better management of medical personnel’s time and medical center’s resources brings as a result a reduction of hospital costs [1], [2].

For all of the above reasons, this paper attempts to propose an alternative approach for patient monitoring, through an intelligent decision maker which determines when patients require immediate readmission, need to schedule an appointment with the physician, or are recovering within the normal range. The decision is made according to the answers given by the patients to a follow-up questionnaire, in addition to their clinical information.

II. GENERAL DESCRIPTION

The purpose of the present project was to develop an intelligent decision maker, which would pose a solution to the problem of monitoring postoperative patients in ambulatory surgery. This project focused specifically on solving the limitation in previous solutions of consuming time of medical personnel.

To determine the need for readmission, a generic questionnaire containing key factors about patient status, including possible complications, was developed. According to [7], reliable and validated generic questionnaires could produce similar results to disease-specific questionnaires, and in the current project it could be used for patients of different kinds of surgeries. In this sense, five general surgeries were selected to be followed-up: appendectomy, cholecystectomy, herniorrhaphy, exploratory laparotomy and cesarean section.

The basic structure of the survey, including the design of the question bank, was defined with the medical team according to the most common complications in ambulatory surgery. Among those complications there were included pain, infection, nausea, bleeding, urinary retention and overall dissatisfaction [1], [8].

All the parameters considered to compute the final decision score of the questionnaire had different weights,
since some complications had greater contribution than others. To determine these weights, several authors proposed to perform a factor analysis, or a variant thereof called principal-component analysis, considering the correlation matrix between the different elements [7], [9]. To obtain this matrix it was necessary to conduct a thorough study on how to correlate the independent variables, including different complications and comorbidities of patients, through data obtained by means of surveys.

Due to time constraints to perform a set of surveys, as well as difficulty to find information in the literature reviews about the correlation of each of the factors included in measurement scale, the weight of the items in the questionnaire were defined implementing a soft computing technique, developed in the computational tool MATLAB.

Depending on the answers of each item in the questionnaire and the medical records of the patient, the intelligent system had to give an estimated value indicating the recovery status, and based on that value, the system had to define whether or not to alert the medical personnel, in order to readmit the patient.

The intelligent system was trained according to expert opinion on the issue, considering a large number of possible types of patients that could use the tool, and it was validated in accordance with the decision that medical personnel would take, under new input conditions. The patients training and test data sets were obtained using random generators with uniform distributions, limited to adult patients, whose ages are in the range of 18 to 45 years and who have no mental and/or physical disability.

III. THEORETICAL FRAMEWORK

For a better understanding of the proposed project, it is necessary to review key concepts.

A. Ambulatory surgery

Ambulatory surgery is defined as the surgical procedure performed under local or general anesthesia, where the surgical patient can generally return to home the same day of operation, to carry out there the late postoperative period.

Ambulatory surgery is characterized by reduced costs associated with hospitalization, between 20 and 46%, besides presenting similar results or even overcoming them with respect to the traditional hospital system, increasing the degree of patient satisfaction [10], [11].

B. Postoperative period

This period begins immediately as soon as the patient leaves the surgery, and extends until the patient recovers completely.

The postoperative period for ambulatory surgery patients can be divided into three phases: I: early, II: intermediate and III: late.

1) Phase I: Includes the awakening and recovery of vital reflexes. During this period vital signs are monitored, such as blood pressure and respiratory rate, besides the degree of consciousness.

2) Phase II corresponds to the process of gradual recovery until the patient is ready to go home.

3) Phase III: The process of full recovery, held in the patient’s home [1], [12].

The present project aims to follow up in Phase III or late recovery phase during postoperative period, when patients are discharged.

IV. RELATED PROJECTS

Below, related works covering different solutions to the problem of monitoring patients of ambulatory surgeries, by using diverse techniques and tools, are presented.

The purpose of the article presented in [16] was to validate an objective scoring system proposed by the authors, called ‘Post-Anesthetic Discharge Scoring System’, PADSS, which determines when ambulatory surgery patients are ready to go to their homes, according to their recovery process. This was achieved using a questionnaire that handled quantitative information about the patient, emphasizing five specific criteria: vital signs, blood pressure, heart rate, respiratory rate and temperature.

The proposed system was compared with the existing criteria for discharging patients in the ambulatory surgery unit of The Toronto Hospital, Toronto Western Division, called "Clinical Discharge Criteria." The results obtained show a high correlation of the criteria for discharge between the two methods, indicating that PADSS can be used to replace the Clinical Discharge Criteria.

The advantages of PADSS are that the system is practical, simple, easy to remember and reproducible, eliminating the subjective factor when assigning numerical values to the parameters of recovery.

In [17] the authors present a predictive model which sets the cases of readmission of ambulatory-surgery patients, based on certain factors such as the body mass index, age, ASA (American Society of Anesthesiologists) status, gender, comorbidity, type of surgery and postoperative symptoms. These factors were clustered into four groups: surgical reasons, anesthetic, medical and social.

To register the patient, Post-Anesthetic Discharge Scoring System, PADSS, mentioned in [16], was implemented.

The system was developed using regression models for univariate and multivariate logistic, which established what factors were associated with the need for readmission, and the respective associated weight.

The authors determined that situations such as performing surgery in the morning, give adequate support in the homes, and implement aggressive techniques to treat pain, nausea and vomiting may reduce recidivism of patients in surgery.

In the project presented at [18] it was developed a statistical model to predict the state of patients discharged from ambulatory surgeries, also establishing the probability of readmission. To validate the system, the patients were followed up by telephone, and predictions were compared with responses given by them, specifically on the following parameters: sleep, pain, oral intake tolerance, and bleeding. Predictors were age, gender, ASA status, time of surgery, discharge time, type of anesthesia, surgical specialty and ambulatory surgical Incapacity (ASI).
The results showed that it is possible to make a predictive model in the first hours after discharging patients, where factors such as age, gender, type of anesthesia and ASA have an important weight for prediction.

In [1], a monitoring service for ambulatory surgery patients through phone calls was implemented, made by nurses of the Hospital Dr. Peset of Valencia, Spain. In the phone calls, a set of pre-specified questions were asked and depending on the answer given, it was assigned an established score for each question. The sum of the values obtained could be used as an estimated of the state of the patient.

One of the limitations of the project was the subjective nature of the telephone assessment, which indicated that they should be cautious when interpreting the results. Thus it was defined three relevant aspects: working with a large sample of patients, define the categories of each parameter included in the score, and conduct the evaluation by the same observers. Another limitation was the need of medical personnel to perform the phone calls personally.

To classify patients according to pain, taking into account whether or not they have symptoms of neuropathic pain, in [19] it was designed an artificial neural network and compared with established scoring systems, such as the Neuropathic Pain Questionnaire (NPQ) and Neuropathic Pain Scale (NPS), which involve traditional statistical techniques, besides the method of logistic regression (LR). Different descriptors and pain symptoms were used to characterize patients, since any descriptor enables the characterization by itself.

Previous results demonstrated the applicability of intelligent systems in this type of problem, to obtain results with an accuracy level similar or even slightly higher than traditional techniques. Regarding to LR, similar results were obtained, showing that nonlinear relationships between descriptors do not have a significant role in the classification process.

The systems presented in [1], [16], [17] and [18] include different methodologies to determine the status of patients in postoperative state, using methods of linear and nonlinear modeling, but do not use intelligent systems. The questionnaires that some of them implement are different from each other, since there is not a defined standard survey.

The system implemented in [19] shows that is possible to use soft-computing techniques in place of other traditional statistical techniques used in the scoring manual systems.

V. PROPOSED APPROACH

Fig. 1 presents the preliminary block diagram of the project. In the first stage it was necessary to define the surgeries that would be monitored, to select the complications and elements in the medical history of patients that significantly could affect the decision of the need for readmission. From there, the follow-up questionnaire was designed, specifying the questions of the survey and the type of answers per question that patients could select.

Based on the questionnaire, the parameters of the intelligent system design were determined, assigning the complications and information about medical records of patients as the inputs, and the presence of three significant complications, that indicates if patient need readmission, as the output. These major complications corresponded to:
1) Signs of infection.
2) Signs of hypovolemia.
3) Signs of dehydration.

Each of the questionnaire items was selected in conjunction with an expert in the area, from literature review of the most common complications in ambulatory surgery patients. These questions corresponded to symptoms of at least one of the conditions listed above, as shown in Table I.

The Artificial Neural Networks soft-computing technique was implemented, because of its utility to assign weights to sets of correlated data, which allows developing a score system by using the values produced by the network. With the opinion of the experts it was possible to determine a set of cases where patients require immediate re-entry, or must request an appointment for medical examination. This criterion was applied to a group of randomly-generated patients, with uniform distribution, and formed the basis of patient data for the networks training.

![Fig. 1. Block diagram of the system.](image-url)
The next step was to carry out the verification, in order to determine if the system had been properly trained. In the final stage, the validation of the system was performed by comparing the response of the intelligent system with the decision made by the medical team, using new input data under the same conditions.

VI. EXPERIMENTS AND RESULTS

The inputs of the artificial neural network corresponded to the answers given by patients to the 17 survey questions, and their value could be modified with the presence of certain comorbidities that impact negatively on any of them, as the presence of obesity, hypertension, diabetes, cerebrovascular or cardiovascular diseases, or cancer. For example, if a patient was diabetic and presented a minor bleeding, the corresponding input for bleeding was modified as if the patient had a severe bleeding. The type of responses of each question is presented in Table II.

<table>
<thead>
<tr>
<th>Symptoms</th>
<th>Possible answers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tenderness</td>
<td>No pain / Deep pain / Superficial pain</td>
</tr>
<tr>
<td>Redness</td>
<td>No / Blush on the wound / Redness / Violet</td>
</tr>
<tr>
<td>Local fever</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Swollen lump</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Bleeding</td>
<td>No / Insignificant / Mild / Severe</td>
</tr>
<tr>
<td>Purulent material</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Fever</td>
<td>Below 36.5°C / Between 36.5 and 37.5°C / Above 37.5°C</td>
</tr>
<tr>
<td>Tachycardia</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Cold extremities</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Nausea &amp; Vomiting</td>
<td>No / Vomiting food / Vomiting liquid</td>
</tr>
<tr>
<td>Shortness of breath</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Disruption of wound</td>
<td>No / Open wound / Dehiscence of some sutures</td>
</tr>
<tr>
<td>Thirst</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Dry Mouth</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Decreased urine retention</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Diarrhea</td>
<td>Yes / No</td>
</tr>
<tr>
<td>Abdominal distension</td>
<td>Yes / No</td>
</tr>
</tbody>
</table>

The neural network was designed with one hidden layer, with a maximum of 20 neurons. The transfer functions of the hidden and output layers were modified, and each one could have any of these functions: ‘Logarithmic sigmoid’ (Logsig), ‘Linear’ (Purelin) or ‘Tangent sigmoid’ (Tansig).

For the experiments, 10 repetitions per level were set as initial values for testing. In the event of not reaching a level of stability, they would be modified. The employed neural network scheme is displayed in Fig. 2.

Given these parameters and using the data set for training, a series of experiments was conducted to determine the configuration of artificial neural networks whose success rate was the highest.

To determine the total number of experiments, a Full factorial design or Fully crossed design was conducted, where all possible combinations of all levels were performed. According to this design, if there are \( k \) factors, each one with \( n \) levels and \( r \) repetitions per level, the total number of experiments is given by (1).

\[
NTE = r \prod_{i=1}^{k} n_i
\]

Thus, 10x(3x3x20) = 1800 experiments were performed with all the 3x3x20=180 possible combinations of neural networks configurations. For these experiments, the transfer functions in both layers and the number of neurons in the hidden layer were modified, as listed above, repeated 10 times each one. Afterwards, the highest-performing networks for each of the 180 configurations were selected and displayed, in order to verify the system, based on the training data. Fig. 3 to Fig. 11 present the success percentages of the best networks for each configuration, subdivided according to the type of transfer function. In those figures, the success rate of the decisions for infection, hypovolemia, or dehydration can be compared, plus an average of the three previous values, regarding to the number of neurons in the hidden layer.

The configurations of artificial neural networks with the best performance at the verification stage were the networks with transfer functions ‘Logarithmic sigmoid’ in the hidden layer and ‘Tangent sigmoid’ in the output layer, Fig. 5, and ‘Tangent sigmoid’ both in the hidden and the output layer, Fig. 11.
Fig. 3. Performance of the ANNs with T.F. Logsig-Logsig (LL).

Fig. 4. Performance of the ANNs with T.F. Logsig-Purelin (LP).

Fig. 5. Performance of the ANNs with T.F. Logsig-Tansig (LT).

Fig. 6. Performance of the ANNs with T.F. Purelin-Logsig (PL).

Fig. 7. Performance of the ANNs with T.F. Purelin-Purelin (PP).

Fig. 8. Performance of the ANNs with T.F. Purelin-Tansig (PT).
Fig. 12 to Fig. 14 present the Box and Whisker diagrams of the verification stage, for each configuration of transfer functions in the intelligent system.
V. CONCLUSIONS

From the conducted tests it was possible to verify the validity of using neural networks to determine the need for readmission of ambulatory surgery patients, by means of a follow-up questionnaire.

In the networks presented in Table III and Table IV, the success rate was quite acceptable. It can be observed in Table IV that when decision was No readmission or Emergency readmission, the success rates were greater than 98%. On the other hand, for Hypovolemia both networks accurately classified all the patients according to the symptoms they presented. For Dehydration, the success rate was of 100% in network 169, whereas for Infection it was greater than 90%.

In general, during the validation step network 169 obtained a higher success rate than network 49. However, network 49 presented a better performance in Infection when deciding that patient needed to Schedule a medical appointment. For that reason the outputs of both networks were combined using (2) for the Infection output, obtaining a system with a decision success rate over 96%.

These results suggest that Intelligent System can be implemented as an alternative to design health measurement scales in place of other proposals such as Factor Analysis.

ACKNOWLEDGMENT

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REFERENCES


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TABLE III

<table>
<thead>
<tr>
<th>Decision</th>
<th>Infection</th>
<th>Hypovolemia</th>
<th>Dehydration</th>
</tr>
</thead>
<tbody>
<tr>
<td>No readmission</td>
<td>0.94</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Schedule medical appointment</td>
<td>0.993</td>
<td>1</td>
<td>0.982</td>
</tr>
<tr>
<td>Emergency readmission</td>
<td>0.952</td>
<td>1</td>
<td>0.976</td>
</tr>
</tbody>
</table>

TABLE IV

<table>
<thead>
<tr>
<th>Decision</th>
<th>Infection</th>
<th>Hypovolemia</th>
<th>Dehydration</th>
</tr>
</thead>
<tbody>
<tr>
<td>No readmission</td>
<td>0.987</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Schedule medical appointment</td>
<td>0.907</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Emergency readmission</td>
<td>0.981</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

\[ O_{\text{Infection}} = ANN_{1,\text{Infection}} \cdot C_1 + ANN_{2,\text{Infection}} \cdot C_2 \] (2)

After different tests, the best performance was obtained when \( C_1 \) and \( C_2 \) were equal to 0.5. The results are presented in Table V. According to these results, the success rate for Emergency readmission slightly decreased, but for Schedule medical appointment presented favorable increase, enhancing the performance of the system.

---

TABLE V

<table>
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<tbody>
<tr>
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<td>1</td>
<td>1</td>
</tr>
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<tr>
<td>Emergency readmission</td>
<td>0.966</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>


