ANALYSIS OF BERG BALANCE SCALE IN HIP FRACTURE PATIENTS USING FUZZY CLUSTERING

Aleksandar Jeremic[1], Natasa Radosavljevic[2], Dejan Nikolic[3] and Milica Lazovic[4]

[1]*Department of Electrical and Computer Engineering, McMaster University, Hamilton, ON, Canada*

[2]*Institute for Rehabilitation, Belgrade, Serbia*

[3]*Physical Medicine and Rehabilitation, University Childrens Hospital, Belgrade, Serbia*

[4]*Faculty of Medicine, University of Belgrade, Belgrade, Serbia*

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Abstract: Hip fractures are most frequent cause of hospitalization after the fall in older population and consequently have been subject of great interest in medicine and biomedical engineering. It has been observed that the incidence of hip fractures is rising at the approximate rate of 1-3% per year, with subsequent mortality rates at approximately 33% in first year after the fracture. In this paper we propose to classify patients at the time of admission into several clusters with respect to their ability for successful recovery. To this purpose we first evaluate the efficacy of rehabilitation program based on the balance function improvement measured by Berg Balance Scale (BBS) in elderly (in the remainder of the paper defined as above 65 years of life) after hip fractures, and evaluate influence of gender, age and comorbidity on balance function improvement in these patients. Then we design clustering procedure in which the patients are clustered according to BBS improvement using statistically most significant parameters. We then evaluate the proposed clustering procedure on a data sample consisting of 203 patients that have been admitted to the Institute for Rehabilitation, Belgrade, Serbia.

1 INTRODUCTION

Hip fractures are most frequent cause of hospitalization after the fall in older population (Roudsari et al., 2005) and consequently has been subject of great interest in medicine and biomedical engineering. It has been observed that the incidence of hip fractures is rising at the approximate rate of 1-3% per year, with subsequent mortality rates at approximately 33% in first year after the fracture (Johnell and Kanis, 2004; Roche et al., 2005). Consequently because of the increasingly large number of elderly patients with these fractures significant advances have been made with respect to surgical procedures, post-surgical rehabilitation procedures as well as social support services. It is often emphasized that management and allocation of resources is of utmost importance in patient care. In practical situations the amount of resources is limited and thus proper assignment of priorities may play crucial role in recovery. As an example certain patients experiencing hip fracture may show significant progress if surgeries and rehabilitation programs are allocated in timely manner thus leading to more efficient health care.

One of the most important aspects of rehabilitation in these patients is habilitation for independent walking which has been strongly correlated with the balance establishment and/or improvement in these individuals. Furthermore it has been reported that the balance improvement has demonstrated strong negative correlation with probability of further falls and hip fractures in elderly (Berry et al., 2007). One of the commonly used techniques (measures) for balance evaluation is Berg Balance Scale (BBS) and it has been demonstrated that it is of particular interest in elderly population (Santos et al., 2011). In this paper we propose to classify patients at the time of admission into several clusters with respect to their ability for successful recovery. To this purpose we first evaluate the efficacy of rehabilitation program based on the balance function improvement measured by Berg Balance Scale (BBS) in elderly (in the remainder of the paper defined as above 65 years of life) after hip fractures, and evaluate influence of gender, age and comorbidity on balance function improvement in these patients. Then we design clustering procedure

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in which the patients are clustered according to BBS improvement using statistically most significant parameters. It is often argued that proper administration of intrahospital as well as post-recovery procedures can significantly improve the recovery of patients. To this purpose it would be extremely beneficial to properly triage (cluster) patients at the admission stage in order to ensure optimal distribution of resources. We then evaluate the proposed clustering procedure on a data sample consisting of 203 patients that have been admitted to the Institute for Rehabilitation, Belgrade, Serbia.

The paper is organized as follows. In Section II we describe the data set and the proposed classification models. In Section III we evaluate the applicability of the proposed algorithm using a real data set. Finally, in Section IV we discuss the results and future work.

2 SIGNAL PROCESSING MODELS

2.1 Data Set

The prospective study included 203 patients with hip fractures that were referred into the specialized rehabilitation institution for the rehabilitation program and admitted from january 2011 until June 2011. Prior to the inclusion into the study, eligible participants were informed about the study protocol and rehabilitation program with possible contraindications that might arise over the course of treatment. The informed consent was obtained prior to the inclusion. The study was approved by the Institutional Review Board. Implementation of rehabilitation program was individually prescribed with respect to the patients functional status and continuously monitored for early identification of possible complications that could arise during the treatment. Functional status of every individual in the program was evaluated by the Berg Balance Scale test on 3 occasions: at the admission (Group 1), at discharge from the rehabilitation facility (Group 2) and 3 months after discharge (Group 3). Berg Balance Scale test evaluated 14 tasks (5 static and 9 dynamic) that are graded as 5 points scale with the range from 0 to 4, to the maximal value for the summarized scores of 56 (Stevenson et al., 2010). Ability to predict falls in elderly population suggests the validity of BBS test (9). The BBS is used to measure functional balance that is composed of 3 dimensions: position maintaining, postural adjustment to voluntary movements and reaction to external disturbance (Berg et al., 1995).

2.2 Preprocessing

We organize the data set in a database consisting of 203 rows corresponding to the patients and 33 columns of different features (age, height, weight, respiratory conditions, heart conditions, BBS at the admission, BBS at the discharge, BBS three months after discharge, etc.) Then we analyze cross-correlation between all the features and extract statistically significant ones using Pearson coefficient. In order to study dynamics of rehabilitation we use log-values of BBS score ratios. The rationale behind this approach is that we expect exponential change in balance improvement and thus log (semi-log) models may represent better fit.

2.3 Clustering Algorithm

Once statistically significant features have been selected the problem reduces to clustering of m-dimensional vectors into a set of pre-determined clusters. In order to determine appropriate use of clinical resources as a preliminary approach we propose to determine which patients have largest/smallest capacity for recovery. We propose to determine the significant parameters using Spearman correlation coefficient which is commonly used technique in cases/models where nonlinearity is expected. We then propose to cluster all the patients into several clusters. We investigate two possible scenarios in this paper: a) two-cluster scenario consisting with high rate recovery and low rate recovery patients, and b) three-cluster scenario - low, medium, and high rates of recovery. Note that the number of clusters can be arbitrarily set and is usually controlled by the overall error of classification. In addition, the quality of health care and resource management can be relatively robust to the overall error of classification and thus the overall results in treatments may not change significantly for small variations in number of clusters.

In order to cluster the data set we propose to use fuzzy clustering based on Gath-Geva (Gath and Geva, 1989) clustering which uses Gaussian distance and consequently assumes that the data set arises from mixture of Gaussian distributions. A general outline of the algorithms is as follows: a) arbitrarily assign each patient to a cluster i.e. arbitrarily pick if the patient is high or low rate recovery. Note also that the preliminary clustering can be either done arbitrarily or using a hard clustering algorithms such as K-means, b) update cluster centers, c) reassign objects to the clusters to which the objects are most similar, d) repeat until no change by reassignment. The update of clustering matrix is done using the following approa-

Table 1: General characteristics of patient population with respect to the age and severity index of fracture.

	Age	Severity Index
Total N=203	77 ± 6.11	1.74 ± 0.49
Female N=149	78.28 ± 5.86	1.74 ± 0.43
Male N =54	76.19 ± 6.56	1.76 ± 0.64
Group1 N=65	70.48 ± 3.14	1.72 ± 0.65
Group 2 N=114	79.92 ± 2.88	1.75 ± 0.41
Group 3 N=25	86.56 ± 1.39	1.73 ± 0.37

ch: if there is any distance greater than zero then membership grade is the weighted average of the distances to all the centers else the patient belongs to this cluster and no other clusters. Note that in GG algorithm the distance calculated is Gaussian distance given by

$$d_{ie} = \frac{1}{P_i} \det A_i^{\frac{1}{2}} \exp\left(\frac{1}{2}(x_e - \nu_i)^T A^{-1} (x_e - \nu_i)\right)$$

where ν_i is the cluster center, P_i is the probability that patient x_e belongs to the ith cluster and A_i is the weighted sample covariance matrix the ith cluster with membership values being the weighting coefficients.

3 RESULTS

In order to evaluate the performance of our techniques we should ideally have the possibility to validate usefulness of classification in terms of recovery. However since in this paper we present only *proof of concept* that classification is possible we propose to evaluate efficacy of classification in two ways: a) by comparing variance of each cluster to the quantization error calculated using empirical histogram of recovery rate distributions and b) by evaluating probability of misclassification where we assume that an error occurs at every instance of discrepancy between our clusters and histogram defined clusters. The total number of patients admitted was 203 with general characteristics being described in Table 1.

In order to illustrate statistical properties of BBS value for all the patients in Figures 1-3 we illustrate histograms at the admission, at the discharge and three months after discharge. As expected we can observe shift towards higher values which is expected as a consequence of rehabilitation. After we performed correlation analysis using Spearman coefficients we decided to reduce the number of features for clustering. To simplify the procedure we decided to use three most significant features: age, rate of BBS change during rehabilitation and severity index.

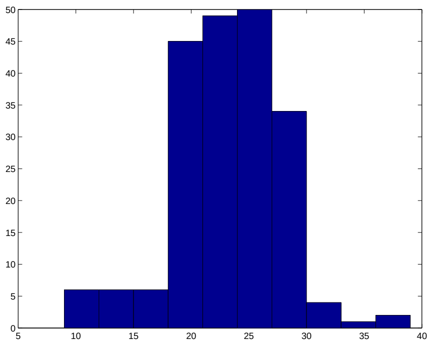

Figure 1: Empirical probability density function of BBS at the admission.

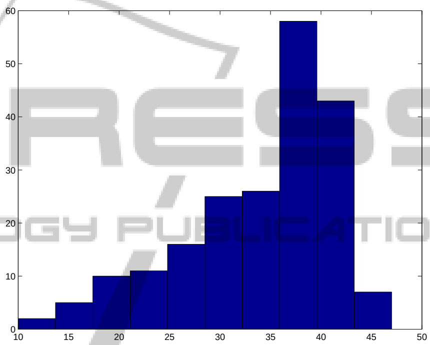

Figure 2: Empirical probability density function of BBS at the discharge.

In Figure 4 we present the result of the clustering assuming there are only two groups. The centers of the clusters are marked with letter x. As expected fuzzy clustering represents an adequate choice due to the arbitrarily shaped cluster regions. In Figure 5 we present the same results when three clusters are used. Observe that the separation of the clusters in the latter case is less visible but this is in general true when the number of clusters is increasing.

The error analysis results are summarized in Table 2. In first column we calculate the mean square

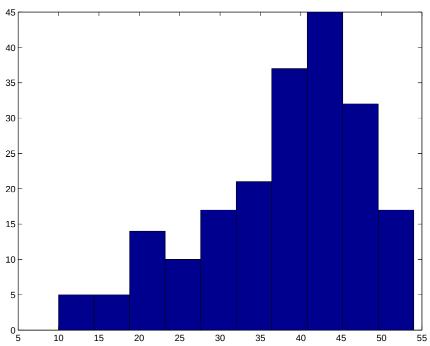

Figure 3: Empirical probability density function of BBS three months after rehabilitation.

Figure 4: Two group clustering.

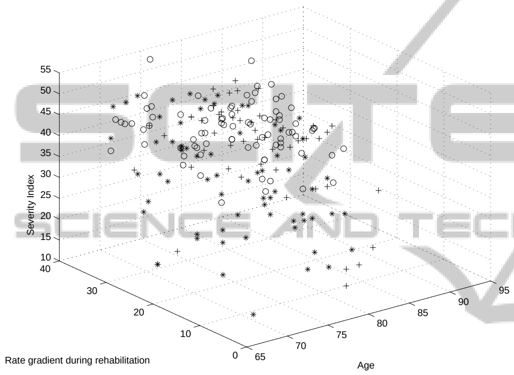

Figure 5: Three group clustering.

error of the cluster relative to the expected quantization error for a given data set. In the second column we calculate the probability of misclassification as explained above. As expected we observe slightly larger error for three-clusters scenario which is expected. It is important to reiterate that in order to truly evaluate performance we need a clinical study in which the results of this clustering are applied in clinical decision making in terms of treatment timelines and rehabilitation techniques.

4 CONCLUSIONS

In this paper we demonstrated ability to classify hip fracture recovery patients admitted to the rehabilitation program. We classified the patients with respect to the dynamics of their recovery that was inferred from gradients of Berg Balance Scale which is commonly used technique for evaluating balance of the patients and hence is one of the indicators of the recovery degree. Our ultimate goal is to develop clustering algorithms for triage purposes which would allow clinical staff and administration to properly plan treatment program based on the available resources. As such this approach requires further study in which the success of recovery between two groups (with and without clustering based triage) would be monitored.

Table 2: Mean square error and probability of error.

	MSE / QE	Probability of error
Two clusters	1.21	0.15
Three clusters	1.13	0.23

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