Predicting Functional Recovery of Stroke Patients using Age Dependent Model

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Abstract: Predicting functional recovery of stroke patients is important from both clinical and academic points of view. From the clinical point of view it is important to patients, families and clinical workers. Most importantly, an accurate prediction enables us to provide more accurate prognoses, set goals, manage therapies and improve management of healthcare resources through optimal discharge procedures. For example, being able to predict recovery of particular limbs we could potentially improve advanced planning of safe transfer in an optimally determined time frame. Functional recovery is usually evaluated using various functional indices that evaluate patients' ability to perform daily living tasks. In this paper we propose to predict functional recovery using two well established functional indices: functional independence measure and Barthels index. We model those indices as a age dependent polynomial functions with unknown coefficients and estimate the unknown parameters. In order to demonstrate applicability of the propose technique we compare the performance of our non-linear polynomial model with the performance on linear MANOVA model.

1 INTRODUCTION

Stroke is a leading cause of a long-term disability and consequently can significantly deteriorate quality of life of the recovery patients. According to The Heart and Stroke foundation report half of the patients recovering from stroke need help with daily activities. Accordingly it would be beneficial to predict functional recovery as it would allow health professionals to provide patients with prognoses, set goals, select therapies and plan discharge. Achieving these goals would make possible to optimize utilization of health care resources in order to reach maximum attainable recovery level.

In recent years there has been considerable research interest in predicting stroke recovery of particular limbs (arms, legs) (Houwink et al., 2013), (Craig et al., 2011) or functional independence recovery i.e. patient ability to perform particular tasks (Veerbeek et al., 2011). Due to inherent patient-to-patient variability most of the proposed models (techniques) require certain experiment based adjustments in order to account for that variability. In (Brown et al., 2015), (Kimura et al., 2017) the authors demonstrated that functional independence measure (FIM) can be potentially used to predict functional recovery of the stroke patients. In addition to FIM, another generic disability measure Barthel index (BI), has been widely used in order to evaluate patients ability to perform daily tasks. In recent reviews multiple authors identified that different variables can work as somewhat successful predictors of various indicators (ability to walk, arm recovery, etc.) (Chumney et al., 2010), (Putten et al., 1999), (Govan et al., 2009). As we have stated earlier in addition to predicting limb recovery it may be equally important to predict patients' functional recovery as it can potentially be used for efficient healthcare management.

In this paper we propose to predict functional independence recovery using coupled parametric model based on functional independence measure (FIM) and Barthel index (BI) measurements. As a preliminary approach we evaluate applicability of the growth curve model (generalized multivariate analysis of variance model) in which the weighting coefficients are calculated optimally based on patient age.

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We first propose parametric model in which the age is accounted for by using parametric exponential functions (known up to a parameter). We then estimate the unknown parameters using part of the data set as training set. We then evaluate the performance of the proposed model by comparing it to the MANOVA model and apply both models to the remaining patients. In future work we expect to include multivariate dependence based on additional parameters such as height, weight, body mass index, habits before the stroke, etc.

The paper is organized as follows. In Section II we describe the data set and the proposed estimation algorithms. 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

We have evaluated 187 eligible participants that were referred to the rehabilitation facility after stroke for inclusion into rehabilitation program and follow-up. To assess eligibility for the inclusion in the study the patients were evaluated by board certified physiatrist and specialist of internal medicine. Prior to the inclusion, all the participants were informed about the study protocol and informed consent was obtained. The study was approved by the Institutional Review Board and was carried out according to the principles of good clinical practice. The eventual onset of early complications was indication for the termination of the rehabilitation program for defined period of time. The exclusion criteria for the study were recurrent hip fractures and inability to completely finish the rehabilitation program or follow-up that was defined by the study. Therefore, the initial group on admission consisted of 217 patients, where 11 did not complete rehabilitation program due to the worsening of health condition and thus transferred to specialized referring hospitals, while 19 subjects dropped out from discharge period to the planned follow-up after 3 months post-discharge.

Functional Independence Measure (FIM) was used to evaluate patient's functional status on 3 occasions: at admission (Admission), on discharge from the rehabilitation facility (Discharge) and 1 and 3 months after discharge (Follow-ups). After discharge, patients were not included into any kind of rehabilitation program and were referred to home of residence. FIM presents valid and reliable test in the estimation of aggregated changes in functional status that appears in the defined period of the study evaluation (Young et al., 2009)-(Dodds et al., 1993). It is composed of 18 categories that are scaled from 1-7 each (Young et al., 2009) We organize the data set in a database consisting of 187 rows corresponding to the patients and 9 columns of (age, FIM at the admission, FIM at the discharge, FIM after 1 month, FIM after 3 months, BI at the admission, etc.)

2.2 Parameter Estimation

In order to be able to predict the functional recovery we first propose standardized MANOVA model in which the data is modelled as

$$Y = AX + E$$

where X is $n \times 5$ matrix consisting of age and FIM and Barthel indices at the admission and discharge, A is a matrix of unknown parameters, and Y is an $n \times 4$ matrix consisting of FIM and Barthel indices at 1 and 3 months after discharge respectively, and E is the matrix of residual errors. This technique is commonly used as a preliminary approach in order to obtain goodness-of-fit assuming that the data can be modelled using linear model.

In the second approach we propose to model the the indices values after the discharge using a new nonlinear polynomial approach in which the indices values are modelled as polynomial functions of the input parameters. Note that originally this approach was used to model time dependent growth change and is commonly used technique if prior knowledge is not available. In this paper we propose to use hierarchical polynomials in order to account for patient-to-patient variability. In this paper we use polynomial model given by

$$Y_{i,j} = \sum_{k=1}^{q} (a_k * age_i^{k-1}) + \alpha FIM_i^{admission} + \beta BI_i^{admisson} + e_{i,1}$$

where q is the polynomial order, a are unknown parameters modelling age dependence, α and β are unknown linear index parameters, and $e_{i,j}$ are residual error (modelling noise).

To evaluate the applicability of the proposed algorithms we find the normalized mean-square error and likelihood ratio test. Note that the above models can be easily extended to include larger number of parameters and this will be discussed further in Section 3.

3 RESULTS

The total number of patients admitted was 187 with age and indices characteristics being given in Figures 1-4.

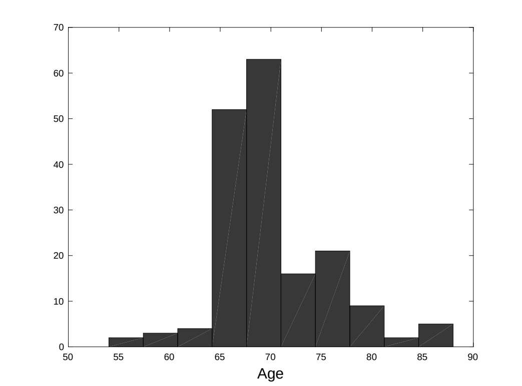

Figure 1: Histogram of patients' age at the admission.

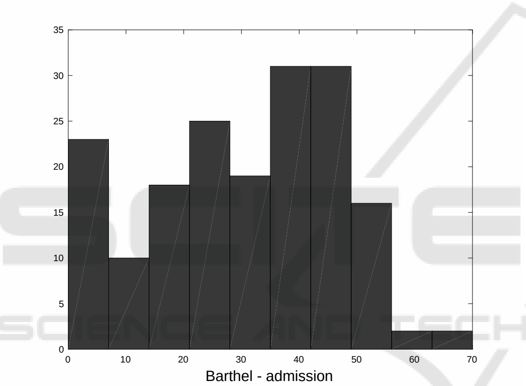

Figure 2: Histogram of Barthel index distribution at the admission.

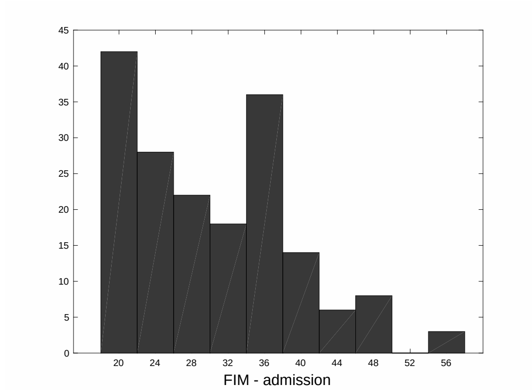

Figure 3: Histogram of FIM index distribution at the admission.

Additionally in Table 1 we show the correlation coefficient of all the FIM and BI with respect to the age. Due to existing inverse correlation relationship the age dependent model can improve our ability to

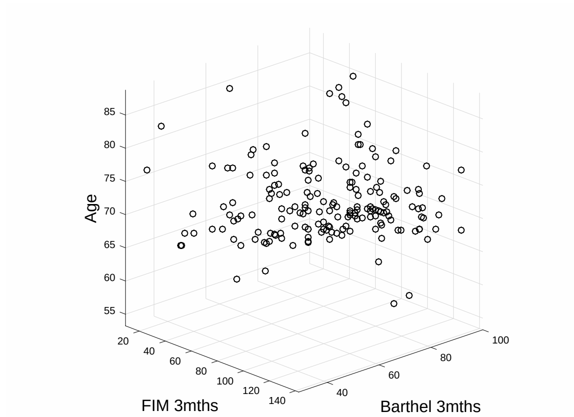

Figure 4: 3D scatter plot of age, FIM and Barthel indices.

predict recovery. In addition the increase in correlation between indices at the discharge indicate that their values at the admission should be used simultaneously in order to improve the performance.

Table 1: Correlation coefficients.

	Age	FIMa	FIM3	BIa	BI3
Age	1.00	-0.05	-0.15	-0.17	-0.13
FIMa	-0.05	1.000	0.69	0.87	0.64
FIM3	-0.15	0.69	1.00	0.66	0.92
BIa	-0.17	0.87	0.66	1.00	0.59
BI3	-0.13	0.64	0.92	0.59	1.00

To illustrate the statistical properties of the data sample we present two scatter plots. In Figure 5 we present the FIM change between admission and 3 months after discharge and in Figure 6 we present similar results for BI.

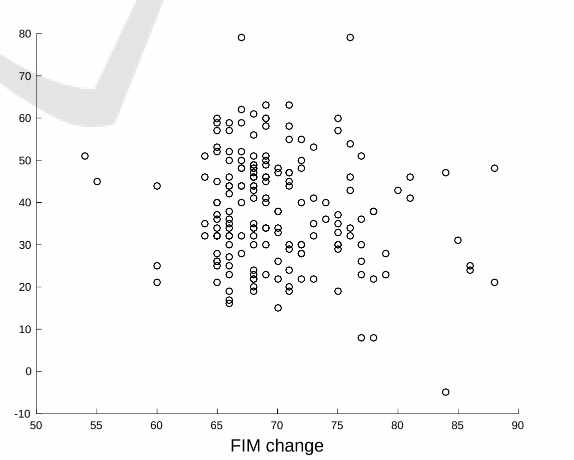

Figure 5: Two-dimensional scatter of age and FIM change.

In Figure 7 we present the prediction result in terms of mean-square error (MSE) for nonlinear model as a function of number of parameters i.e polynomial order. As expected after initial decay the MSE slope decreases significantly which means that the

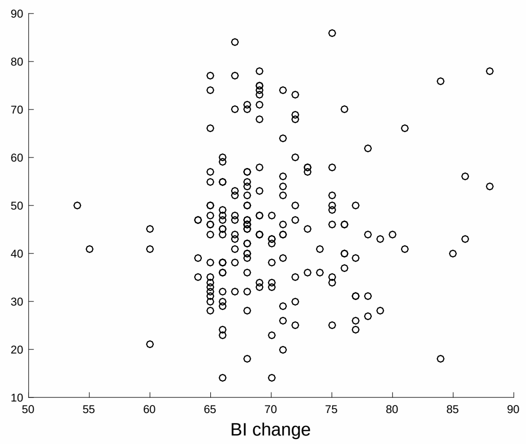

Figure 6: Two-dimensional scatter of age and BI change.

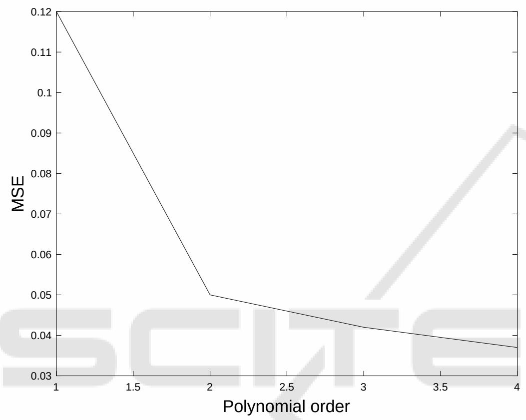

Figure 7: MSE of nonlinear model.

benefits of introducing additional parameters should be examined in more details as they may lead to increase in the computational complexity as well as Cramer-Rao bound.

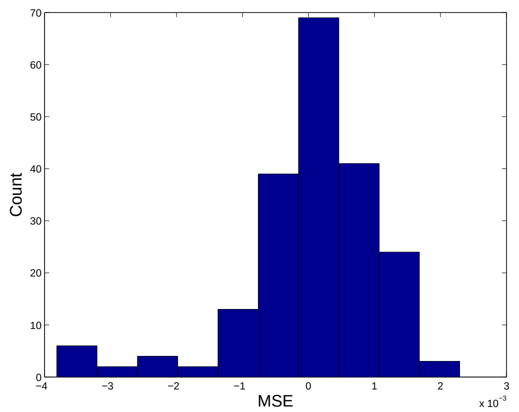

Figure 8: Two group clustering.

The likelihood ratio for two parameters models is given in Table 2. From the results it seems that the nonlinear model provides better fit in terms of the likelihood function for the older patients. However it should be noted that the sample size for the older patients is slightly larger. In addition the nonlinearity may play more important role at younger due to more complex recovery processes and hence may not be captured well by the proposed nonlinear model.

Table 2: Likelihood-ratio.

	Likelihood-ratio nonlinear vs. linear
Age ≥ 65	0.35
Age ≤ 65	0.64

Finally in order to evaluate applicability of our algorithm from the clinical point of view we classify patients based on joint FIM and BI measurements in the following way: if either FIM is larger than 36 or BI is larger than 4 the recovery is labelled as sufficient otherwise the recovery of a particular patient is labelled as insufficient. We estimate the unknown parameters using half of the data set and evaluate its performance using the other half. We repeat selection of the training data set randomly 1000 times. The results of the classification using predicted values are given in Table 3.

Table 3: Classification error.

	Error percentage
Insufficient recovery error	2%
Sufficient recovery error	1%

4 CONCLUSIONS

The importance of early inclusion in rehabilitation program and exercise of older people after the stroke could be explained by the fact that physical activity influences the muscle strength and neural function recovery (Sipila et al., 2011). Such determinants are very important particularly for individual's quality of life. It has been often hypothesized that the success of recovery is extremely dependent on the timeliness and adequacy of the treatment. While it is desirable to provide the best possible care as soon as possible the actual limitations that may exist in health-care systems due to a limited number of medical staff as well as limited capacity in rehabilitation programs may create need for appropriate planning and/or scheduling.

To this purpose in this paper we proposed an algorithm which can potentially be used to predict the functional recovery which is one of the most important factors that indicate ability for self-functioning of the patients and return to daily activities. As a preliminary approach we proposed and compared two parameters linear and nonlinear models using mean square error and likelihood-ratio. In addition the residual vector may not be Gaussian distributed especially in which case an effort should be made to investigate different estimation techniques that may be more suitable for non-Gaussian models. Finally, a clinically study with a larger number of patients and additional types of observation should be performed is it may provide better insight and improve quality of the prediction models.

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