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Patient Ambulations Predict Hospital Readmission

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***Abstract*— Improved functional ability and physical activity are strongly associated with a broad range of positive health outcomes including reduced risk of hospital readmission. This study presents an algorithm for detecting ambulations from time-resolved step counts gathered from remote monitoring of patients receiving hospital care in their homes. It examines the statistical power of these ambulations in predicting hospital readmission. A diverse demographic cohort of 233 patients of age 70.5±16.8 years are evaluated in a retrospective analysis. Eleven statistical features are derived from raw time series data, and their F-statistics are assessed in discriminating between patients who were and were not readmitted within 30 days of discharge. Using these features, logistic regression models are trained to predict readmission. The results show that the fraction of days with at least one ambulation was the strongest feature, with an F-statistic of 17.2. The models demonstrate AUROC performances of 0.741, 0.766 and 0.769 using stratified 5-fold train-test splits in all included patients (n=233), congestive heart failure (CHF, n=105) and non-CHF (n=128) patient subgroups, respectively. This study suggests that patient ambulation metrics derived from wearable sensors can offer powerful predictors of adverse clinical outcomes such as hospital readmission, even in the absence of other features such as physiological vital signs.**

***Index Terms*— readmission, ambulation, step count, heart failure, physical activity, regression, actigraphy, accelerometer**

I. Introduction

Hospital readmission, typically defined as patient admission within 30 days of a discharge, is an obvious source of distress for patients and a financial burden for hospitals[1]. Thus, estimating and reducing readmission risk is an important problem for the healthcare system. A number of schemes to predict readmission have been proposed. Perhaps the most-used to date is the LACE algorithm, incorporating length-of-stay, initial acuity of illness, comorbidities, and number of recent hospital visits[2]. Other readmission predictors include additional demographic and health history features as well as clinical data from the hospital stay[3].

Congestive heart failure (CHF) is a highly prevalent chronic condition and leading cause of readmission[4]. General-purpose readmission predictors may underperform when applied to CHF patients[5], and dedicated readmission models have been developed specifically for use with CHF[6]. Exercise-based rehabilitation, including walking, is an intervention that may reduce readmission rates among CHF patients[7]. Similarly, higher rates of activity among general medicine patients in hospital correlates with reduced length-of-stay[8]. It follows that measurements of physical activity offer promise in predicting readmission among both CHF patients and broader hospital populations.

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Recent work from Jeong et al. measures walking behaviors in patients recovering from cardiac surgery[9]. Several derived ambulation features were evaluated as predictors of readmission. The study installed a custom real-time location system in the hospital ward to monitor patients' movements along a corridor. This measurement system provides accurate, straighforward reports of walking distance, but it lacks the simplicity and flexibility of wearable accelerometer sensors. Furthermore, it is limited to monitoring in a single location.

Our study investigates the walking behaviors of a diverse patient cohort undergoing multi-day hospital-style care in their homes. Wearable sensors track the cumulative step counts for all patients. We introduce a new algorithm to identify discrete walking bouts from cumulative step-count time series data. Statistical features of these ambulations are then examined as predictors of readmission both in CHF patients and in the broader patient cohort.

II. Materials and Methods

A. Dataset

All data were collected from ambulatory patients enrolled in the Hospital at Home Program[10]. Patients were admitted through the hospital emergency department for a variety of acute conditions and subsequently monitored at home for one or more days. Each patient was fitted with a wearable sensor (VitalConnect, San Jose, USA) to record vital signs and physical activity, including cumulative step count. The step counts reported by the onboard firmware (1 Hz sample rate) served as the raw data in this study. The Hospital at Home cohort includes a control group of 35 patients receiving treatment in a traditional inpatient environment. The control group was excluded from our analysis since the hospital environment provides fewer opportunities for physical activity when compared to patients homes. Because this study examines 30-day readmission rates as a clinical endpoint, patients whose readmission status was not known were also excluded. This left a cohort of 320 patients (196 female, mean age = 69.9 ± 16.9). Filtering on data quality, as described in the "Preprocessing" section, limited the study cohort to 233 patients.

B. Ambulation Detection Algorithm

The proposed ambulation detection algorithm identifies walking episodes when the sensor-reported cumulative step counts are increasing. The detection sensitivity is controlled by two parameters: Maximum Time Gap (MxG) and Minimum Duration (MnD). Both parameters have units of seconds. Once steps are detected, the MxG parameter gives

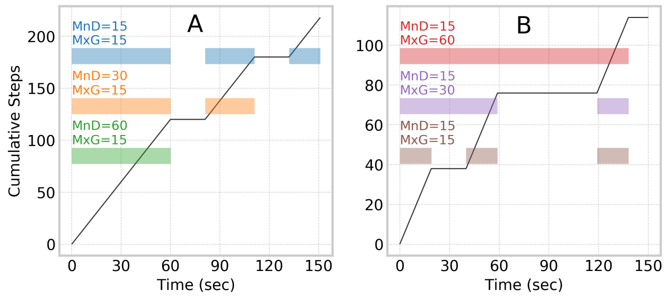

Fig. 1. Ambulation detection results for several values of parameters MnD and MxG. Black lines denote simulated cumulative step counts. Each horizontal bar gives the time interval for one detected ambulation. A. Varying duration parameter MnD, for fixed value of MxG = 15 seconds. B. Varying gap parameter MxG, for fixed value of MnD = 15 seconds.

the longest permissible pause before marking the end of the ambulation. The MnD parameter is the shortest time interval of accumulating steps (including pauses allowed by MxG) that will be counted as an ambulation; any potential ambulation with a duration less than MnD will be discarded.

Using synthetic step count data, Fig. 1 illustrates how the values of the MxG and MnD parameters control the ambulation detection. Larger values of MnD will reduce the detection sensitivity, reducing both the count and total time duration of the identified ambulations, as shown in Fig. 1A. Larger MxG values will merge previously separate ambulations. Thus, increasing MxG will result in fewer detected ambulations, but more total ambulation time, as shown in Fig. 1B. When run on a patients' cumulative step count time series, the output of the ambulation detection algorithm is simply the start and end times of all ambulations for given values of MnD and MxG.

C. *Preprocessing*

Fig. 2 provides an overview of the analysis steps, beginning with data preprocessing. We concatenated cumulative step counts for patients using multiple devices (due to battery discharge or adhesive failure). Any data beyond the hospital discharge date were discarded. Step counts for each patient were segmented into calendar days starting and ending at midnight. Data for any day with less than 80% of all possible coverage was discarded. This procedure aims to reduce time-dependent bias in the missing data; data loss during nighttime inactivity would have little impact on total steps and ambulations, but loss during waking hours could produce significant undercounting of steps and ambulations. After this filtering method, data for 233 patients remained (141 female, mean age 70.5 $\pm$ 16.8). Of this group, 30 patients were readmitted within 30 days of discharge.

D. *Computing Ambulation Features*

For each patient, the algorithm described above (Fig. 1) identified ambulations using all combinations of 6 values for both MnD (10, 15, 30, 60, 90, 120 sec) and MxG (15, 30, 45, 60, 90, 120 sec). Next, we extracted 8 ambulation features from the ambulations identified with each of the 36 parameter sets. The first feature, Mean number of ambulations per day, counts all daily ambulations of any length. Daily compliance 1/2/3+ ambulations gives the fraction of calendar days in which the patient performed at least 1, 2, or 3 ambulations.

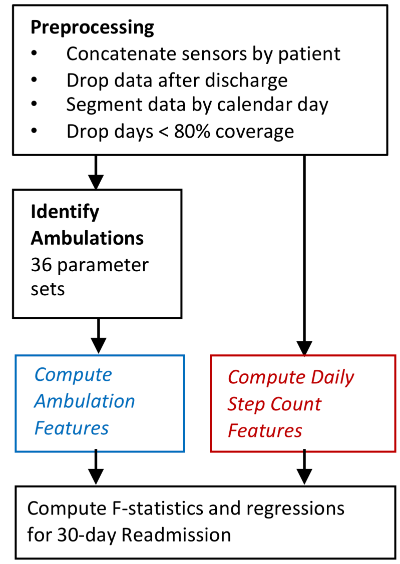

Fig. 2. Data analysis steps: preprocessing, detecting ambulations, extracting and evaluating features, and training regression models.

A step rate f (in Hz) is computed for each ambulation; this is simply the total steps divided by the duration. Ambulations containing longer step-free periods (permissible with larger values of MxG) will thus have lower step rates. The feature Fastest ambulation gives a patient's largest overall step rate (in steps per second) for a single ambulation.

We also computed an approximation of total distance for each ambulation. Our formula assumes that step length varies linearly with step rate, implying that gait speed (in m/s) is a quadratic function of step rate[11][12]. Equation (1) presents this formula, where d is the distance in meters, and f is the mean step rate, as described above.

$$d = (0.47f + 0.72f^2)t \tag{1}$$

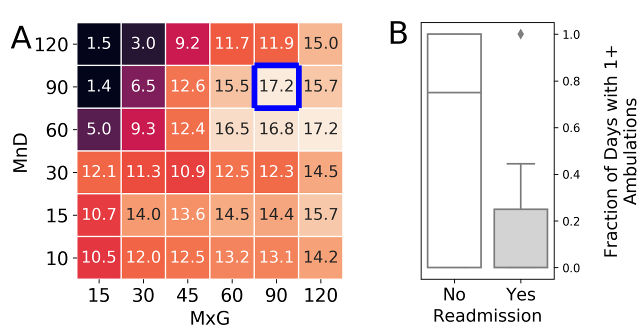

Fig. 3. A) F-scores for feature Daily Compliance 1+ Ambulations as predictor of 30-day readmission. Each tile gives F for given combination of parameters MnD and MxG. Highest F value highlighted in blue. B) Boxplot of feature values for the highlighted parameter set.

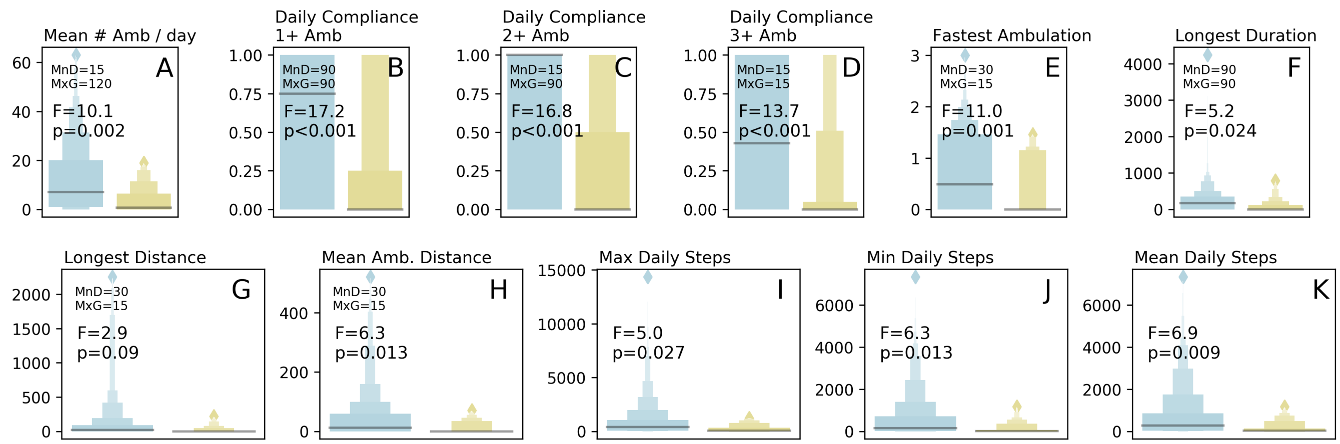

Fig. 4. Distributions of ambulation features (A-H) and daily step features (I-K) for patients not readmitted (blue) and readmitted (yellow) within 30 days of discharge. F-scores and corresponding p-values are overlayed. For the ambulation features, the distributions for parameter combination (MnD / MxG) with best F are shown.

The coefficients of Eq. 1 were fit from calibration data published in Figure 1 of [12]. Note that this expression assumes a constant step rate f over the ambulation. This condition may not be met consistently, particularly when longer step-free gaps are permitted by larger values for parameter MxG. The feature "Longest ambulation distance" is simply the maximum computed distance among all ambulations over a patient's stay. Finally, the "Mean ambulation distance" feature is the average computed distance overal all of a patient's ambulations.

E. Computing Daily Step Features

We also derived three simple daily step features from each calendar day's total step counts. These features do not use the ambulation detection scheme described above and thus require no parameters (i.e. MnD and MxG do not apply). The Min daily step count and Max daily step count features are simply the total step counts on calendar days when the patient had the fewest and most steps. Mean daily step count is the average of the total step counts on each day.

F. Estimating Feature Significance

One-way analysis of variance (ANOVA) was used to compute F-scores and corresponding p-values for each ambulation and daily step feature, comparing those patients readmitted (n=30) and not readmitted (n=203). We ran the ANOVA calculation for ambulations detected under all 36 ambulation parameter combinations (MnD and MxG) to clarify the impact of the parameters on the predictive value of the resulting features. In each case, the parameter set yielding the highest F-score was identified. An example is given in Fig. 3, illustrating the 36 F-scores for the feature "Daily compliance 1+ ambulations", and highlighting the best parameter combination.

G. Regressions Predicting 30-day Readmission

We then examined these 11 features as candidates for a logistic regression model to predict readmission. These candidates comprised 8 ambulation features (each calculated using parameter set yielding best F-score) and 3 daily step features. We computed the natural logarithm for all features to compress long tails present in some feature distributions. All features were then normalized by removing the mean and scaling to unit variance. Next, we trained a logistic regression on all features, repeating with increasingly strong L1 regularization penalties to iteratively eliminate features one by one. This procedure generated 11 distinct feature sets (first 11 features, then 10 features, etc. until only 1 feature remained).

Finally, we ran 5-fold stratified train-test splits on the data, repeating once for each of the 11 feature sets obtained through the regularization procedure. The overall feature selection and cross-validation procedure was then re-run on two subsets of the cohort: those patients with (n=105) and without (n=128) a diagnosis of CHF. Our aim was to determine whether the presence / absence of CHF impacts the predictive power of the model and/or affects which features are most relevant.

The ambulation detection algorithm and all subsequent analysis, modeling, and visualization was coded using Python, including scipy.stats, scikit-learn, matplotlib, and seaborn.

III. Results

Mean and median values for all ambulation and daily step features are consistently lower (less walking) for the readmission group than for the non-readmission group, as shown in Fig. 4. These differences are significant ($p < 0.05$) for all features except "Longest Ambulation Distance (G)" ($p = 0.09$). For the ambulation features, the results with best-performing (highest F-score) parameters are shown. Daily compliance with 1+ Ambulation (B) is the strongest ambulation feature (F=17.2). The Mean Steps per Day is the strongest daily step feature, albeit with a lower score (F=6.9).

Fig. 5 presents the receiver-operator-characteristic (ROC) curves for logistic regression prediction of 30-day readmis-

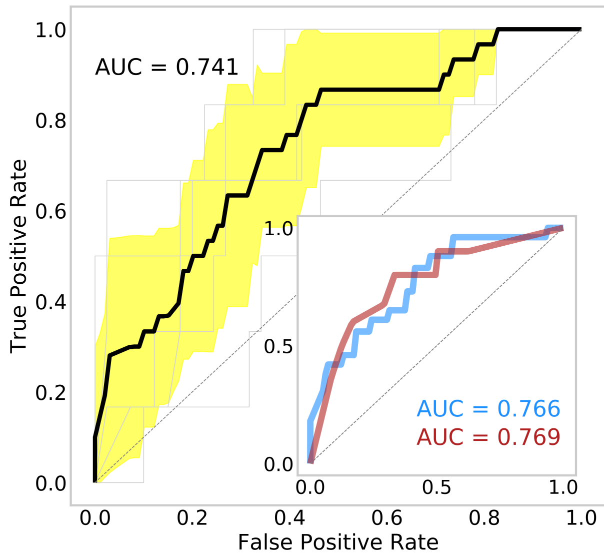

Fig. 5. Mean ROC plots for logistic regression models predicting 30-day readmission for all patients (black line), CHF patients (inset, blue line), and patients without CHF diagnosis (inset, red line). In the main plot, gray lines are performance of individual 5-fold train/test splits and the yellow region encloses one standard deviation.

sion for all patients, CHF patients, and non-CHF patients. Readmission is the positive prediction in this analysis. As shown in text insets on the plot, the mean AUROC statistic for the 5 train/test splits is similar for each cohort: 0.741, 0.766, and 0.769 for all, CHF, and non-CHF patients respectively. In each case, the regularization procedure to select features limited the model to just 2 features. For the regressions on all patients and CHF patients, the feature selection yielded Daily Compliance 1+ Ambulations and Mean Daily Step Count. For non-CHF patients, the feature selection yielded Daily Compliance 1+ Ambulations and Daily Compliance 3+ Ambulations.

IV. Discussion

Starting with time-resolved cumulative steps data, we have extracted statistics describing patients' ambulations, or discrete bouts of walking. We then applied these statistical features in regression models to predict hospital readmission. The work presented here draws parallels to a recent JAMA publication of Jeong et al. which defines an ambulation as a walking bout meeting or exceeding a specific threshold of roughly 66 meters as measured by real-time patient location monitoring[9]. Jeong's strongest predictor of readmission was the fraction of days (compliance) with at least one ambulation. Notably, our work also shows single-ambulation compliance to be the best feature. In our study this ambulation feature yields a maximal F score of 17.2 with walking bouts of at least 90 seconds duration (MnD), while allowing for substantial step-free pauses of up to 90 seconds during the ambulation (MxG). In our analysis the simple daily step feature "Mean Daily Step Count" presents a weaker F-score of 6.9, although the inclusion of this feature in our regression models did optimize performance for the the CHF population as well as for the complete patient cohort.

Our models show AUROC values of 0.741, 0.766, and 0.769 for all patients, CHF patients, and non-CHF patients, respectively. This compares to a 0.925 AUROC from the JAMA readmission model. We see some plausible explanations for this discrepancy. First, accelerometry-based step counting can perform suboptimally with shuffling or otherwise abnormal gaits common in elderly subjects[13], and identifying walking bouts by tracking patients' location sidesteps this limitation. Secondly, the patient cohorts in these two studies are quite different. The previously-published study focuses solely on patients in hospital recovering from cardiac surgery. Exercise capacity, quantified through timed walking tests[14], is a widely-recognized predictor of cardiac outcomes. In contrast, the patients examined in our study present a much more clinically diverse cohort. Despite these differences, our models produce useful predictions for readmission in patients with a wide variety of acute and chronic diagnoses. Importantly, using readily available wearable devices to detect ambulations avoids the infrastructure requirements of a hospital proximity monitoring system while still yielding statistically valuable results.

Emerging techniques can boost the performance of accelerometer-based step counting for older patients[15] with limited ambulation and relatively impaired gait characteristics. Future work will involve integrating improved step detection algorithms to more accurately identify walking bouts in patients under diverse settings. The machine-learning models presented in this study employ step-derived ambulation features alone with the primary goal of determining their significance for hospital readmission prediction. Ongoing work will incorporate additional accelerometer-derived features such as general activity levels[16] and posture. Actigraphy-based ambulations and other features are often overlooked, but they could help push the envelop to enhance the real-world performance for predicting clinical outcomes such as hospital readmission in conjunction with well-established clinical and demographic features[2][3].

V. Conclusion

This work offers a new method to identify semi-continuous ambulatory bouts from cumulative step count time series data. We examine these ambulations as predictors of 30-day hospital readmission, a clinically and financially important outcome. This novel statistical treatment of step counts may offer promise in other clinical contexts, particularly in conjunction with additional features derived from wearable sensors.

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