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Predicting Human Movement with Multiple Accelerometers Using Movelets

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Abstract

Purpose—The study aims were: 1) to develop transparent algorithms that use short segments of training data for predicting activity types; and 2) to compare prediction performance of proposed algorithms using single accelerometers and multiple accelerometers.

Methods—Sixteen participants (age, 80.6 yr (4.8 yr); BMI, 26.1 kg·m^{-2} (2.5 kg·m^{-2})) performed fifteen life-style activities in the laboratory, each wearing three accelerometers at the right hip, left and right wrists. Triaxial accelerometry data were collected at 80 Hz using Actigraph GT3X+. Prediction algorithms were developed, which, instead of extracting features, build activity specific dictionaries composed of short signal segments called movelets. Three alternative approaches were proposed to integrate the information from the multiple accelerometers.

Results—With at most several seconds of training data per activity, the prediction accuracy at the second-level temporal resolution was very high for lying, standing, normal/fast walking, and standing up from a chair (the median prediction accuracy ranged from 88.2% to 99.9% based on the single-accelerometer movelet approach). For these activities wrist-worn accelerometers performed almost as well as hip-worn accelerometers (the median difference in accuracy between wrist and hip ranged from −2.7% to 5.8%). Modest improvements in prediction accuracy were achieved by integrating information from multiple accelerometers.

Discussion and conclusions—It is possible to achieve high prediction accuracy at the secondlevel temporal resolution with very limited training data. To increase prediction accuracy from the simultaneous use of multiple accelerometers, a careful selection of integrative approaches is required.

Keywords

accelerometer; physical activity; signal processing; pattern recognition; time series

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INTRODUCTION

Par # 1

The objective and detailed characterization of daily physical activity is crucial for research studies where physical activity is an exposure or outcome. Researchers have increasingly relied on accelerometers for measuring physical activity in observational studies and clinical trials (1, 5, 6, 9, 18). A fundamental question is how to decipher and interpret the accelerometry signals into meaningful information such as activity intensity, energy expenditure, and movement types (20, 21, 22, 25).

Par # 2

Various methods have been previously suggested for recognition of activity types, including linear/quadratic discriminant analysis (13), Hidden Markov Chains (10), artificial neural networks (19, 23, 24), support vector machines (12, 15) and combined methods (17, 28). Bao et al. (3) and Preece et al. (14) reviewed and evaluated methods used in the classification of normal activities. The major limitations of the other methods are: 1) they usually require at least a 1-minute window for a feature extraction approach; 2) they do not capture finer movements that last less than 1 minute, such as falling or standing up from a chair; and 3) the prediction process is usually hard to understand and interpret. For example, when the prediction algorithm predicts correctly it remains unclear which features contribute and what their relative contributions to activity discrimination is; similarly, when the prediction algorithm fails, it is unclear exactly what features created the activity prediction confusion.

Par # 3

This paper provides movelet-based prediction algorithms that can address these limitations. The methodology is fully transparent, easy to understand, and requires minimal training data. The intuition behind is that movements with similar accelerometry patterns are likely to correspond to the same type of activity. The single-accelerometer movelet approach proposed by Bai and colleagues (2) was developed for one triaxial accelerometer and this paper extends it to multiple accelerometers. A movelet is the collection of the three acceleration time series recorded by the device in a window of given length, say 1 second. The sets of movelets constructed from the accelerometry data with annotated labels are organized by activity types, i.e. “chapters”, which play the role of accelerometry “dictionaries” for different activity types. Predictions of accelerometry data without annotated labels are obtained by identifying the chapter that is most similar to the data in terms of distance; the similarity is quantified by Standard Euclidean distance between vectors. This can be extended to multiple accelerometers in at least two ways: 1) by building separate movelet dictionaries and then combining predictions using voting or sequential decisions; or 2) by designing a joint dictionary, where a movelet is a collection of nine time series (3 for each accelerometer). The movelets idea (2) uses a dictionary learning approach that has been used extensively in speech recognition and is likely to be one of the fundamental algorithms for movement recognition in game consoles. The “shapelets” algorithms also uses dictionary learning to recognize shapes of objects from images and videos (7, 27). A recent development of the “fast shapelets” method includes an application to accelerometry-based activity type recognition (16). A recently published conference paper (8) proposed a movement prediction framework based on accelerometry data similar to the one in (2). Both papers (8,16) were published a year later than (2). Zheng et al. (29) divided accelerometry signals into non-overlapping windows and adopted a multi-scale ensemble method to relax the window size specification; our movelets-based methods decompose accelerometry signals into overlapping windows (i.e., movelets) and thus accommodate that different activities occur at different temporal scales. Here we focus on interpretability and generalization of the movelets-based approach in (2) from one to multiple accelerometers, on studying what types of integration approaches work best, on better characterizing complex movements, and on applying the methods to some of the most complex in-lab data available.

METHODS

Par # 4 Participants

Sixteen older adults (age, 80.6 yr (4.8 yr); BMI, 26.1 $kg \cdot m^{-2}$ (2.5 $kg \cdot m^{-2}$); 50.0% female) enrolled in the Study of Energy and Aging (SEA) Pilot were invited to participate in an additional study visit to validate hip and wrist accelerometry. Of the 38 participants in SEA, 16 were interested and completed this ancillary study. This study was approved by the Institutional Review Board of the University of Pittsburgh and National Institute on Aging and all participants gave written informed consent.

Par # 5 Data Collection

The participants were instructed to perform 15 different types of activities according to a protocol in a research clinic, including lying still face-up (alias: lying), standing still (alias: standing), washing plates (alias: washDish), kneading a ball of dough (alias: dough), putting jacket on (alias: dressing), folding towels and stacking them nearby (alias: foldTowel), vacuuming carpet (alias: vacuum), simulated shopping (alias: shop), writing (alias: write), dealing cards (alias: cards), standing up from a chair and sitting back down (alias: chairStand), walking at a normal speed with (alias: normalWalk Swing) and without arm swing (alias: normalWalk noSwing), walking at a fast speed with (alias: fastWalk Swing) and without arm swing (alias: fastWalk noSwing). In the rest of the paper, the activity types are referred to by their aliases. Each participant wore three Actigraph GT3X+ devices simultaneously, which were located at the right hip, right wrist and left wrist, respectively. For each accelerometer, the collected data contain a triaxial time series of accelerations expressed in units of gravity, i.e., $g=9.81m/s^2$. The three axes are labeled as “SuperiorInferior”"AnteriorPosterior” and “LeftRight” according to axes’ directions with respect to the participants in a standard standing position. The data were collected at a sampling frequency of 80Hz. Based on the protocol and the start/end time for each activity, a time series of activity type labels is constructed to annotate the accelerometry data.

Par # 6 Actigraph GT3X+

The Actigraph GT3X+ device is a triaxial acceleration sensor developed by ActiGraph, LLC. It is a triaxial ±6g seismic acceleration sensor housed in a small (4.6cm × 3.3cm

×1.5cm) light weight (19 g) encasing. The user-defined sampling rate of the Actigraph GT3X+ can range from 30 to 100 Hz in 10 Hz increments.

Par # 7 Single-accelerometer movelet approach

We first review the movelets approach (2) developed for predicting activity type using a single accelerometer. The basic idea is to decompose the triaxial time series into movelets, overlapping short segments of data representing a given activity. The prediction of the activity type is based upon the similarity (distance) between the movelets that are not labeled and the ones that are. The entire process is similar to having a dictionary of words (movelets) with their associated meaning (labels). Given a new word (unlabeled movelet), the procedure simply requires looking up the word with closest meaning in the dictionary (labeled movelets) and assigning the corresponding label to the new word (unlabeled movelet). The basic idea is simple: a) cut the time series that correspond to known and unknown activities into small overlapping 1-second intervals; and b) match each time series corresponding to an unknown activity to the most similar time series corresponding to a known activity. For notation and complete description of the single-accelerometer movelet approach see (2).

Par # 8 Integrative movelets approaches

It is reasonable to expect that accelerometers worn at different body locations contain nontrivial complementary information about movements. However, it is not clear whether and how this information can be combined to augment the prediction performance. Here we propose three practical approaches for combining information. Combining classifiers to improve prediction is an intensely studied topic in statistics and machine learning. In statistics, Breiman (4) and Wolpert (26) discussed model stacking and averaging. Lam (11) provided a review of different methods of combining classifiers in machine learning. We propose three easy to understand and scale up integrative approaches: movelets voting, movelets decision tree and expanded movelets. The movelets voting approach integrates the three accelerometers by allowing the single-accelerometer movelet approach to vote for the activity types and then by accepting the majority votes. The movelets decision tree builds up a simple hierarchy of decisions based on movelets. The hip-worn accelerometer first discriminates among the top-level groups of activities, followed by the low-level prediction using wrist-worn accelerometers for specific activity types. The expanded movelets simply redefines movelets as a combination of 9 1-second time series (3 for each accelerometer); weights can be imposed to accelerometers attached to different positions. In this study, equal weights for hip, right, and left wrist accelerometers were adopted.

Par # 9

Because of definition ambiguity, the breaks between two successive activities as well as the transition periods at the beginning and end of each activity are removed from the data. In the following analysis, data for a half-minute period for each activity of each participant are used as the testing data. The length of the movelet H is taken to be 80 observations, i.e., a 1-second. A 1- second window is appropriate because it contains enough information to identify a movement without including much redundant information. A dictionary of 15 chapters corresponding to each of the 15 activities in the study is created for each accelerometer and each participant. For activities with an explicit start and end, such as chairStand, one replicate is used as training data. For movements with periodic features, such as normalWalk and fastWalk, a 2-second segment is utilized as training data. For other continuous movements without explicit periodicity, a segment of length 2.5 seconds is used as training data. In order to make comparison, we kept the training and testing data consistent across different methods for each subject. Movelet dictionaries are subject-specific in the single movelet approach. In the integrative movelets approaches, movelet dictionaries are subject-accelerometer specific; for each accelerometer and each subject, we have constructed a dictionary of activities based on the training data. Dictionaries are distinct for each subject to account for the individual variations in movement patterns across subjects. For one subject, dictionaries were designed to be accelerometer-specific to capture different characteristics of movements recorded from different replacements. In the future we will explore the possibility of using the dictionary of one or multiple subjects to predict the movement of a different subject.

RESULTS

Par # 10

Figure 1 displays the boxplot of the prediction accuracy, i.e., the proportions of correctly classified observations, for 15 activity types of sixteen participants using hip-worn, right wrist-worn, and left wrist-worn accelerometers. The X axis indicates the various activities and the Y axis corresponds to the proportion of correctly classified observations. Different colors were used for each prediction approach: 1) red for movelets based on hip accelerometers; 2) blue for movelets based on right wrist accelerometers; 3) green for movelets based on left wrist accelerometers; 4) yellow for the expanded movelets approach; 5) orange for the movelets voting approach; and 6) grey for the movelets decision tree approach. Note that a new activity type, normalWalk combined merges normalWalk Swing and normalWalk noSwing into one category; and fastWalk combined is fastWalk Swing plus fastWalk noSwing. The activity labels on the X axis are ordered with respect to median prediction accuracy of the hip-worn accelerometer (red). Table 1 presents the median and interquantile range of prediction accuracies across participants for different activity types.

Par # 11 Results for single-accelerometer movelet approach

For resting activities (lying and standing) all accelerometers provide accurate predictions. For normalWalk combined and fastWalk combined, the wrist-worn accelerometers perform as well as the hip-worn accelerometers. The right wrist-worn and left wrist-worn accelerometers outperform hip-worn accelerometers in predicting normalWalk Swing, normalWalk noSwing, fastWalk Swing, fastWalk noSwing, and chairStand. Write and cards belong to the group of upper body activities while sitting. Accelerometers worn at three different positions yield very accurate predictions for writing (see the red, blue and green boxplots in Figure 1 corresponding to write). Right wrist accelerometers falsely predict on average 10.2% of cards to be write. For cards, left wrist-worn accelerometers provide higher median prediction accuracy than right wrist-worn accelerometers and both outperform the hip-worn accelerometers. Hip-worn accelerometers do not record the subtle movements of hands, and often incorrectly classified cards as dough (5.4% average across participants) and foldTowel (5.3% average across participants). On average, 12.8%, 13.1%, and 9.4% of dressing is falsely classified as foldTowel based on hip-, right, and left wrist-worn accelerometers, respectively. For activities dough, washDish, vacuum, dressing, foldTowel, and shop, all three accelerometers show lower median prediction accuracy and larger variability across participants.

Par # 12 Results for integrative movelets approaches

For the activities lying, normalWalk combined, write, stand, normalWalk Swing, fastWalk Swing, and cards, the expanded movelets approach yields the highest prediction accuracy with the least variability across participants. A substantial increase in prediction accuracy for cards is observed for the expanded movelets approach. To provide a visual representation, Figure 2 shows the matching processes of two participants for whom the expanded movelets approach provides better prediction for cards than all the single-accelerometer movelet approach on its own. The movelets voting approach is inferior to either one of the single-accelerometer movelet approach or the expanded movelets approaches for all the activities with the exception of dough, washDish, vaccum, and shop. The movelets decision tree provides relatively good performance for lying, write, and stand. For other activities, it tends to underperform.

Par # 13 Cross validation

We conducted a four-folded cross validation to further evaluate the proposed methods. More precisely, every time we used another part of the data for training and testing and have investigated the sensitivity of the proposed approach. For activities lying, walking, stand, chairStand, and write, the within-subject variability of the prediction accuracy is much smaller than the between-subject variability. For most of the household activities, the within-subject variability of prediction accuracy is larger and the average prediction accuracy over folds is also generally low; this is due to the ambiguity of sub-movements that are shared among multiple household activities. Results suggest that for activities lying, walking, stand, chairStand, and write, the movelet-based approaches provide highly consistent results when using different training sets.

DISCUSSION

Par # 14 Discussion on movelets approaches

This work provides movelet-based prediction of activity type at the second-level temporal resolution using triaxial accelerometers placed at the right hip, left and right wrists. Compared to feature extraction-based methods, the movelet-based methods have two advantages. First, instead of extracting features, the movelet algorithm preserves the original signal that can be visually inspected. The matching process between known and unknown movelets mimics the natural human pattern recognition, which makes the process transparent. If prediction fails in a one-second interval, human visual inspection can usually reveal the reason. Second, movelets can achieve high prediction accuracy at the second level even using very limited training data (several seconds per activity type). This is the first approach that can achieve such performance while remaining fully transparent and easy to understand.

Par # 15

To illustrate how these advantages work in practice, we present several examples here. First, it was found that wrist-worn accelerometers predict walking better than hip-worn accelerometers. This is unexpected and counter intuitive, as these movements are fundamentally performed by producing lower body acceleration. As a second example, the results showed that the accelerometers worn at the left wrist outperformed the one worn at the right wrist in recognizing cards, which is also unexpected. To investigate these, Figure 3 displays the matching processes for normalWalk, fastWalk, and cards. Activity labels are coded in different colors; the annotated labels and predicted labels are plotted in parallel accompanying the original signals. Given a time point, if the annotated label and the predicted label are of the same color then the activity type is correctly predicted.

Par # 16

Consider the matching process for walking with and without arm swing as measured at the hip (first row, left panel) and right wrist (second row, left panel) in Figure 3. As the person transitions from normal walk without arm swing to normal walk with arm swing, the time series associated with hip movement do not display visually observable changes. In contrast, the wrist accelerometry indicates a strong change. Most interestingly, the blue accelerometry curve shifts to a much higher level than before, probably because of the change in the angle of the accelerometer. Such strong angle changes can be easily observed and detected using movelets and should explain how information is being combined. The single-accelerometer movelet approach is confused between the two types of movements when using the hip data only. In contrast, the predicted labels based on wrist data are almost perfectly accurate. A similar story holds for fast walking with or without arm swing (row 3 and 4 panels). Now examine the right panels in the first and second rows of Figure 3. It is shown that the right wrist accelerometer yields more variable signal than the left wrist one, which makes it harder to distinguish the right wrist accelerometer signals from other upper body activities. As a third example, the prediction accuracy for the upper limb activities while standing was lower and yielded larger variability across participants. This probably happens because of the high level of overlap in movement and ambiguity of some sub-movements across labeled activities. At the same time, the raw signals of these activities are also similar with visual inspection of the matching process.

Par # 17

Three integrative movelets approaches were proposed to incorporate information from multiple accelerometers. The expanded movelets approach yields the best overall performance among the three integrative movelets approaches. Movelets voting is conceptually straightforward. Since the integration of information occurs after using single-accelerometer movelet approach for each accelerometer, it can simultaneously process acceleration information from different sources and save computing time. At the same time, integration with majority votes of categorical activities labels loses some of the rich information embedded in the original signals. The expanded movelets approach merges all available information and provides the flexibility of weighting different information sources. This method yields exceptional prediction in well controlled environments, though may be more prone to errors when one of the devices malfunctions or moves to a different position on the body.

Par # 18

The weights on the sources can be assigned depending on activity types. Determining optimal weights for different sources is not covered in this paper, but it will be investigated in the future. The movelets decision tree approach integrates information adaptively. An important assumption is that the top level of the decision tree is well designed to provide coarse discrimination between activity groups, while lower level decisions are well designed to make within-group predictions. In the movelets decision tree approach the prediction error in the first level is propagated into the second level. Thus, designing the tree hierarchy is rather delicate and, likely, application specific. To increase prediction accuracy from the simultaneous use of multiple accelerometers, a careful selection of integrative algorithms is required.

Par # 19 Methodological implications

The order of magnitudes of local average accelerations among the three axes is crucial for detecting and differentiating various postures; this happens because the order is a proxy of the orientation of the device relative to earth gravity. For example, our results showed that high accuracy was achieved for lying and standing. The visual inspection of the matching process reveals that the main difference between the accelerometry signals for lying and standing is that the local average of individual time series is different in magnitude and rank. While standing still, the gravity would appear as acceleration mainly along the AnteriorPosterior axis. Gravity affects differently each axis and the size of the effect depends fundamentally on the angles the axes of the accelerometer form with the gravity direction. While far from being a perfect proxy for position, this is enough to differentiate between standing and lying. This is a case where the variability of time series along their long-term averages is of secondary importance, while the discrimination between the two resting positions is done by the shift in the relative magnitude of the mean functions.

Par # 20

Our findings have potential implication on accelerometers' placement decisions in epidemiological studies. First, both accelerometers worn at the dominant hand and non-dominant hand can predict lying, standing, normal walking, and fast walking as well as the hip-worn accelerometers. This provides support for using wrist-worn accelerometers. Second, handedness should also be a consideration in accelerometer placement, which can affect prediction performance. Our results showed that activities like cards where the dominant hand moves more, the non-dominant hand accelerometers yielded higher prediction accuracy. Third, the decision of placement should be customized to the study goals. The results showed that hip-worn accelerometers performed poorly in distinguishing walking with arm swing versus walking without arm swing, while wrist-worn accelerometers yielded good results. Consider a scenario when investigators decide to use hip-worn accelerometers and are interested in distinguishing between different types of walking. It will be quite difficult to differentiate between walking normally and walking carrying a small object (no arm swing). Thus, it seems reasonable to simply define a label

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called normal walking that includes both arm swing and no swing. Alternatively, a wrist accelerometer could be used instead or in addition to the hip one. It was also shown that trunk movements such as walking are easily recognized by all accelerometers, while finer movements that occur at the extremities of the human body are predominantly captured by wrist-worn accelerometers.

CONCLUSION

Par # 21

We have seen a trend that more and more devices are now designed to output raw triaxial data and more and more researchers have startedto collect the raw data. There is also increasing interest in evaluating data that are being lost by analyzing the coarse activity data at the hour or day level versus the raw accelerometry data recorded at the sub-second level. The movelets approaches proposed here provide a self-consistent and transparent framework for thinking about and quantifying the data at the sub-second level. The movelets approaches allow the scientist to understand the complex measurement, have access to the entire processing pipeline, and access different levels of data compression via reproducible code and verifiable results.

Par # 22

In this study, all movement predictions were obtained from participants in the research clinic wearing devices installed by trained technicians. The activities are intended to represent activities that happen in the participant's own environment. As much as one tries to standardize lab experiments, the data are likely to provide only a partial snapshot of the heterogeneous activities individuals perform in their own houses. It remains unclear how in-lab data prediction algorithms perform in free-living environments, especially in the absence of labeled in-home data on hundreds of individuals. Also, we have not yet investigated how well methods could be trained on one or multiple participants and then applied to other participants. However, these issues provide opportunities for future work.

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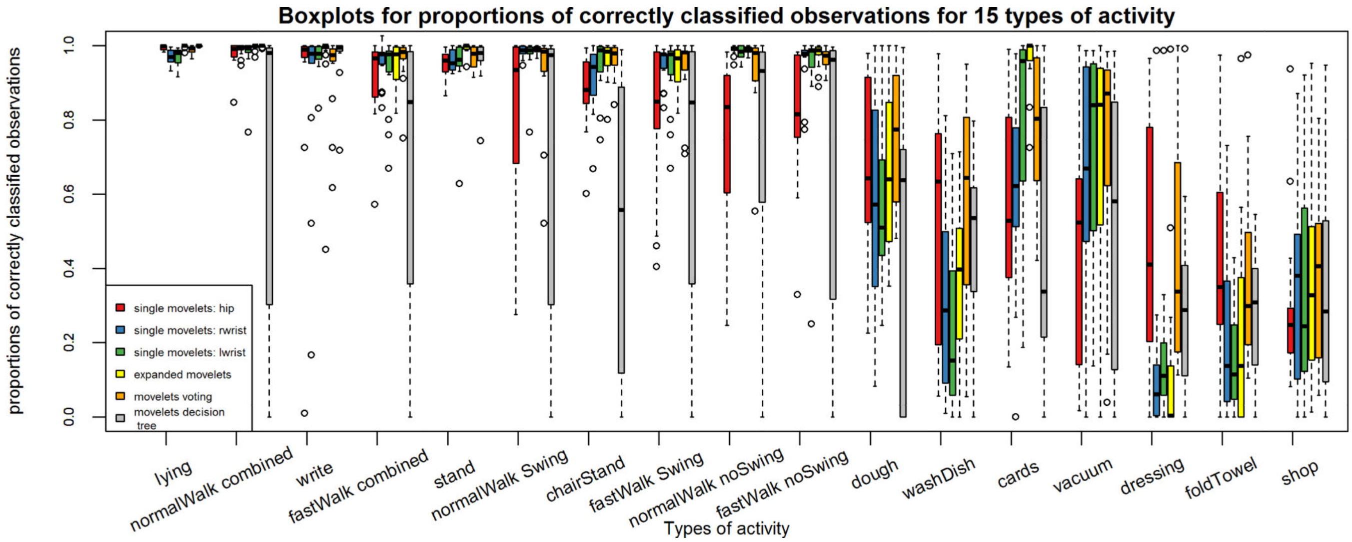

Figure 1.

Boxplot for prediction accuracy (i.e., proportions of correctly classified observations) for 15 types of activity using hip-worn accelerometer (red), right wrist-worn accelerometers (blue), and left wrist-worn accelerometers (green), and using integrative approaches expanded movelets (yellow), movelets voting (orange), and movelets decision tree (grey). normalWalk combined is the combined category of normalWalk Swing and normalWalk noSwing; and fastWalk combined is the combined category of fastWalk Swing and normalWalk noSwing. The activity labels on the X axis are ordered decreasingly by the median prediction accuracy of hipworn accelerometers (red).

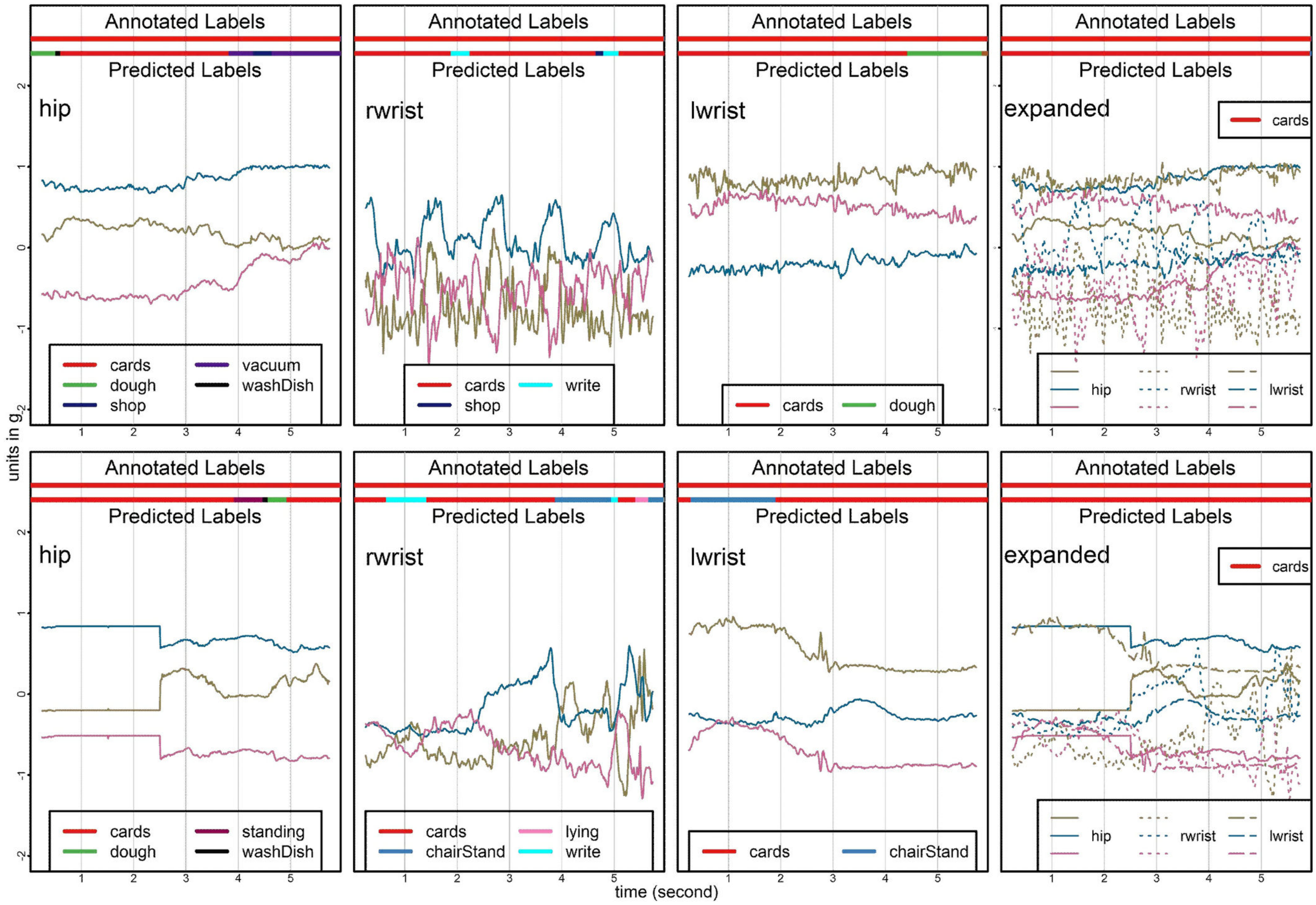

Figure 2.

Examples of prediction results using expanded movelets approach. Time series of raw signals on three axes are plotted accompanied by annotated labels and predicted labels. Each row of panels corresponds to one participant. The four columns display the prediction results for cards using the single hip-worn accelerometer, the single right wrist-worn accelerometer, the single left wrist-worn accelerometer, and the expanded movelets approach.

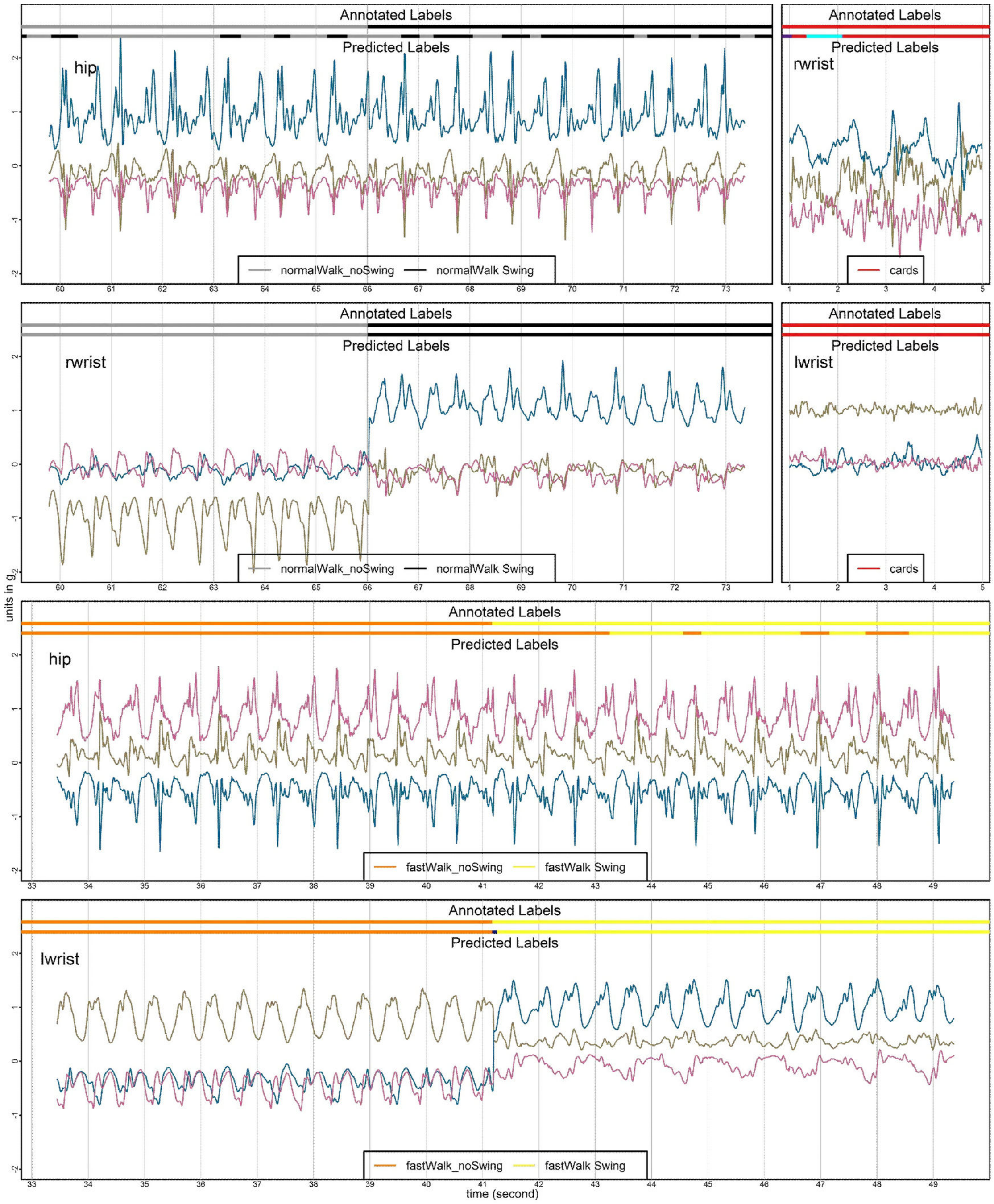

Figure 3.

Examples of prediction results using single-accelerometer movelet approach. Time series of raw signals on three axes are plotted accompanied by annotated labels and predicted labels. Activities are color-coded. The examples are: 1) wrist-worn accelerometers can better distinguish between normalWalk Swing and normalWalk noSwing (the left panels in 1st and 2nd rows) and between fastWalk Swing and fastWalk noSwing (the panels in 3rd and 4th rows); and 2) left wrist-worn accelerometers can predict cards with higher accuracy than right wrist-worn accelerometers (the right panels in 1st and 2nd rows).

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Table 1

Median prediction accuracy (interquartile range)across participants for different types of activities using single-accelerometer movelet approach based on hip-, right wrist-, and left wrist-worn accelerometers, and using expanded movelets, movelets voting, and movelets decision tree. Activities are ordered decreasingly by the median prediction accuracy of hip-worn accelerometers.

	single-accelerometer movelet: hip (%)	single-accelerometer movelet: right wrist (%)	single-accelerometer movelet: left wrist (%)	expanded movelets (%)	movelets voting (%)	movelets decision tree (%)
lying	99.87 (0.97)	97.05 (2.92)	98.05 (2.75)	100.00 (0.00)	99.33 (1.21)	100.00 (0.24)
normalWalk combined	99.15 (2.88)	99.36 (0.91)	99.35 (1.66)	100.00 (0.19)	100.00 (0.05)	98.13 (53.93)
write	98.91 (2.89)	97.91 (4.45)	97.81 (3.25)	100.00 (0.31)	97.52 (2.90)	99.58 (1.25)
fastWalk combined	96.61 (11.99)	96.05 (2.89)	97.76 (5.08)	97.76 (7.54)	98.40 (2.42)	84.80 (44.7)
stand	96.09 (4.35)	95.31 (4.80)	96.25 (4.89)	100.00 (0.95)	97.81 (5.21)	98.13 (3.51)
normalWalk Swing	93.50 (29.69)	98.87 (1.99)	98.86 (1.77)	99.19 (1.17)	98.45 (5.75)	97.55 (53.68)
chairStand	88.09 (10.84)	94.31 (10.08)	98.81 (5.96)	98.42 (4.83)	98.04 (3.99)	55.76 (69.97)
fastWalk Swing	84.97 (19.38)	95.87 (3.62)	97.68 (5.46)	96.70 (7.25)	98.22 (4.85)	84.75 (44.67)
normalWalk noSwing	83.52 (28.89)	99.22 (0.84)	98.45 (2.85)	99.13 (1.22)	98.16 (8.27)	93.19 (34.52)
fastWalk noSwing	81.56 (21.39)	97.85 (1.13)	98.73 (4.70)	98.89 (1.58)	97.32 (3.16)	96.30 (61.7)
dough	64.28 (37.39)	57.22 (42.3)	51.09 (25.54)	64.06 (34.7)	77.44 (32.97)	63.75 (71.15)
washDish	63.44 (56.64)	28.71 (37.82)	15.20 (30.51)	39.7 (28.67)	64.45 (44.41)	53.61 (24.44)
cards	52.81 (39.75)	62.21 (23.27)	95.94 (34.2)	100.00 (3.00)	80.31 (32.56)	33.75 (61.79)
vacuum	52.32 (47.15)	67.02 (45.5)	84.05 (44.22)	84.08 (40.28)	87.19 (26.77)	58.03 (65.15)
dressing	41.07 (55.72)	6.00 (11.74)	11.00 (13.26)	0.27 (8.68)	33.78 (49.06)	28.77 (24.69)
foldTowel	34.93 (33.73)	13.66 (31.02)	11.35 (18.81)	13.66 (35.47)	29.92 (28.77)	30.83 (18.64)
shop	24.72 (10.88)	37.97 (35.35)	24.43 (41.08)	32.8 (32.24)	40.54 (34.9)	28.40 (40.65)