Towards Robust Framework for On-line Human Activity Reporting Using Accelerometer Readings

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Abstract. This paper investigates subsequent matching approach and feature-based classification for activity recognition using accelerometer readings. Recognition is done by similarity measure based on Dynamic Time Warping (DTW) on each acceleration axis. Ensemble method is proposed and comparative study is executed showing better and more stable results. Our scenario assumes that activity is recognized with very small latency. Results shows that hybrid approach is promising for activity reporting, i.e. different walking patterns, using of tools. The proposed solution is designed to be a part of decision support in fire and rescue actions at the fire ground.

1 Introduction

Activity recognition of a person in motion is an important task in many fields such as ubiquitous computing, medical diagnosis [6,25], or inertial-based dead reckoning. One of the possible approaches concern using accelerometers mounted on different parts of the human body that reports its acceleration in three axes. Readings from such devices can be employed in activity estimation using, for example, machine learning. Recent advances in mobile technology make those devices cheaper and more precise, which makes them more accessible for large-scale application and broad scientific research. In this paper, we investigate subsequent matching approach of time series readings for the problem of activity recognition.

Before going into the details let us clarify the notation. By *series* we mean a sequence $\sigma = [a_1, \ldots, a_N]$, where $N \in \mathbb{N}$ is the length of the time series and $a_i := a(t_i) = \big(x(t_i), y(t_i), z(t_i)\big)$, $i = 1, \ldots, N$, are accelerations in local inertial system. Each acceleration in the time series we call a *signal*.

The problem of on-line activity recognition can be stated as finding of a function c which assigns to fragments of time series (from different parts of the body) a tag, i.e.

$$c_m(h) = c(a^{\sigma}_{h-m}, \ldots, a^{\sigma}_{h}, a^{\tau}_{h-m}, \ldots, a^{\tau}_{h}, \ldots) \rightsquigarrow \mathfrak{T}, \tag{1}$$

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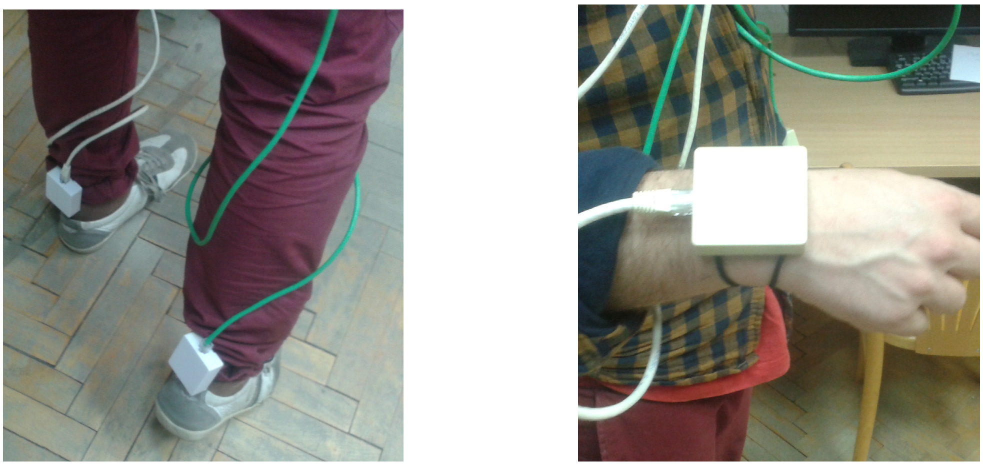


(a) legs (b) hands

Fig. 1. Mounting points of accelerometers

where $\mathfrak{T}$ is a set of predefined activity descriptions (tags, see Section 3), $h = m+1,\ldots,N$, $m \geq 1$ is an activity recognition *window size*, and σ, τ, ... denotes that signal is collected from hand, leg, pelvis etc. Moreover, *lead time* (i.e. the time after the action which is spend on calculations) minimizing issue is crucial for interactive and real-time reporting applications.

In the context of the activity recognition systems few aspects should be considered. Firstly, ability of the classification scenario to generalize between different individuals (*subjects*). It is noticeable that different subjects have different walking/gesture patterns to such extend that it can be even used for user identification [7,8]. Secondly, specificity of whole system is important. For instance, model-based approach assumes existence of very specific events in time series that are not easy to discover for general application. We try to overcome this problem by building a framework that combines approaches (1) and (2) described above.

We evaluated our method experimentally using custom-build recording device with sensors mounted on different part of human body. Results that concers different walking patterns shows that described method can fullfil on-line processing requirements outputing the same or better results than state-of-the-art methods.

The contributions of this paper are as follows: (1) study of distance-based approach for activity recognition, (2) comparison study of different approaches, and (3) preliminary proposition of a hybrid method.

2 Related Work

In the context of this paper, we can consider three general approaches for time series classification: (1) feature-based, (2) distance-based, and (3) model-based. First group combines feature extraction and windowing techniques with machine learning (for detailed description see survey [19]). In the second case predefined set of patterns is matched to incoming series using some distance measurements.

This approach is proven to be efficient in, for example, hands gesture recognition [12]. Model-based approach assumes that acceleration changes denote some events in movement (e.g. detachment of the heel from the ground [3] etc.). Such events can be identified by various methods and its order of appearance can be described using statistical models.

The first papers concerning estimation of behaviour using accelerometers were related to daily activities [5,18]. Those approaches were based on feature extraction from time series. Moreover, with the spread of low-cost accelerometers there were attempts to use higher number of devices, e.g. for all segments of the body [21].

The common solution in the most recent works is to combine feature extracting methods with machine learning algorithms [17]. For example, using this idea in [4] authors defined characteristics such as: mean, standard deviation, skewness, kurtosis and eccentricity. Afterwards, these parameters are processed by a simple neural network, which gives the possibility to recognize states such as: standing, sitting, lying-back, lying-on, walking, running, running upstairs, and downstairs. In the above-mentioned paper the authors rate this method to be around 85%–90% effective. Unfortunately, continued work and re-tests carried out after a period of approximately 1.5 years showed that the quality of the classifier was significantly weaker.

Signal is usually processed in relatively small parts of the data called moving windows. The sub-problem, therefore, is to answer the question how to apply the window. The simplest solution is to use fixed size of moving window. More sophisticated methods are based on event detection [9]. Another usage of the event detection may be the development of movement language [15,20,22]. Exhaustive survey [16] gives a state-of-the-art, which shows that nowadays methods have about 80% up to 95% accuracy.

Various authors propose to put sensors in different places of the human body. The most natural are: top of the foot, ankle, elbow, wrist, head, waist. For example, in some papers data obtained from a sensor worn on the waist allow to detect step, or even estimates its length [2,23].

Another way to recognize a human behaviour is to perform a subsequence matching against predefined time series patterns. This can be done with, for instance, simple Euclidean distance measurement. Taking into consideration the ability of the signal to shift or scale a better way to do this is to use Dynamic Time Warping [13] or Longest Common Subsequence [10]. Those solutions are very promising [1].

3 Data Acquisition

Accelerometer readings for our experiments are collected by a prototype recorder of our design. It consists of five ADXL345 accelerometers (mounted on hands, legs and torso), Arduino board, and SD card. Sensors was able to determine linear acceleration in range [-8g, 8g] at 100hz with 13 bits of resolution.

Data were collected from five subjects. Each recording session consisted of two phases: training data collection and test movement. Firstly, subjects were asked to perform some action (such as walking, running, etc.) over the straight line. *Training data* recorded in this way can be considered as "ideal". In the *test data* collection phase, however, subjects were able to move freely over the predefined path. Speed, time and form of movement was completely up to them with exception that all of the previously recorded activities should be performed. By that means the test time series was distorted, introducing unknown deviation from training data such as turnings and *transition states*.

When considering normal human activity it is very difficult to specify clear boundaries between different activities and, therefore, it is challenging to perform good quality tagging of test data. This is due following reasons: (1) the activities are often mixed together in short periods, and (2) the existence of transient states between activities. Furthermore, evaluation on "ideal" data can be misleading and one can easily achieve almost one hundred percent accuracy. Therefore, proposed above data acquisition method is closer to the real-life applications than cross-validated testing on training sample (i.e. training on data with exclusion of the tested person).

In this paper, we are using the following self-describing tags: `walk`, `run`, `stairs_up`, `stairs_down`, `stairs_up_run`, `stairs_down_run`.

4 Pattern Extraction and Matching

The whole process of constructing patterns using the training set is illustrated in Figure 2. Following intuition from [12, Section 2], we assume that activity can be either composed of consecutive events or one event can denote whole activity. Examples of such activities are: walking (which is composed of individual steps), or opening doors (which is an indivisible event). Those different training sets are illustrated in Figure 2 as *Training Set A* and *Training Set B*, respectively.

Readings from the three axes of relative coordinate system are transformed so that we end up with only one time series, i.e. multivariate series is transformed into univariate one. For this reason, we use the following mapping: $\widehat{a}(t) := \sqrt{x(t)^2 + y(t)^2 + z(t)^2}$, $t = t_1, \ldots, t_N$. Such transformation is widely used in similar applications. Roughly speaking, it describes spectral energy of the system [19, Section 4.3].

Subsequent matching approach in our case means that patterns from training data are discovered at first. They represent events that unambiguously identify an activity. Patterns within one tag are then divided into classes, due to length of the sample. More formally, it can be said that with training data $\{p^{i,j,k} := [b_1^{i,j,k}, \ldots, b_{l_{j,k}}^{i,j,k}]\}_{i,j,k} \subset \mathcal{S}_{l_{j,k}}$ we associate pattern $\hat{p}^{j,k} := [\hat{b}_1^{j,k}, \ldots, \hat{b}_{l_{j,k}}^{j,k}] \in \mathcal{S}_{l_{j,k}}$, where $\mathcal{S}_N$ is the space of all series of length N, index $i \in \{1, \ldots, i_{j,k}\}$ enumerates examples in training set, $k \in \{1, \ldots, k_j\}$ indicates classes, and $j \in \mathfrak{T}$. This pattern is a representation of the considered training data set; see Figure 4.

4.1 Pattern Extraction

In the case of multi-event activities, training series at first need to be divided into cyclic events (example of such segmentation is depicted in Figure 3). Event can

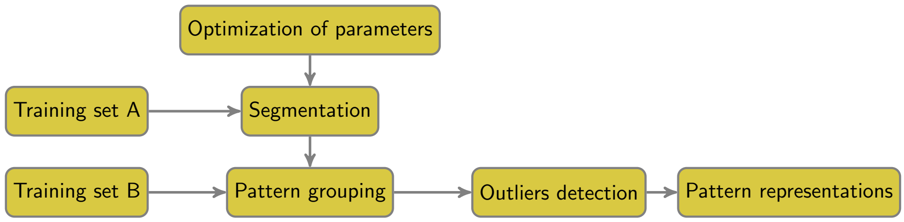


Fig. 2. Pattern Extraction pipeline

be considered as shortest subsequence with highest autocorrelation coefficient. Formally, we can express the length of the event in training series $\widehat{a}(t)$ as:

$$\text{event\_length}\big(\widehat{a}(t)\big) := \underset{i}{\operatorname{argmax}} \operatorname{corr}\big(\widehat{a}(t), \widehat{a}(t)^{i}\big), \tag{2}$$

where $\widehat{a}(t)^i$ is "series shift" by i (i.e. $\widehat{a}^i(t_j) := a(t_{i-j})$, $j = i+1, \ldots, N$). It is a matter of choice which autocorrelation number one can choose (first peak or the maximum peak). For example, considering torso readings first peak denotes steps, while position of maximum peek stands for the length of two steps for all tested subjects (due to common asymmetric gait).

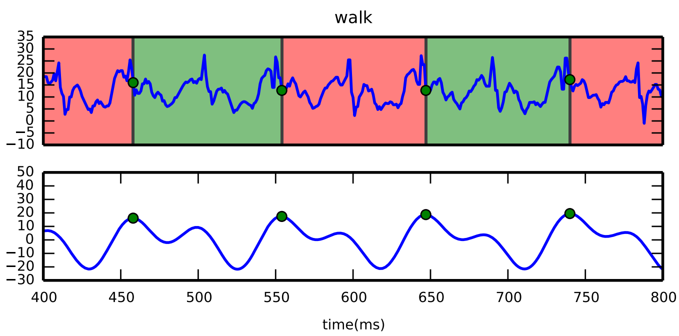


Fig. 3. Segmentation of the training signal. Upper row is the mapped signal $\widehat{a}(t)$ and discovered segments. Lower row contains wavelet filter.

Segmentation in the training data is created using filtered signal $\widehat{a}(t)$. Wavelet filter is used with the base function being the *Mexican hat* of length equal to $m := \text{event\_length}\big(\widehat{a}(t)\big)$. Afterwards, in the filtered signal we are seeking for a local maxima or minima. We assume that different patterns have their end and start markers exhibiting some acceleration peaks. However, if the action has several such peaks it may be difficult to find the corresponding one. Thus, we solved this issue by searching the extremes which distance from the current state is not greater that m.

Clustering of the patterns is obtained by hierarchical-agglomeration clustering with dendrogram cutting factor $t = 0.5 \times \max(\mathit{distances})$. By *outliers* we mean such observations that are contained in "small" groups, i.e. those that number of elements is less than 10% of the all examples. These often come from "edges" of the signal or are mistakes in tagging or recording.

4.2 Pattern Representation

There are two main goals for choosing the representation of patterns: (1) performance of classification, and (2) lower computational cost. Unfortunately, these objectives are mutually exclusive. In the first case the function that is optimized determines the distances of individual groups of tags, while in the second case we minimize the amount of compared patterns.

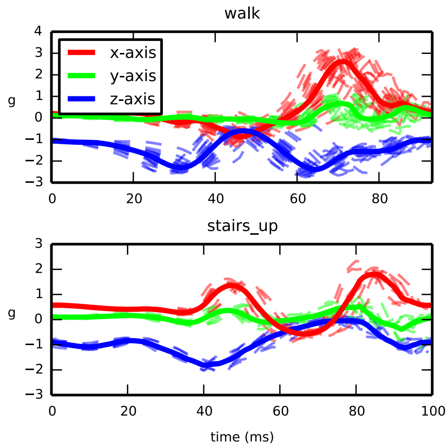


Fig. 4. Example of two patterns from one cluster; dotted line is a original example and thick solid line is a pattern representation (in this case it is *centroid*)

In this paper, we do not compare all of the patterns but only representatives of each clusters. There are a lot of possibilities of choosing the right representative and for the means of this paper we are using centroids of the clusters. Example is depicted in Figure 4.

4.3 Distance Measurements

This section concerns comparing of time series. One of the most popular methods for comparing the patterns is *Dynamic Time Warping* (DTW). DTW is a method that finds an optimal alignment between two given time series. Intuitively, time series are warped in a non-linear manner to fit each other.

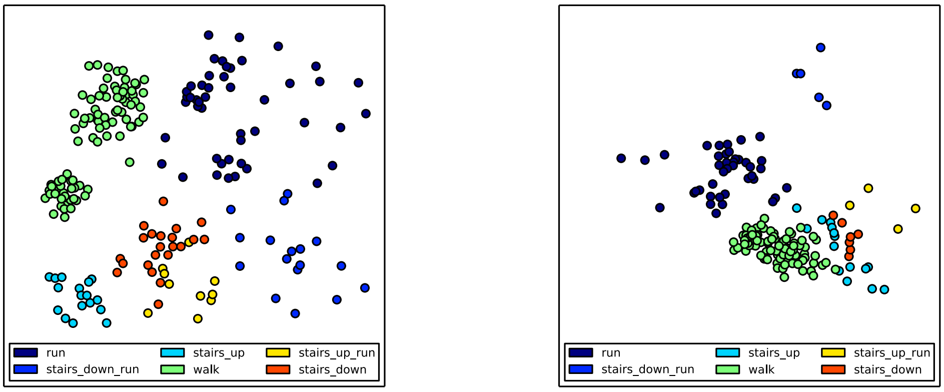
Following this idea as *similarity measure* for patterns p_1 and p_2 we take measure ρ defined as

$$\rho(p_1, p_2) := \alpha_x \rho_1(x_1, x_2) + \alpha_y \rho_2(y_1, y_2) + \alpha_z \rho_3(z_1, z_2), \tag{3}$$

where ρ_l are DTWs and constants $\alpha_x, \alpha_y, \alpha_z \in (0, 1)$, $\alpha_x + \alpha_y + \alpha_z = 1$, are chosen by simultaneous maximisation of the expressions

$$\Delta_i := \frac{1}{|\mathfrak{T}|} \sum_{\substack{i \neq j \\ j \in \mathfrak{T}}} \sum_{k \in \{1,\dots,k_j\}} \rho\big(\hat{p}^{i,k}, \hat{p}^{j,k}\big), \quad i \in \mathfrak{T}. \tag{4}$$

By brute force optimisation method we end up with constants $(0.3, 0.1, 0.6)$, which, roughly speaking, favours match z and x axes rather than y axis.



(a) Patterns distances.

(b) Feature distances using peek-to-peek detection.

Fig. 5. Separation of examples in both methods

4.4 Subsequent Matching Approach

In the subsequent matching approach as a classifier we choose

$$c_m(h) := \operatorname*{argmin}_{j \in \mathfrak{T}} \left\{ \min_{k \in \{1,\dots,k_j\}} \frac{\rho\big(\hat{p}^{j,k}, [\widehat{a}_{h-m+1}, \dots, \widehat{a}_h]\big)}{m} \right\}. \tag{5}$$

It is easy to see that we classify each time point by means of its moving window. Later, such classifier we call `1nn-centr`. Other variants of it will appear in Section 6, where we discuss the issue of combining of this approach with feature-based approach.

Remark. When you look closely on the last expression you will notice that it is just 1-NN classifier but over the set of representations.

5 Feature-Based Approach

This section describes a feature-based approach threaten in this work as a baseline for activity recognition due to its popularity in related papers. This approach consists of steps leading to a list of features calculated using a sliding window.

Basically, *moving window* is a subset of time series composed by consecutive elements (i.e. $[\widehat{a}_q, \widehat{a}_{q+1}, \ldots, \widehat{a}_r] \subset \sigma$). Essentially, there are three possibilities how it can be obtained: (1) we can assume that the window can have fixed size, (2) window can have starting and ending trigger, and (3) there can be events (e.g. peaks that can be interpreted as touching the ground by heel) indicating beginnings and endings [19, Section 4]. Second and third approaches are different in such a way that the first needs two markers, and the latter just one. Since the first variant is most straightforward we focused on this one.

Having moving window of length $m \in \mathbb{N}$ *sliding window* $\mathcal{W}(f, \cdot, m) \colon \mathcal{S}_N \to \mathcal{S}_{N-m}$ with feature $f \colon \mathbb{R}^m \to \mathbb{R}$ is defined in the following way

$$\mathcal{W}(f, \sigma, m) := \big[f(\widehat{a}_1, \ldots, \widehat{a}_m), f(\widehat{a}_2, \ldots, \widehat{a}_{m+1}), \ldots, f(\widehat{a}_{N-m+1}, \ldots, \widehat{a}_N)\big]. \quad (6)$$

Since time series is noisy, it have to be smoothed first. For this reason, we utilize Kalman filter, because it has large signal-to-noise ratio and correlation coefficient [24]. It is worth to note that other filter (such as, e.g., wavelet filter) can be chosen as well. However, in case of wavelet filter one has to choose specific component of the wavelet decomposition and concentrates on it.

Relying on the results from [11], we use the list of features as follows: *(a)* total variation, *(b)* fractional dimension, *(c)* standard deviation, *(d)* mean deviation, and *(e)* mean. Therefore, in the training set each tag has five features. Training dataset can now be classified using machine learning techniques.

In order to determine the level of similarity of different activities we projected dataset onto the plane using Multidimensional Scaling (MDS). In Figure 5 the reader can see MDS on the set of similarity measures between: *(a)* patterns, and *(b)* features. Clearly, the case (a) is more easily separable than (b), even in the case of many subjects.

6 Experimental Results

We tested classification performance over the collected dataset using reading from single accelerometer as it is described in Section 3. In order to perform comparative evaluation of feature-based and distance-based approach we constructed simplified classifier in the following way

$$c_m(h) = c(a^\sigma_{h-m}, \ldots, a^\sigma_h) \rightsquigarrow \mathfrak{T}, \quad h = m+1, \ldots, N. \quad (7)$$

Evaluation was performed in three settings: (1) one-to-one — accuracy and recall was measured for each person, using just his training data, (2) leave-one-out — cross-validated evaluation is performed, e.g. classifiers are trained on four subjects and tested on the excluded one, (3) all-to-one — all of the training series were used for classifiers learning. First and third scenario can be considered as personalized system, the second case, however, shows how each classifier generalize between humans.

Table 1. Confusion matrix for the Majority classifier

	run	stairs_down_run	stairs_up	walk	stairs_down	stairs_up_run
run	**.77 ± .19**	.02 ± .07	.00 ± .01	**.14 ± .18**	.00 ± .00	.07 ± .08
stairs_down_run	**.41 ± .34**	**.57 ± .36**	.00 ± .00	.01 ± .05	.00 ± .00	.01 ± .05
stairs_up	.05 ± .15	.00 ± .00	**.76 ± .31**	.04 ± .06	.00 ± .00	**.15 ± .26**
walk	.05 ± .06	.00 ± .00	.02 ± .02	**.90 ± .07**	.00 ± .00	.03 ± .03
stairs_down	.00 ± .00	.00 ± .00	.00 ± .00	.00 ± .00	**1. ± .00**	.00 ± .00
stairs_up	**.47 ± .30**	.00 ± .00	.06 ± .14	.09 ± .10	.00 ± .00	**.38 ± .28**

6.1 Hybrid Approach

In order to assess our approach we created two more classifiers. Both are versions of the classifier described in Section 4.4. The first one is called 1nn-patterns and is given by the formula

$$c_m(h) := \operatorname*{argmin}_{j \in \mathfrak{T}} \left\{ \min_{\substack{i \in \{1,\ldots,i_{j,k}\} \\ k \in \{1,\ldots,k_j\}}} \frac{\rho\big(p^{i,j,k}, [a_{h-m+1}, \ldots, a_h]\big)}{m} \right\}. \tag{8}$$

The approach which combines features and patterns is achieved by modifying the similarity measurements by the following formula

$$c_m(h) := \operatorname*{argmin}_{j \in \mathfrak{T}} \left\{ \min_{k \in \{1,\ldots,k_j\}} \frac{pr_{\mathsf{lsvm}}(j; \sigma_h) \cdot \rho\big(\hat{p}^{j,k}, \sigma_h\big)}{m} \right\}, \tag{9}$$

where $\sigma_h := [a_{h-m+1}, \ldots, a_h]$ and $pr_{\mathsf{lsvm}}(j; \sigma_h)$ denotes classification probability of tag $j \in \mathfrak{T}$ for window σ_h using Linear SVM classifier, which we choose, because it was fast and has good classification score. Such classifier we called 1nn-centr*.

Remark. Proposed recipe for a hybrid approach is very simple and promising method for activity recognition.

This method can easily be modified to work on-line, since the most computationally demanding operation is DTW (with complexity of $\mathcal{O}(m^2)$). In the worst case one can apply any method of time series indexation.

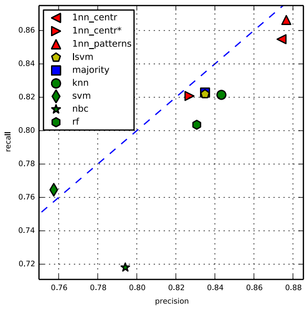
6.2 Classification of Walk Patterns

Tables 1 and 2 contain confusion matrices for all subjects in all settings for Majority classifier over features and 1nn-pattern classification, respectively. Bold values indicates those scores which are greater than 0.1. It is worth to note that both classifiers fail in different way. For instance, 1nn-patterns generates the largest number of false positives in the case of stairs_down, while Majority gives very good results when considering this tag. This suggests that those classifiers are independent to some extent and ensemble classification is promising approach.

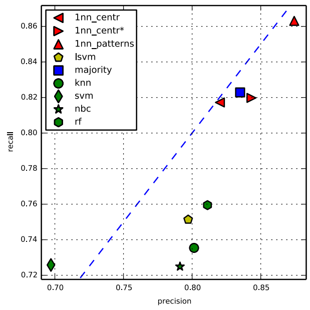
Figure 6 depicts classification accuracy and recall. Results indicates that for each setting 1nn-patterns achieves better accuracy by 3.25%, 4.58% and 6.78% on each setting, respectively. Surprisingly, even for leave-one-out settings is better, which indicates that it has good generalization ability. This classifier, however, is

Table 2. Confusion matrix for `1nn-patterns` classifier

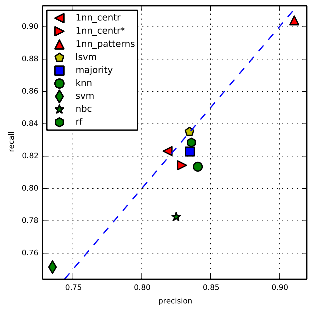
	run	stairs_down_run	stairs_up	walk	stairs_down	stairs_up_run
run	**.79 ± .19**	.01 ± .04	.01 ± .02	.07 ± .13	**.11 ± .07**	.01 ± .04
stairs_down_run	.03 ± .07	**.67 ± .30**	.00 ± .00	.02 ± .06	**.18 ± .17**	**.10 ± .21**
stairs_up	.00 ± .00	.02 ± .08	**.80 ± .24**	.03 ± .08	**.12 ± .10**	.04 ± .10
walk	.01 ± .02	.01 ± .02	.00 ± .01	**.88 ± .08**	.09 ± .04	.01 ± .04
stairs_down	.00 ± .00	.00 ± .00	.00 ± .00	.00 ± .00	**1. ± .00**	.00 ± .00
stairs_up	.03 ± .11	**.15 ± .24**	.01 ± .03	.06 ± .05	**.14 ± .07**	**.61 ± .30**



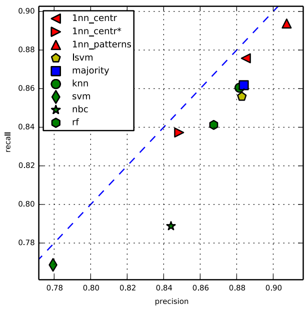
(a) one-to-one



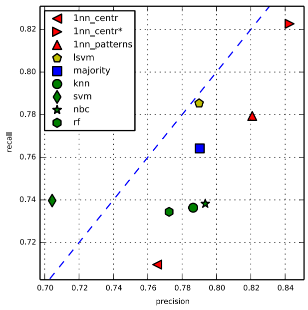
(b) leave-one-out



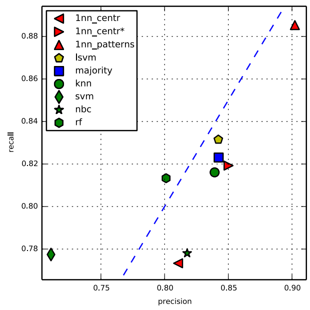
(c) all-to-one



(d) one-to-one



(e) leave-one-out



(f) all-to-one

Fig. 6. Precision vs recall of classification based upon readings from right leg (upper row, subfigures a–c) and left leg (lower row, subfigures d–e). Non-triangles are feature-based classification over combined signal $\widehat{\sigma}$ with moving window of the size of 101 (approximately one second), smoothed by the Kalman filter. Triangles depicts pattern-based classification (Section 6), whole pattern set (`1nn-patterns`), representations (`1nn-centr`), and combined `lsvm` classifier with `1nn-centr` according to formula (9).

not applicable in on-line processing due to computation cost as opposed to `1nn-centr`, which is quite fast, however, it does not give the expected results (standard deviation of the precision is high). `1nn-centr*` gives more stable results which are better or, at least, not worse than features-based classifiers. An interesting case is Figure 6 (e), where `1nn-centr*` is the best.

7 Conclusion & Future Work

In this paper, we proposed a framework oriented toward on-line activity recognition. We compared two approaches for this task using readings from accelerometers mounted on different parts of the body. Our experimental results shows that hybrid approach (using feature-based and subsequent matching approach) is promising for activity reporting.

This work is a part of larger project called *ICRA*[1], in which it is a submodule responsible for fire fighters activity reporting. One of the goal of the ICRA system is to assess risks at the emergency scene. In the most cases the risk is related to the activities performed by fire fighters. Therefore, the activity recognition plays a pivotal rôle in risk assessment [14].

As part of the further work we would like to prepare a set of data, which will be held during simulated operations with the encounter of fire. Subsequently, we will also test the way in which our framework performs for single-event activities, like, for example, operating with tools and environment.

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