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Your Body Defines Your Fall Detection System: A Somatotype-based Feature Selection Method

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***Abstract*—Fall detection for the elderly is in great demand in order to mitigate the effect of falls. As fall detection system is a safety shield on which people's lives depend, high detection sensitivity is always the pursuit of fall detection system. Previous works prove that the sensitivity is correlated to the type of detection features. But generating personalized optimal detection features is difficult due to its high computation complexity. In this paper, we propose a somatotype-based feature selection method which can give user's optimal features without extra cost. Based on the finding that user's optimal detection features can be determined by their somatotype features (i.e., height and body mass index), we partition all users into different clusters according to their somatotype features and calculate the optimal features for each cluster. Several experiments prove that feature selection carried on somatotype based group can increase the detection accuracy effectively.**

I. Introduction

With the arrival of aging society, physical and mental health problems of the elderly attract more attention. While accidents appear more frequently for the elderly, accidental fall is the most universal one and can very likely cause serious problems. According to the data from the Center for Disease Control and Prevention, more than a third of adults over 65 years old fall at least one time each year. Moreover, the number of falls increases with the increase of age of human. For example, the fall counts of the elderly over 75 is almost five times more than that of younger people [1]. In addition, the falls without first aid treatment may result in serious consequences, including physical damages, e.g., bruising, bleeding, fracture, and even worse, dying and mental damages, e.g., fearing of activity. Shumwaycook et al. show that these damages frequently come up and bring huge medical costs [2]. Apparently, with the high possibility of falling accidentally, the elderly always face potential threat to their health, as well as individual pecuniary conditions. Actually, although accidental fall is hard to be avoided due to the senescence of body function, the risk of fall can be managed and controlled. As mentioned in [3], urgent securing is the most important thing while falls happen, since the injury degree is related to securing time. Thus, discovering and publishing the falling events as soon as possible is the top priority.

Over the past few years, a popular solution of discovering falls is called fall detection method, which prefers to monitor user's actions real-timely. Although there exist various kinds of fall detection methods, we mainly address the wearable fall detection without loss of generality. Earlier works tend to provide the fall detection system with a unified model for all users [4]. They capture user's action features, including activities of daily living and fall, and then build classification model to detect falls based on these data. Generally, the classification model mainly contains two types, threshold-based and learning-based model. However, these traditional methods don't take the individual differences into account, resulting in a just passable detection accuracy.

Actually, the individual difference is mainly reflected by two elements, the type of action features and the value of thresholds (if using pattern recognition-based model to judge falls, this parameter will be replaced by the trained parameters of learning model). Ren et al. [5] propose a threshold-personalized fall detection system called Chameleon. By combining the group-based threshold strategy with individual threshold adjustment strategy, this method builds a threshold extraction model based on weight so that solving the low precision problem caused by fixed threshold. This method of generating personalized thresholds is almost perfect. On the other hand, the fall detection methods can also benefit from selecting personalized action features. Kansiz et al. find that different action features have different effect on detection accuracy [6]. They propose a feature selection method which can extract an optimal feature vector for classification. As its name indicates, the optimal feature vector can maximize the classification accuracy. Considering the computational complexity, this work only selects the unified optimal feature vector for all users without personalization.

In this paper, we propose a somatotype-based feature selection method, which can generate personalized optimal features with low complexity. We choose One-Class Support Vector Machine (OCSVM) as fall detector and training its parameters according to the theory proposed in [5]. The unsolved problem is how to select optimal features for each individual with applicable complexity. To briefly summarize our method, we define an action feature set $F^n = \{f_1, f_2, \cdots, f_i, \cdots, f_n\}$ and another set $\mathbb{F}$ containing all non-empty subsets of F^n. Each element in $\mathbb{F}$ is an action feature vector, and we can calculate its corresponding accuracy for each user. For user j, the action feature vector with the highest accuracy is defined as his optimal action feature

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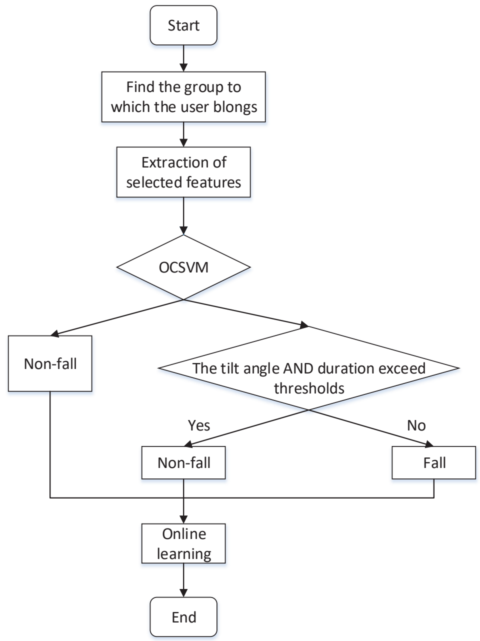


Fig. 1: Flowchart of personalized and adaptive fall detection algorithm.

vector (OAFV), denoted by $\mathfrak{F}_j$. Apparently, the computation complexity is too high to be used in actual condition. To decrease the complexity , we divide all participants into several groups according to the similarity of their OAFV and calculate the optimal group feature vector (OGFV) for each group. Our experiments show that the OGFV can achieve similar accuracy to OAFV. Unfortunately, this clustering still rely on the complex calculating process, so that finding an practicable clustering principles is necessary. Thus, we select the somatotype features as the clustering criterion, instead of action features. We surprisingly find that the two clustering results are almost the same. In other words, we can partition users according to their somatotype without losing accuracy. Thus, we calculate the optimal feature vector based on somatotype (OFVS) for each cluster. A flowchart of the proposed system is shown in Figure 1. Experimental results prove that the somatotype-based feature selection method can effectively improve the performance of the fall detection.

In general, the contribution of this paper is as follows:

(1)We proposed a somatotype-based feature selection method for fall detection, which significantly improve the detection accuracy without extra cost.

(2)We validate that the OAFV is indeed corresponding to somatotype.

II. Related work

Fall detection approaches based on wearable devices always rely on garments, smart phones or sensor nodes with embedded sensors to detect the motion of the subject [7][8]. It has become a main trend of the current research due to its lower cost, higher flexibility and operability. What's more, wearable devices will not restrict user's activity or leak privacy information.

Generally, traversing all wearable devices, the most important elements are accelerator and gyroscope. The accelerator is capable of acquiring magnitude and acceleration direction. Dai et al. [9] use the three-axis accelerator which is embedded in the smart phone to obtain acceleration signal, and extract the amplitude and inclination of the combined acceleration to judge fall. Once detecting a fall, first aid messages will be published directly to alarm through the phone. The false negative rate is 2.67% and false positive rate is 8.7%. Gyroscope can measure the direction of one or more axes. So we can use it to analyze and infer the postures of human body. Bourke et al. [10] utilize angular acceleration, angular velocity and angle of the human body to detect fall, which can be captured and calculated by a two-axis gyroscope. In order to further improve the detection accuracy, multi-sensor based approaches have been widely used. Baek et al. [11] design a necklace as fall detector which combine three-axis accelerator and gyroscope. The sensitivity is greater than 80% and specificity is 100%.

After capturing activity data, the judgment model will take effect, which mainly contains threshold-based and pattern recognition models. Threshold based model sets a fixed size sliding time window firstly. Then within one sliding window, if the features reach the preset thresholds, the system regards that a fall has taken place [12]. Pattern recognition models, such as support vector machines (SVM) [13], decision tree [14], K-Nearest Neighbor(KNN) [15] and so on, tend to build fall detection classification models through training action data. Lustrek et al. [16] compare several popular pattern recognition methods, they find that SVM performs better in fall detection.

To further improve accuracy, feature selection method is usually used to select the most appropriate classification features. In the literature [6], Kansiz et al. extract 43 time-domain features from 3-axis accelerometer data and build a classification model using supervised learning methods. They demonstrates that general fall detection model needs 5 to 10 discriminative features. And the experiments show that the proposed system can recognize the fall events with approximately 90% success ratio.

III. Somatotype-based feature selection method

A. Notation

As the experimental results is an important composition of the derivation process, we will elaborate the experimental settings in this section.

1) Alternative action features: To select optimal features for users, we should have the comprehensive acquaintance with the frequently-used features in fall detection. In wear-

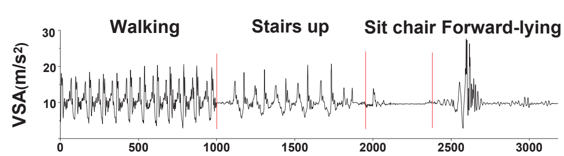


Fig. 2: VSA of four different activities.

Fig. 3: VSP of four different activities.

able fall detection system, the most frequently used features are $vector\ sum\ of\ the\ three\ axes\ acceleration$ (VSA) and $vector\ sum\ of\ the\ three\ axes\ palstance$ (VSP). VSA can be expressed as

$$VSA = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

where a_x is the sample value of the x-axis representing the acceleration of the x-axis with the unit of m/s^2, while a_y and a_z are defined similarly. VSP is given by

$$VSP = \sqrt{p_x^2 + p_y^2 + p_z^2} \tag{2}$$

where p_x is the sample value of the x-axis representing the palstance of the x-axis, with the unit of rad/s, while p_y and p_z are defined in a similar way. They can be captured directly by accelerator and gyroscope. Moreover, they are applicable in recognising user's behaviours, as shown in Fig. 2 and Fig. 3.

The wave forms of different features present great difference, so that being regarded as the principles of detecting falls. Based on the two basic features, another 11 features are also widely used in fall detection according to [7][8], shown in Table I.

2) Dataset: We carry out experiments in the MobiFall dataset v2.0 which is a public available dataset. This dataset is captured by a Samsung Galaxy S3 smart phone with accelerator sampling frequency at 100 Hz and amplitude ranging at $\pm 20m/s^2$. Here we give a short description of this dataset. This dataset is collected from 24 participants, including 17 males and 7 females, whose ages range from 22 to 47. These participants perform falls and activities of daily living(ADLs) while carrying phones. Four different types of falls are captured, including Forward-lying, Sideward-lying, Backward-lying and Front-knees-lying. And the ADL is consisted of nine different activities, including Standing, Walking, Jogging, Jumping, Stairs up, Stairs down, Sit chair, Car-step in and Car-step out. The whole dataset contains 279 Falls and 339 ADLs for each participant performs several activities. And these activities are recorded by the accelerator and gyroscope.

3) Performance Index: To provide an ideal experimental environment, we must construct the fall detection system, referring to the state-of-art works. Considering the actual condition, the data of ADL are much more convenient to be captured than falls as the falling activity rarely takes place. OCSVM is an adaptive learning model as its training process only needs one class data. Furthermore, participants' feedbacks of the detection results can help to improve the detection system. Thus, the online learning module is also necessary. Each false detection result, including true negative and false positive condition, should be recorded and used to update the OCSVM model.

Then we will give the evaluation criterion of the fall detection system. The three criterions, sensitivity, specificity and accuracy, are widely used in evaluating fall detection. They can be expressed as

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

Algorithm 1 Calculate OAFV

Input: Feature set $\mathbb{F}$, user i
Output: the OAFV $\mathfrak{f}_i$

```
Define the highest detection accuracy â = 0;
for all element f_j in F do
    Calculate the detection accuracy a_j = OCSVM(f_j)
    if â < a_j then
        Set 𝔣_i = f_j, â = a_j;
    else if â == a_j then
        if |𝔣_i| > |f_j| then
            Set 𝔣_i = f_j, â = a_j;
        end if
    end if
end for
return 𝔣_i
```

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

where TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively. Sensitivity refers to the probability that the system can correctly identify the fall of the incident. The specificity of the system is the probability that the system can correctly identify the event of ADL. The accuracy of the system refers to the probability of all correctly-determining events.

B. Feature Extraction and Selection

Features can quantify the sensor signal reasonably. And we will carry out fall detection after choosing the most appropriate features, so that normal behavior and fall behavior will be separated more accurately.

We choose wrapper feature selection algorithm here. The reason is that the optimal feature subset selected by this algorithm is much smaller than other algorithms. Firstly, selecting the candidate feature subset in the feature set through search strategy, and then the classification algorithm is used as a bootstrap algorithm to evaluate each feature subset. This process should be preceded iteratively until the selected feature subset is satisfied. This algorithm is very beneficial to the identification of key features, and can achieve an high accuracy.

C. Teoretical analysis of grouping by height and BMI

In this section, we will propose our somatotype-based feature selection method and give its derivation process.

1) Calculating OAFV: As mentioned before, the ideal method can generate personalized OAFV without extra cost. Firstly, we generate the OAFV for each user. According to [6], the detection accuracy will be affected by the type of training features. Thus, for a given feature set F^n, we generate another set which contains all non-empty subsets of F^n, denoted by

$$\mathbb{F} = \{\{f_1\}, \{f_1, f_2\}, ..., F_n\}. \tag{6}$$

The element in $\mathbb{F}$ is named by action feature vector, which is used to train the parameter of OCSVM. For each user, we calculate the detection accuracy of each action feature vector and choose the highest one as his OAFV. The detail procedures are shown in Algorithm 1. Considering the com-

TABLE I: Extracted thirteen time-domain action features.

Features's name	Description of Feature
ave_{VSA},ave_{VSP}(2)	Average values of VSA and VSP.
$\triangle VSA$,$\triangle VSP$(2)	The absolute values of the difference between the maximum and minimum values of VSA and VSP.
$\triangle t_{VSA}$,$\triangle t_{VSP}$(2)	Time differences between of maximum and minimum values of VSA and VSP.
std_{VSA},std_{VSP}(2)	Standart deviation values for VSA and VSP.
E_{VSA}(1)	$\Sigma_{i=1}^{n} VSA^2$,Activity energy.
S(1)	$\sqrt{(maxa_x - mina_x)^2 + (maxa_y - mina_y)^2 + (maxa_z - mina_z)^2}$ ($mina_x$,$mina_y$ and $mina_z$ are the minimum values of accelerator's each axis), Slope.
$\triangle\phi$(1)	$\phi(t) = \frac{180^\circ \times \arccos(a_z(t)/VSA(t))}{\pi}$, The absolute value of the difference between the maximum and minimum values of ϕ.
$\triangle pitch$,$\triangle roll$(2)	$pitch = \arctan(a_x/\sqrt{a_y^2 + a_z^2})$,$roll = \arctan(a_y/\sqrt{a_x^2 + a_z^2})$ The absolute value of the difference between the maximum and minimum values of pitch and roll.

putation complexity, if two feature vectors are corresponding to the same accuracy, we will choose the one with less features.

We carry out a series of experiments to show the difference of accuracy among different action feature vectors. As is shown in Fig. 4, we calculate the highest and average value of evaluation criterions respectively for all users. Obviously, the OAFV performs much better. And this result also validates that there indeed exists an personalized OAFV for each person.

2) Cluster: However, the above method cannot be used in practice for two reasons. For one thing it needs a large amount of computing resource to generate personalized OAFV. The amount of feature vectors in $\mathbb{F}$ can be calculated by $|\mathbb{F}| = 2^{|F^n|} - 1$. Thus training $\mathbb{F}$ OCSVM model is a huge work. For another it has to face the problem of cold starting. It need quite long time to capture training data and train model before it comes into service. Intuitively, if there exists clusters with fixed optimal features and trained model, these problems can be solved. Thus, we will introduce the clustering method in this section.

According to the experimental results in Section III-C1, each participant has a personalized OAFV. To utilize clustering algorithm, we transfer the OAFV into numeric ones. For example, if existing an OAFV $\mathfrak{F}_i = \{f_1, f_2\}$, it will be transferred into $\mathfrak{F}_i = \{1,1,0,0,0,0,0,0,0,0,0,0,0\}$. Then we partition all users into several clusters using K-Means while the distance between two vectors is represented by Euclidean metric. We calculate the OGFV for all clusters using similar method to Algorithm 1. Actually, the OGFV of one cluster is the union of OAFV of all users in this cluster. Then we carry on the comparison between the accuracy of OAFV and OGFV for each user, and the results are shown in Fig. 5. We can see that their accuracies are almost the same. Thus, this action-based clustering method is applicable in the aspect of detection performance. Unfortunately, its clustering principle is still complicated. One user cannot be partitioned into a determined cluster without a series of training. We look forward to a much more concise method.

3) Somatype-based feature selection method: In this section, we aim at finding an applicable clustering principle. Considering the following instance, if we regard the human body as a cylinder, then the angular velocity and acceleration of the fall will change accordingly when its height and basal diameter change. True, the human's behaviours are much more complex than a cylinder, but it inspires us to explore the relationship between user's OGFV and somatotype features.

To validate our suppose, we generate a somatotype vector s_i for each user, which includes gender, age, height, weight and BMI. The set of all users' somatotype vectors is denoted by S. And we implement the K-means clustering method on S. Then the somatotype-clustered user set is denoted by $U_s = \{C_{s1}, C_{s2}, ...C_{si}, ..., C_{sK}\}$, where C_{si} represents the ith cluster containing a series of users. We utilize the euclidean metric to measure the similarity of the action and somatotype-clustered set, while the distance of each dimension is calculated by Jaccard Index, which is shown as follow,

$$J(C_{a,i}, C_{s,j}) = \frac{C_{a,i} \cap C_{s,j}}{C_{a,i} \cup C_{s,j}} \tag{7}$$

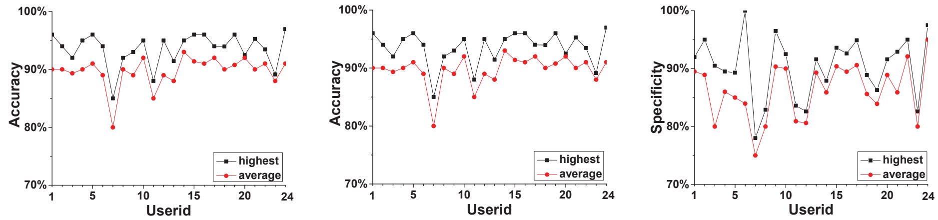
Based on the MobiFall dataset v2.0, the similarity of two clustering method is 0.867. Moreover, we calculate the OGFV for the somatotype-based clusters. Their performances on fall detection are shown in Fig. 6. Apparently, the somatotype-based clustering method can achieve similar performance to action-based one. And the user can be partitioned into a fixed cluster according to his somatotype features while using this system firstly. Thus, this method can be utilized in actual application. We implement a series experiments on different datasets to validate our finding.

IV. Results and analysis

In this section, we implement several experiments on the MobiFall dataset v2.0 to validate the high sensitivity and applicability of our method. Firstly we elucidate our experimental settings. According to the somatotype-based clustering method mentioned in Section III, we partition all participants into 6 clusters, i.e., SL, SM, SH, TL, TM and TH. These clusters are mainly determined by participants' heights and BMIs, e.g., the one whose height is less than 156cm and BMI is less than 18 belongs to cluster SL. Our experimental testbed consists of 2.40GHZ Xeon with 32GB RAM, which runs windows XP.

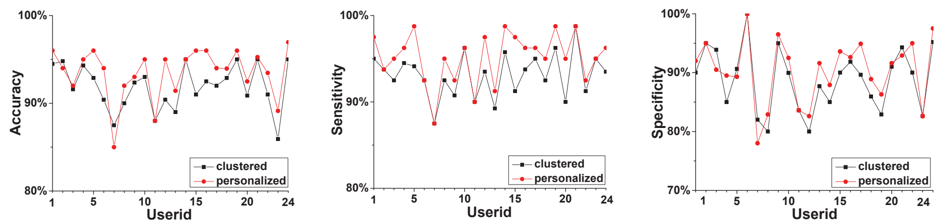
A. Detection Performance

To exhibit the detection performance of our method, we need to calculate the OFVSs for each cluster. A 10-fold cross-validation is applied: the dataset is *randomly*



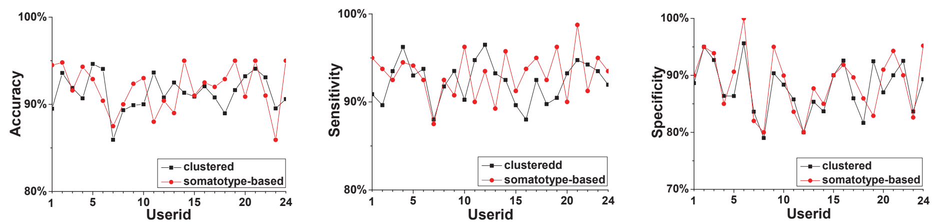
(a)Accuracy (b)Sensitivity (c)Specificity

Fig. 4: Twenty-four participants' performance results according to their own optimal action feature vector.



(a)Accuracy (b)Sensitivity (c)Specificity

Fig. 5: Twenty-four participants' performance results according to the optimal action feature vectors of the groups to which they blong. Groups are divided by action features.



(a)Accuracy (b)Sensitivity (c)Specificity

Fig. 6: Twenty-four participants' performance results according to the optimal action feature vectors of the groups to which they blong. Groups are divided by physiological features.

divided into 10 equal-sized subsets; 9 subsets are used to calculate OFVSs while the odd one validates the detection performance. This procedure is repeated 10 times.

Not unexpectedly, although the training data is selected randomly each time, the OFVS of every cluster is always the same, shown in Table II. And the detection performance is shown in Fig. 8. For an OFVS of a given cluster, we calculate its detection performance for all clusters. Apparently, each cluster can achieve the best performance with its corresponding OFVS.

B. Detection Cost

The applicability of our method mainly reflects in the condition that a new user begins using it. Traditional methods always need a quite long time to capture user's activity data.

TABLE II: Each group's optimal feature set.

Group	Selected features
SL	std_{VSA}, $\triangle roll$
SM	$\triangle pitch$
SH	$\triangle VSA$, std_{VSA}
TL	$\triangle\phi$, std_{VSP}
TM	$\triangle\phi$, $\triangle pitch$, $\triangle VSP$
TH	ave_{VSP}, std_{VSP}
P	ave_{VSA}, std_{VSA}, ave_{VSP}, std_{VSP}

As is shown in Fig. 7, the sensitivity increases with the increase of the scale of training data. During this period, the fall detection system is unreliable. On the contrary, our method can perfectly solve this cool-starting problem. The new user will be directly allocated to one clusters as well as his OAFV according to his somatotype features. Thus, the computation and storage cost are not necessary.

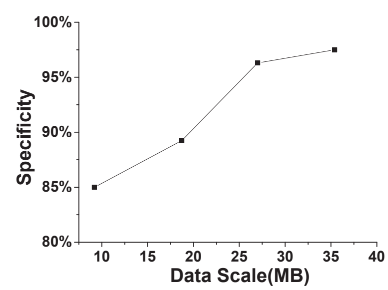
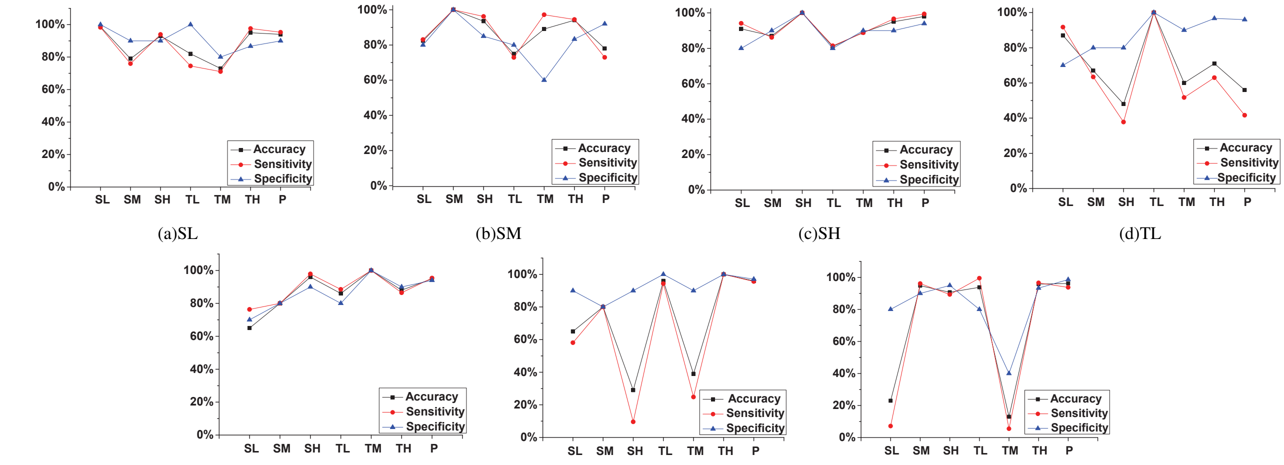


Fig. 7: Data Scale.

V. Conclusions

In this paper, we have developed a somatotype-based feature selection method and proposed a more accurate fall detection system with the personalized features and online OCSVM learning algorithm. On group level, 13 features have been extracted and then we have selected the optimal feature subset for the six groups which have different heights



(a)SL (b)SM (c)SH (d)TL

(e)TM (f)TH (g)P

Fig. 8: Comparison experiments' results of using other groups' optimal action feature vectors to detect falls.

and BMIs. On an individual level, we have built the normal model by an online OCSVM scheme, which is flexible and can be updated to adapt to new emerging postures. Two rules have been added to reduce the FN of the proposed fall detection system. The algorithm solves the problem of the low accuracy caused by using unified classification model for every person.

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