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Accelerometer-Based Motion Classification Using Support Vector Machine

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ABSTRACT
This article is based on the classification of data acquired from accelerometers, which are now commonly utilized in everyday life due to technological advancements, using the support vector machine technique. The little size and low price of accelerometers allowed their application. Support vector machines were used to classify the collected data, and their performance was evaluated.
***Keywords* –** accelerometer, classification, machine learning, support vector machine, confusion matrix

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I. INTRODUCTION

Accelerometers are utilized in numerous industries, including the automotive industry and mobile device technology. Its application fields have grown because to the growth of technology and the software industry. Previously, it was exclusively utilized as electrical equipment. For categorization in motion-related applications, software algorithms are utilized. The methods established here are crucial for adjusting accelerometers to diverse environments.

Numerous applications involving the processing of accelerometer data utilizing software algorithms are described in the literature. Wan et al. categorized accelerometer data for early detection of falls in hip protectors used to lessen the impact of falls in the elderly using a hybrid classifier comprised of Hidden Markov Model (HMM) and Support Vector Machines in their study [1]. Cheng and Jhan suggested a graded Adaboost-Support Vector Machine classifier for 3-axis accelerometer signals for fall detection in their study. They said that they accurately categorized the chest and waist circumference-related accelerometer signals [2]. Using 3-axis accelerometer data and Multi-Class Support Vector Machine, He classified 17 complicated human movements in his study [3]. Based on data acquired from accelerometers affixed to animals and the vector machine method, Martiskainen et al. identified eight distinct situations in their study. [4]. Zhang et al. evaluated data collected from an accelerometer coupled to a waist belt to monitor daily activities using rule-based reasoning and a hierarchical categorization developed with support vector machines in their study [5]. He and Jin classified four unique categories of human movement using discrete cosine transform (DCT), principal component analysis (PCA), and support vector machine (SVM) in their investigation [6]. Ahlrichs et al. used a Support Vector Machine for detection as the initial step in the method they devised to track gait freezing in Parkinson's disease patients utilizing accelerometer data in their study [7].

As can be seen, the algorithms employed are the most important aspect of the utilization of accelerometers in various applications. In this work, therefore, the success of the Support Vector Machine algorithm, which is favored in the literature for a variety of applications, in accelerometers is demonstrated. The success of SVM in classification applications and the algorithm's ability to be implemented in electronic circuits are the primary reasons why it was chosen at this level.

The completed work is categorized into four primary areas. Chapter 1 presents an overview of accelerometer usage using Support Vector Machines. In the second chapter, information regarding the SVM approach is presented, along with various applications that can be deemed fundamental in the literature. In Chapter 3, broad information regarding the methods used to evaluate the success of the employed method is presented. In the final chapter, Chapter 4, results are presented.

II. MATERIAL AND METHOD

2.1 DATA SETS

In this study, uncalibrated accelerometer data taken from a chest-mounted accelerometer with a sample frequency of 52 Hz were utilized. The data collected from 15 participants was utilized to categorize seven movements. More than one hundred thousand samples were collected for each participant along the X, Y, and Z axes. activities:

1) Working on the Computer (WoC)
2) Standing, Walking, and Stair Climbing (SWS)
3) Standing (S)
4) Walking (W)
5) Going Up / Down the Stairs (GUD)
6) Walking and Talking to Someone (WT)
7)Talking While Standing (TwS) has been determined.

The distribution of approximately 2 million data gathered from 15 participants according to situations and participants is presented in Table 1. The number of data distributions across the classes varies, as is evident from this. It has an immediate impact on the performance of the study in this instance.

Table 1. Participant-Data Distribution

Participant	WoC	SWS	S	W	GUD	WT	TwS
1	33677	928	11179	26860	3191	2917	83748
2	44150	3490	23745	22175	3910	7100	33431
3	41765	5475	4293	25900	2657	1400	20940
4	31540	4810	21405	23300	3745	1910	35490
5	30980	5370	13420	26750	3000	2880	77600
6	44040	3460	23495	22040	3935	6989	36711
7	32750	3600	10519	26770	2960	2700	83701
8	44040	3485	24605	22035	3900	5980	33750
9	36090	320	11330	26730	3115	2495	83660
10	44050	3435	23596	22149	3890	7449	22231
11	54170	2330	8775	17750	3225	1049	17151
12	48750	4340	11730	30130	3650	1200	14901
13	18280	1650	8220	17650	3400	1201	17249
14	52875	505	12785	29315	3620	1500	15500
15	51600	4680	7910	17510	3300	1000	17500

2.2 METHOD-SUPPORT VECTOR MACHINE (SVM)

Support vector machines are a statistical learning-based machine learning technique used in classification and regression research. As a fundamental premise in SVM classification research, it is desired to define a hyperplane separating the classes. It was originally developed for two-class data, then generalized for multi-class and nonlinear data [8], [9]. If all data cannot be classified with a hyperplane, several kernel functions are utilized in classification processes.

In the literature, SVMs are utilized in a variety of classification applications, including image classification, handwriting identification, text classification, and motion classification. In their study, Zhang et al. utilized support vector machines to overcome the motion recognition issue in the virtual reality environment. Genetic algorithm was applied to optimize Support Vector machine parameters [10]. Pei et al. categorized accelerometer and magnetometer data using the Least Square Supported Vector Machines (LS-SVM) classification technique into eight categories [11]. Wu et al. employed convolutional neural network (CNN) and support vector machine (DVM) to categorize 4-channel mechanomyography (MMG) signals from thigh muscles in their study [12].In their research, Li et al. used a least squares support vector machine (LS-SVM) to categorize nine typical hand actions in the control of the prosthetic hand [13]. Yan et al. classified surface electromyographic (sEMG) signals using least squares support vector machines (LS-SVMs) in their investigation. They indicated that it applies to four actions in the prosthetic limb classification [14]. Fen and Feng employed Support Vector Machine and Gradient Histogram (HOG) to categorize photos of people captured from a moving platform in their investigation [15]. Ma et al. used support vector machines (SVM) to classify acceleration sensor data for motion classification in their investigation. As a kernel function, they employed the longest common subsequences (LCSS) algorithm [16].

III. PERFORMANCE EVALUATION

Confusion matrices were utilized to evaluate the classification's success measurement. For the metrics of accuracy, recall, precision, and F1 score, confusion matrices were constructed. These figures represent the classification estimation rates of the classifiers. Equations utilized in the generation of comparison matrices for the characteristics of precision, recall, sensitivity, and F1 score Equation displayed 1–4 [17].

$$\text{Accuracy} = \frac{\text{TP+TN}}{(\text{TN+FP+TP+FN})} \quad (1)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (2)$$

$$Sensitivity = \frac{TP}{TP+FP} \quad (3)$$

$$\text{F1}-\text{score} = 2\text{x}\frac{\text{Sensitivity } x \text{ Recall}}{Sensitivity+Recall} \quad (4)$$

TP (True Positive), as used in equations 1 through 4, refers to the positives accurately classified by the algorithm. FP (False Positive) denotes instances that an algorithm labels as positive when they should be categorized as negative. FN (False Negative) refers to instances that the algorithm has incorrectly identified as negative. TN (True Negative) refers to circumstances that the algorithm correctly labels as negative.

The Accuracy ratio in Equation 1 represents the proportion of correct classifications to the total number of classifications. The recall provided in equation 2 and used to calculate the F1-score in equation 4 represents the proportion of correctly categorized samples relative to the total number of samples that must be correctly identified. The accuracy stated in Equation 3 and used to compute the F1-score in Equation 4 refers to the proportion of samples identified as correct relative to the total number of samples classified as correct. The F1- score indicates the precision of data. In measuring the accuracy of classified data, the harmonic mean of sensitivity and recall values is utilized as opposed to the averages of sensitivity and recall values. This prevents the evaluation of extreme scenarios.

IV. RESULTS and DISCUSSIONS

When the literature is examined, it is seen that the confusion matrix is used to measure the classification success[18], [19].

For this reason, in order to analyze the result of the study carried out, the accuracy, recall, sensitivity and F1-Score values presented in Equations 1-4, respectively, were examined and the results were presented in Table 2-5 in the confusion matrices.

Table 2. Accuracy confusion matrix

ACTUAL \ PREDICTED	WoC	SWS	S	W	GUD	WT	TwS
WoC	**0,87**	0,04	0,02	0,01	0,02	0,03	0,01
SWS	0,01	**0,82**	0,06	0,02	0,02	0,03	0,04
S	0,01	0,02	**0,9**	0,01	0,02	0,03	0,01
W	0,03	0,01	0,02	**0,89**	0,01	0,02	0,02
GUD	0,01	0,02	0,01	0,02	**0,91**	0,02	0,01
WT	0,01	0,01	0,02	0,01	0,01	**0,92**	0,02
TwS	0,02	0,01	0,01	0,01	0,01	0,01	**0,93**

Table 3. Recall Confusion Matrix

ACTUAL \ PREDICTED	WoC	SWS	S	W	GUD	WT	TwS
WoC	**0,88**	0,03	0,01	0,02	0,02	0,03	0,01
SWS	0,01	**0,8**	0,05	0,02	0,02	0,04	0,06
S	0,02	0,01	**0,89**	0,02	0,02	0,03	0,01
W	0,02	0,02	0,02	**0,89**	0,01	0,02	0,02
GUD	0,01	0,03	0,02	0,02	**0,87**	0,03	0,02
WT	0,02	0,01	0,02	0,01	0,02	**0,9**	0,02
TwS	0,03	0,02	0,01	0,02	0,01	0,01	**0,9**

Table 4. Sensitivity confusion matrix

ACTUAL \ PREDICTED	WoC	SWS	S	W	GUD	WT	TwS
WoC	**0,89**	0,02	0,01	0,02	0,02	0,03	0,01
SWS	0,01	**0,81**	0,04	0,01	0,03	0,05	0,05
S	0,01	0,02	**0,87**	0,03	0,03	0,03	0,01
W	0,03	0,01	0,03	**0,86**	0,02	0,03	0,02
GUD	0,02	0,02	0,03	0,01	**0,84**	0,04	0,04
WT	0,03	0,02	0,03	0,01	0,01	**0,89**	0,01
TwS	0,04	0,03	0,03	0,01	0,02	0,02	**0,85**

Table 5. F1-Score Confusion matrix

ACTUAL \ PREDICTED	WoC	SWS	S	W	GUD	WT	TwS
WoC	**0,88**	0,02	0,01	0,02	0,02	0,03	0,01
SWS	0,01	**0,80**	0,04	0,01	0,02	0,04	0,05
S	0,01	0,01	**0,88**	0,02	0,02	0,03	0,01
W	0,02	0,01	0,02	**0,87**	0,01	0,02	0,02
GUD	0,01	0,02	0,02	0,01	**0,85**	0,03	0,03
WT	0,02	0,01	0,02	0,01	0,01	**0,89**	0,01
TwS	0,03	0,02	0,02	0,01	0,01	0,01	**0,87**

When the overall success of the system was evaluated, its average accuracy value was 0.89, its average recall value was 0.87, its average sensitivity value was 0.85, and its average F1-Score was 0.86. It has been determined that the classification of accelerometer-based motion using the method employed in this study yields results comparable to those found in numerous other studies.

V. CONCLUSION

In this study, the SVM method, which is frequently employed in the literature, was employed. The primary reason for selecting this algorithm is that it can function on systems with minimal hardware resources. As demonstrated by the outcomes of this algorithm, a very high success rate has been attained.

However, the number of samples from each class in the employed data set varies. This circumstance has a negative effect on the success of the study. In the studies that will be conducted as a continuation of this one, care should be taken to ensure that the number of elements in each class is relatively close.

In future research, the success of the system can be improved by employing a data set with a comparable number of elements and the most recent deep learning architectures. In this instance, however, it should be determined that the hardware should be upgraded.

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