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Discrimination of Waist Motions Based on Surface EMG for Waist Power Assist Suit Using Support Vector Machine

Kouta Kashiwagi, Takashi Nakakuki and Chiharu Ishii

Abstract— **This paper presents a signal processing for discrimination of waist motions including forward and backward bendings and right and left twists. The system is planed to implement to a waist power assist suit that physically helps a caregiver in personal care tasks. The motion discrimination is based on surface electromyogram (SEMG) of right and left erector spinae muscles that dominate the motions of interest, and accomplished by using four SVMs in which each SVM is a binary classifier for each of four motions. We construct a strong multi-class classifier based on combination use of four SVMs. With a peripheral FFT-based prefilter, the start point of motion is estimated, and employed for a trigger to calculate a feature vector. We show that the proposed processing has a promising discrimination and false-positive rates for implementation. In addition, we summarize some essential problems to improve the performance of the system as future works.**

I. INTRODUCTION

In Japan, people aged 65 or over currently account for 23.1 percent of the total population, and we are well on the way to an super aging society [1]. The Japanese government's white book reports that the population aging rate will continue to increase steadily and reaches about 40 percent in 2055, which is not a special case in Japan, rather it is a common issue in many countries. Recently, the problem of nursing care have been emerging that a numerical disbalance between people who need nursing care (as a demand) and caregivers (as a supply) becomes prominent. Since nursing care is typically a hard work regarding both physical and mental burdens, the study on how workload of caregivers can be reduced is one of the major works in various research fields including robotics.

Recently, a power assist suit, which is a wearable robot and assists his/her muscular power with actuator, is expected to be one of the promising remedies in the near future. Actually, some commercial products or prototypes have already been released [2], [3], [4], [5], [6], [7]. Those power assist suits are classified according to the types of actuators and sensors. Regarding actuators, the weight and size are the most important specifications and should be as light as possible unlike industrial robots since the suit presupposes worn by person. At the moment, motor-driven or artificial muscle actuator is commonly-used for powered suits. Representative examples are the robot suit HAL (Cyberdyne Inc.) [2] and Muscle Suit [3], respectively.

K. Kashiwagi is with Major of Mechanical Engineering, Kogakuin University, Tokyo, Japan am11023@ns.kogakuin.ac.jp

T. Nakakuki is with Department of Mechanical Systems Engineering, Kogakuin University, Tokyo, Japan t-nakaku@cc.kogakuin.ac.jp

C. Ishii is with Department of Mechanical Engineering, Hosei University, Tokyo, Japan c-ishii@hosei.ac.jp

Fig. 1. Our waist power assist suit (prototype)

Regarding selection of sensors, there are mainly two strategies, pressure (touch) sensors [3] and surface electromyogram (SEMG) [2] that detects membrane potential change in a muscle from an electrode placed on skin surface. The difference is explained with the following simple example. Consider a motion of bending your arm, and the motion is assumed to be physically assisted by any rotating actuator. Then, the former detects the motion after your arm makes contact with any touch sensor. The merit is that we know the direction and the strength of motion, and the signal processing from sensor to motion detection can be simple. On the other hand, with the latter, we can detect an relevant potential change before the motion, followed by quick assist compared with a simple touch sensor.

Currently, we have been developing a motor-driven power assist suit to physically assist waist motions of caregivers in personal care tasks in which the target motions are forward and backward bendings (FW and BW) and right and left twists (RW and LW). Fig. 1 shows the appearance in wearing the suit. The motivation comes from a situation that (i) not few people suffer from their backache in personal care tasks such as transfer from bed to wheelchair holding person, and (ii) the suit should be cheap and easy-to-use so that the target motions should be narrowed. Although there are several powered suits supporting waist motions [3], [4], they commonly assist only FW and BW motions, not including RW and LW. In order to quickly detect the motion and assist his/her muscle, we propose a motion discrimination system based on SEMG of right and left erector spinae muscles that dominate FW, BW, RW and LW motions. The signal flow from raw SEMG signals to discrimination is summarized as follows. When any waist motion occurs, the start point of the motion is estimated from SEMG signals by using FFT-based low pass filter that has been proposed in [8]. Then, a feature (input) vector is generated with 512 sampling data stored in memory before the estimated start point, and classifiers by support vector machine (SVM) predict which waist motion occurs. As is well known, the calculation method of feature vector plays a major part in machine learning. As a method to calculate a feature vector from SEMG signals for motion discrimination, we utilize the calculation in [8] that is also employed in other studies [9].

The following sections are organized as follows. In the Section II, we introduce the structure of our waist power assist suit. The Section III describes about SEMG data acquisition in which training and test data for SVM are collected from six people. In the Section IV, a proposed motion discrimination system is explained in detail, and the performance is evaluated with test data in the Section V. We summarize our concluding remarks and future plans in the Section VI.

II. STRUCTURE OF WAIST POWER ASSIST SUIT

Our power assist suit consists of three units including shoulder, lumbar and leg parts (Fig. 2). The lumber unit has right and left motor boxes that are coupled by a rotating shaft, and rotate independently. Figs. 3 and 4 demonstrate forward bending and twist motions, respectively where FW and BW motions, which require a considerably large rotating torque for actuator, are driven by rotating both motors in the same direction, and RW and LW motions are realized by differently rotating each motor without any additional motors. It is noted that a combinatorial motion such as FW and RW can be also assisted by properly setting each rotation axis. Therefore, the merit of this structure is to assist four waist motions with the minimum number of motors that leads to weight saving of the total weight. The detailed specification of actuator is summarized in Tables II and III in which DC motor (Sanyo Denki, co., ltd.) with harmonic drive speed reducer (Harmonic Drive Systems, inc.) is adopted. It should be highlighted that the maximal torque is 141 Nm. Regarding wearing, we just have to wear the suit by fixing the shoulder and the leg units with belts as shown in Fig. 1, expecting that a caregiver can easily wear and remove it that is quite important specification on daily use.

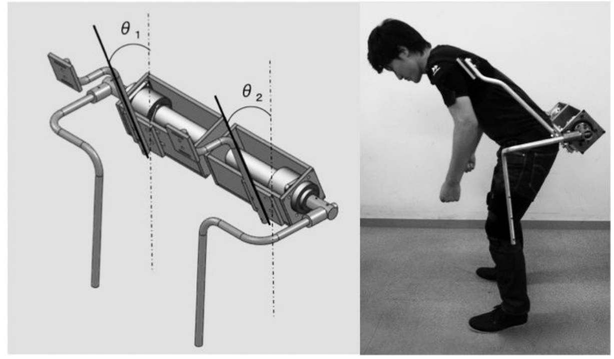

Fig. 3. Bending motion

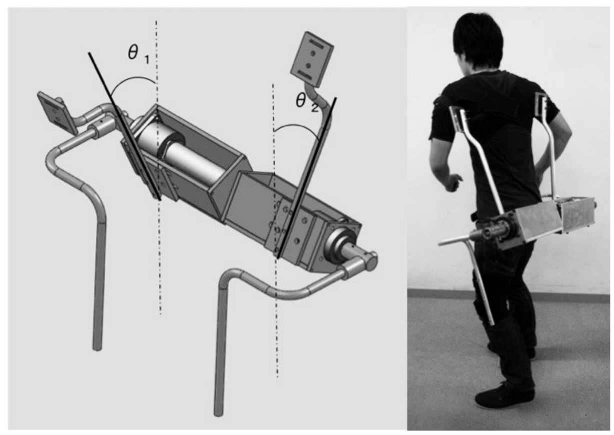

Fig. 4. Twisting motion

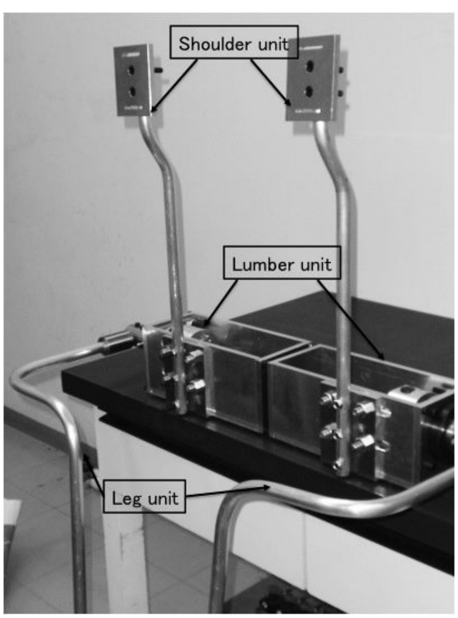

Fig. 2. Appearance of the waist power assist suit (prototype)

Fig. 5 overviews the whole signal processing from raw SEMG signals to motor control. The SEMG signals from right and left erector spinae muscles are transmitted to the discrimination system via A/D converter, and the system decides which waist motion(s) is operating by using SVM, which is the main topic of this paper. With the discrimination result, motor torque is controlled to assist the motion. In the following sections, we explain the discrimination system in detail.

TABLE I

SPECIFICATION OF DC MOTOR

Item		Unit
Company	SANYO DENKI	
Type	T511B-012EL8	
Rated output	110	[W]
Rated speed	3000	[r/min]
Maximum speed	3000	[r/min]
Rated torque	0.270	[Nm]
Continuous stall torque	0.358	[Nm]
Instant. maximum stall torque	0.784	[Nm]
Weight	1.2	[kg]

TABLE II

SPECIFICATION OF HARMONIC DRIVE SPEED REDUCER

Item		Unit
Company	Harmonic Drive Systems	
Type	CSF-20-100-GH-J6FAL	
Reduction ratio	100	
Rated torque at 2000r/min	40	[Nm]
Average toeque	49	[Nm]
Peak torque at start and stop	82	[Nm]
Maximum momentary torque	147	[Nm]
Maximum input speed	6500	[r/min]
Weight	1.8	[kg]

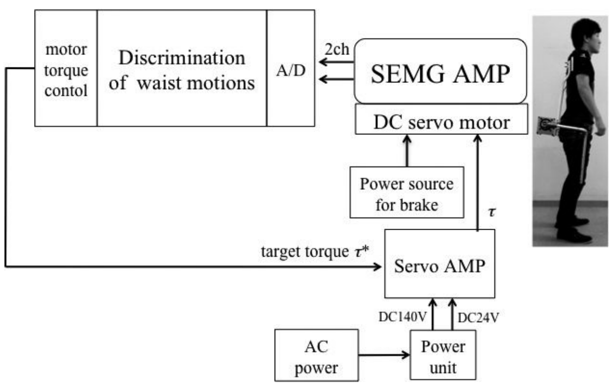

Fig. 5. Whole signal processing

III. TRAINING AND TEST DATA ACQUISITION

For training and evaluating SVM, the SEMG signals of four waist motions (FW, BW, RW and LW) are measured from left and right erector spinae muscles. Fig. 6 shows the actual position of attaching the electrodes and ground terminal. Since the SEMG sensor can detect a potential change of erector spinae muscles even if the attachment position is slightly shifted in daily use, we just have to attach the electrodes around the circles shown in Fig. 6. The sampling frequency of A/D converter is set to $F_s = 2$kHz since a band frequency is at most 500Hz as mentioned in [8]. In data acquisition, we establish the following protocol to obtain FW, BW, RW and LW data.

(i) FW and BW data acquisition

standing posture → spend a second for FW motion → maintain bending 90° at the waist for two seconds → spend a second for BW motion → standing posture

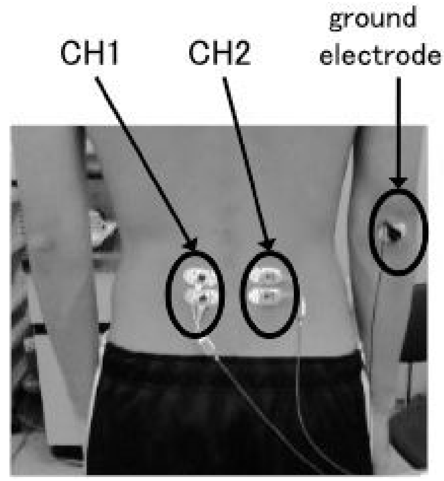

Fig. 6. The attachment position of electrodes and ground terminal

(ii) RW and LW data acquisition

standing posture → spend a second for RW (LW) motion → maintain twisting at the waist for two seconds → spend a second LW (RW) motion → standing posture

For each case, the sequence is repeated 30 times, and a series of data acquisition is performed for six individuals (named A-F), followed by 720 data (= 30 data × 4 motions × 6 individuals). It should be noted that although a larger number of training data are better for learning SVM, since broadness of the distribution of training data differed little beyond 30 data, the number of iteration is reasonable also from a viewpoint of physical strain in data acquisition.

IV. MOTION DISCRIMINATION SYSTEM USING SVM

SVM is a kind of classifier that can be applied to linear or nonlinear multiclass classification problems [10]. The concept for classification is that a separating hyperplane is created to miximize the minimum value in margins between the hyperplane and training samples in which training samples with the minimum margin are called support vectors, and the hyperplane is therefore characterized by them. It is a beneficial property that the calculation for obtaining the hyperplane is formulated as a convex quadratic programming problem. In addition, SVM can solve nonlinear classification problems by introducing a technique called "kernel trick" where input space constructed by training samples is mapped into a high dimensional feature space with a coordinate transformation, and the linear classification is performed there.

Fig. 7 shows the block diagram of motion discrimination system that is mainly two subsystems, start flag generator (SFG) and motion discrimination block (MDB). The quantized SEMG signals at the A/D converter are transmitted to SFG and MDB. In SFG, (i) any membrane potential change is detected by evaluating smoothed SEMG signals, (ii) a start

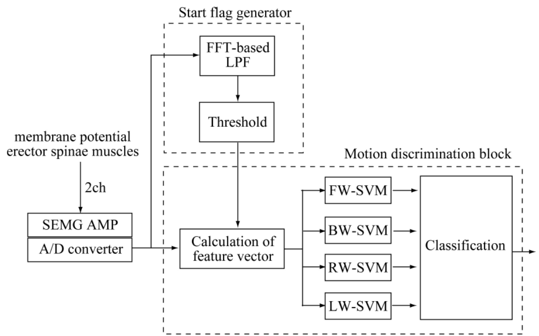

Fig. 7. Flow of signal processing

point of motion is estimated if detected, and (iii) a start flag, which is 0 in no motion and 1 in motion, is sent to MDB. Then, a rising edge of start flag is employed as a timing for calculating feature vector in MDB, and the vector is tested in each of four SVMs. With all outputs of SVMs, classification block decides which motion is about to perform. In what follows, we describe the specification of signal processing in detail.

A. Start flag generator

Since a raw SEMG signal is quite noisy, we utilize a FFT-based low pass filter and motion detection method proposed in [8]. Let two SEMG signals from left and right electrodes be EMG(c, n), $(c = 1, 2)$ where n denotes a sample number of quantized SEMG signal. We calculate the power spectrum $F(c, f)$ with respect to f-th frequency element by fast Fourier transformation,

$$F(c,f) = \left| \sum_{n=1}^{N} EMG(c,n)(e^{-j2\pi/N})^{(n-1)(f-1)} \right| \quad (1)$$

where N is the number of data points ($N = 512$). The signal $Y(n)$ is defined by

$$Y(n) = \frac{1}{N} \sum_{c=1}^{2} \sum_{f=1}^{N} \left(F(c,f)\ ^2 \right) \quad (2)$$

It is known that $Y(n)$ becomes a kind of smoothed signal, and N determines the degree of smoothing. Then, a start flag of motion is defined by

$$Y_{ref}(n) = \begin{cases} 1 & \text{if} \quad Y_{(n)} > T_H \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where T_H is a threshold, and should be set to a value that the number of false negative is as low as possible, which means that the start flag is generated even in a case with relatively weak motion. At the same time, a threshold should be selected considering a basal noise level. Fig. 6 illustrates a typical example regarding a raw SEMG signal, the smoothed signal, and the generated start flag. The time delay τ is calculated by $dt \times 512$ [sec] where dt is a sampling time of A/D converter.

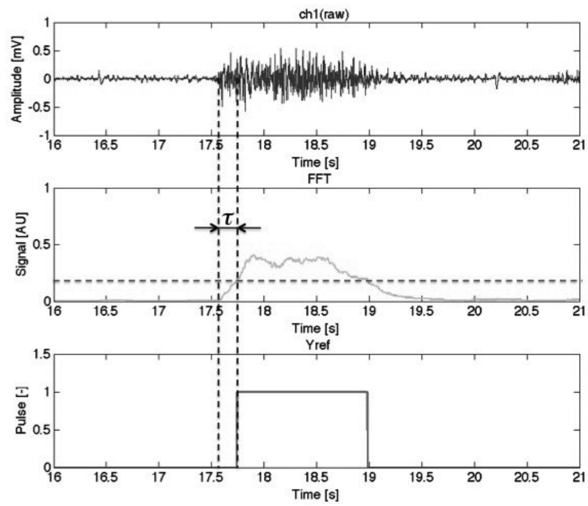

Fig. 8. Example of start flag generation

Remark I: Although we evaluate other smoothing filters such as averaging and median with various N, we conclude that the FFT-based filter is effective in our case.

B. Calculation of feature Vector

Feature vector is generated with N data points at the time when the start flag changes from low to high, by using the following definition [8].

$$MAV(c) = \frac{1}{N} \left| \sum_{n=i}^{i+N} EMG(c,n) \right| \quad (4)$$

which is the absolute average value of SEMG signal from a rising edge to N data points. The distribution of feature vectors for each individual is depicted in Fig. 9. Since the distributions are considerably different among individuals, the parameters of SVMs are optimized for each individual.

C. SVM block

In this study, we construct a strong classifier for FW, BW, RW and LW motions based on two dimensional feature vector. In general, it is easier to discriminate several classes by using combinatorial binary classifiers instead of single multi-class classifier. Thus, we also prepare four SVMs which are binary classifiers for FW, BW, RW or LW, and determine the motion based on the Table III. It should be noted that with such a strategy the system can detect a combinatorial motion such as FW+RW.

V. RESULTS AND DISCUSSIONS

A. Learning

As shown in the Section III, we collect 720 samples (30 samples $\times$ 4 motions $\times$ 6 people). However, unlike the distribution shown in Fig. 9, distributions from three individuals (Testee D, E and F) becomes chaotic (Fig. 10) where feature vectors with respect to FW, RW and LW

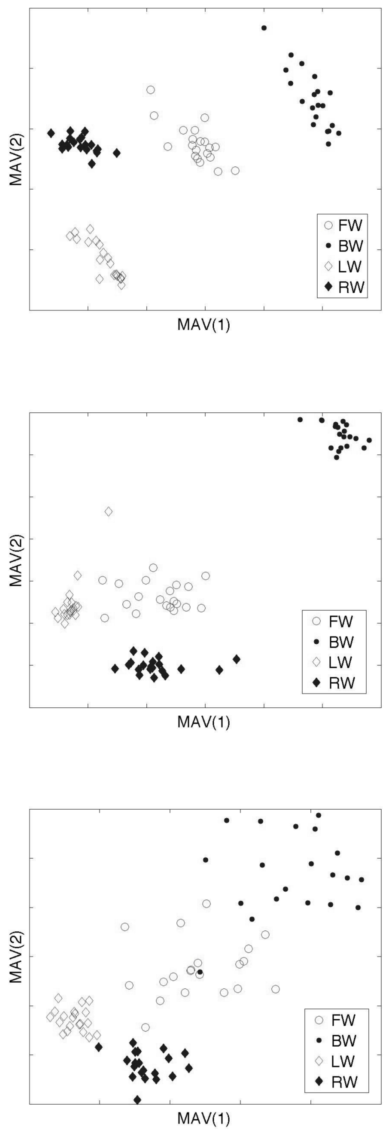

Fig. 9. Separable distribution (Testee A, B and C)

TABLE III

COMBINATION OF BINARY SVM CLASSIFIERS

Estimated motion	FW-SVM	BW-SVM	RW-SVM	LW-SVM
forword bending	1	0	0	0
backword bending	0	1	0	0
right twisting	0	0	1	0
left twisting	0	0	0	1
forword + right	1	0	1	0

motions are mixed. Thus, in what follows, we deal with only Testee A, B and C that show separable distributions. As mentioned in the previous section, we optimize SVMs for each of three individual. As a comparison, we also show the results in a case that SVM is optimized with mixed training data from all three individuals. For example, in a case of FW,

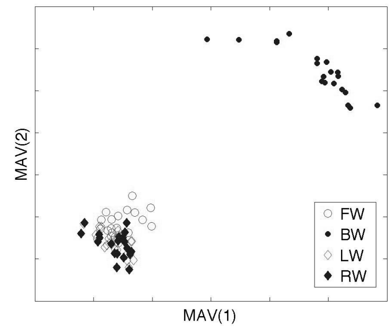

Fig. 10. Inseparable distribution (Testee D)

20 samples are from FW motion, and other 60 samples from BW/RW/LW. Thus, the corresponding reference vector also contains 20 elements with 1 and 60 elements with 0. Fig. 11 illustrates a classification result of four motions for testee A. In all learning, Gaussian kernel is utilized with $\gamma = 10.0$ and $\sigma^2 = 0.4$. Regarding SVM solver, LS-SVMlab1.7 [11] is employed on Matlab (MathWorks, Inc.).

B. Discrimination and false-positive rates

After learning of SVMs, we evaluate the discrimination and false-positive rates with 40 test samples. We check the following two tests.

Discrimination rate: For each SVM, the SEMG data from the corresponding motion are checked where each SVM should output "1" for every test samples. We count the number of correct answer, and summarized in Table IV.

False-positive rate: For each SVM, the SEMG data from four motions are checked where each SVM should output "1" for the test samples that are from the corresponding motion, and "0" for the test samples that are from other motions (Table V).

From Tables IV and V, we conclude that the rates for Testee A, B and C are promising whereas the rates in mixed case is considerably low. On the other hand, if we see the results on FW-SVM of Testee A, RW-SVM of Testee B and BW-SVM of Testee C, the discrimination rates are not high. More worse, the false-positive rates regarding FW-SVM of Testee B and C are not good. Although additional training might improve the performance, since a SEMG signal alters depending on his/her physical condition even if the electrodes are very carefully attached on the same positions, including additional touch or pressure sensors would be required that is our future works.

VI. CONCLUSIONS

In this paper, we construct a signal processing for discriminating four waist motions FW, BW, RW and LW by using multiple SVMs based on two SEMG signals from left

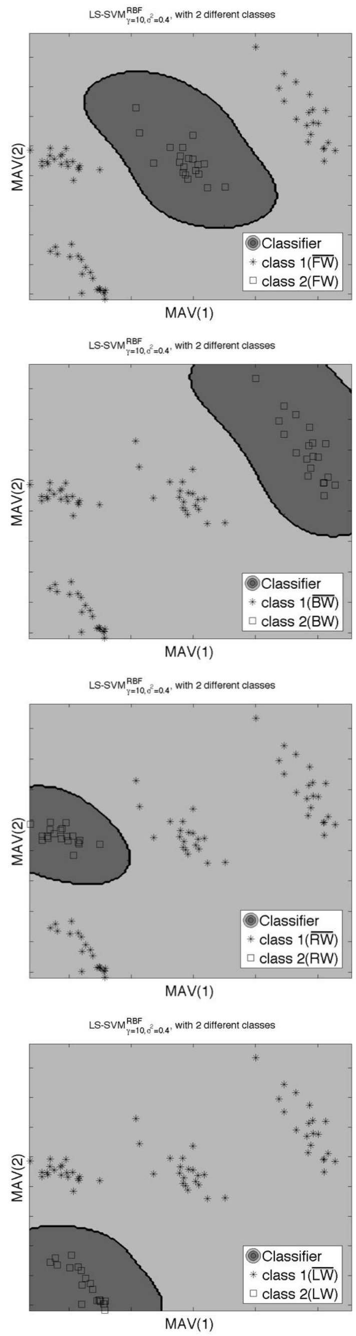

Fig. 11. Binary classification (Testee A)

and right erector spinae muscles. With a peripheral FFT-based prefilter, a start point of motion is detected, and its rising edge is employed as a trigger to calculate the feature vector. We show that the proposed processing has promising discrimination and false-positive rates.

VII. ACKNOWLEDGMENT

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TABLE IV

RESULTS OF DISCRIMINATION RATE

Motion	FW	BW	RW	LW	Average
A	90.0% (9/10)	100% (10/10)	100% (10/10)	100% (10/10)	97.5% (39/40)
B	100% (10/10)	100% (10/10)	70.0% (7/10)	100% (10/10)	92.5% (37/40)
C	100% (10/10)	80.0% (8/10)	100% (10/10)	100% (10/10)	95.0% (38/40)
Mix	70.0% (21/30)	96.7% (29/30)	76.7% (23/30)	76.7% (23/30)	80.0% (96/120)

TABLE V

RESULTS OF FALSE-POSITIVE RATE

Motion	FW	BW	RW	LW	Average
A	0% (0/30)	0% (0/30)	0% (0/30)	0% (0/30)	0% (0/120)
B	2.5% (1/30)	0% (0/30)	0% (0/30)	0% (0/30)	0.6% (1/120)
C	5.0% (2/30)	0% (0/30)	0% (0/30)	0% (0/30)	1.3% (2/120)
Mix	6.7% (6/90)	1.1% (1/90)	11.1% (10/90)	6.7% (6/90)	6.4% (23/360)

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