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Hand Tremor Based Biometric Recognition Using Leap Motion Device

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ABSTRACT In this paper, the applicability of hand tremor-based biometric recognition via leap motion device is investigated. The hypothesis is that the hand tremor is unique for humans and can be utilized as a biometric identification. In order to verify our hypothesis, spatiotemporal hand tremor signals are acquired from subjects. The objective is to establish a live and secure identification system to avoid mimic and cloning of password by attackers. Various feature extraction methods, including statistical, fast Fourier transform, discrete wavelet transform, and 1-D local binary pattern are used. For evaluating recognition performance, Naïve Bayes and Multi-Layer Perceptron are utilized as linear-simple and nonlinear-complex classifiers, respectively. Since the conducted experiments produced promising results (above 95% of classification accuracy rate), it is considered that the proposed approach has the potential to be used as a new biometric identification manner in the field of security.

INDEX TERMS Authentication, biometrics, hand tremors, human computer interaction, leap motion, machine learning, neurophysiology, neuroscience, recognition, security.

I. INTRODUCTION

With the development of technology, we are faced with many authentication operations in our daily life. Such as banking transactions, access to private areas, social networks, and e-mails are just a few of them. With the increasing security needs, identity verification is a significant application in our modern era, and has been used in a great deal. Traditional authentication systems are usually based on login names and passwords. However, password-based operations are vulnerable to attack, and as a result, biometric authentication approaches are generally adopted as an alternative especially for high-security system requirements. Advanced secure identification needs have led to the expansion of the biometric market [1]. Biometric Science uses the physical and behavioral characteristics of individuals to identify and differentiate one person from the other. Iris [2], voice [2], facial [3], fingerprint [4], and palm-print [5] based recognitions are well-known and extensively used identification approaches. Yet, they still have various safety deficiencies, thus, should be implemented carefully. For example, malicious people able to deceive the facial and iris recognition systems by showing photos. Again, finger and palm prints can be bypassed via latex, and voice recognition can be infiltrated through artificial voice records. As the aforementioned biometrics rely solely on physical characteristics, they can be reproduced by means of high technology apparatus. To overcome this problem, researchers try to incorporate behavioral biometrics in identification systems since the behavioral patterns are intrinsically much harder to imitate. In this context, biometric identification approaches based on electrocardiogram (ECG) signals resulting from the heartbeat of the person have been developed [1], [6]–[9]. Those studies have shown that heartbeat based ECG signals can be considered as a robust biometric trait and provides secure identification although the data acquisition setup needs professional expertise and have a high cost. Thus, ECG-based identification may not provide a practical usage for the end users so far.

As Buckwald also pointed out, a new, small, and cost-effective motion detection and gesture recognition device called ‘‘leap motion’’ can be used as an alternative [10]. Some studies have attempted to identify individuals by using hand geometry, gestures, and shape via leap motion [11]–[13]. The operational capability of leap motion under sub millimeters forms the magic side, which can be utilized for the hand tremor based recognition. Besides, it is reported that the leap motion device has a position measuring accuracy (amount of displacement of any 3D object in Cartesian coordinate system) of 0.2 mm and 1.2 mm in static and dynamic setups, respectively [14]. Again, according to another study [14], hand tremor can be defined almost periodically as the natural and uncontrolled shaking of the hand muscles. In general, depending on ages, the amount of displacement ranges from 0.4 mm to 1.1 mm for young and old individuals, respectively [15], [16]. Recently, various studies have been conducted on detection and analysis of hand tremor. For example, Daneault *et al.* [17] used a smartphone as a standalone platform for detection and monitoring of pathological tremors. Likewise, Chen *et al.* [18] proposed three algorithms to quantify the essential tremor and its amplitude by using leap motion device. They declared that the leap motion exhibits comparable results against available clinical measurement devices such as accelerometers, digital tablets, electromyography (EMG), and motion-capturing cameras in terms of accuracy and operational comfort. To the knowledge of the author, hand tremor based user identification (recognition) study with leap motion device has not been studied yet. Therefore, this paper introduces the very first study of the biometric recognition based on the hand tremors with leap motion. The major contributions of this paper are the issues dealt with as described in the following.

- Finding out whether the hand tremor signal is unique to the individual and it can be considered as a biometric trait for user identification by using leap motion device.
- Data preprocessing (computing relative displacement amount from the raw data).
- Analysis of optimal data acquisition time interval and finding out the lower bound to achieve statistically consistent and confident results.
- Examining the channel (X, Y, and Z axes) with the maximum discrimination power.
- Proposing hybrid feature extraction methods for 1D hand tremor signal.

The paper is structured as follows. Data acquisition strategies are introduced in Section 2. Then, Section 3 reveals the materials and methods that are used in this research. Experimental results are presented in Section 4. Finally, concluding remarks and future perspectives are drawn at the last section.

II. DATA ACQUISITION

Data acquisition setup consists of the leap motion device, personal computer, and data acquisition software. Leap motion is an optical 3D motion sensing and gesture recognition device, and has a 0.01 mm spatial measurement precision with up to 200 Hz camera frequency. According to the manufacturer specification, minimum system requirement for running leap motion is as follows; Windows 7+ or MacOS X 10.7+, AMD Phenom II or Intel Core i3/i5/i7 processor, 2 GB RAM and USB 2.0 port. Reference axes of leap motion device are given in Fig. 1. it is seen it uses a right-handed coordinate system. In addition to this, leap motion device can operate in low-resource mode for relatively slow computer architectures or it can avoid poor performance by automatically pausing tracking if it encounters bad conditions. Fig. 2 illustrates virtual interaction box (VIB) limits, which indicates user hand should navigate within the bound of VIB. Whole data were acquired with respect to the VIB, which means user positioned center of their hand at the origin of XZplane and 200 mm above the device along Y+ direction.

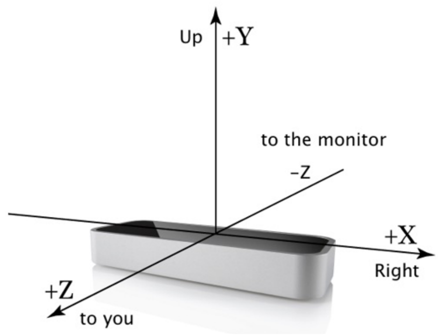

FIGURE 1. Reference axes of leap motion.

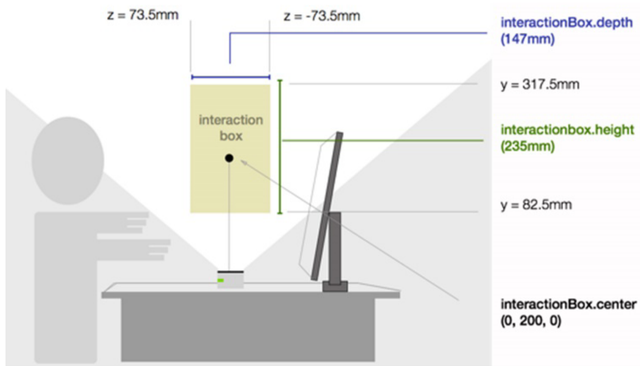

FIGURE 2. Virtual interaction sketch of leap motion device with 147, 235 and 235 mm, depth, height and width, respectively. Note that user hand is positioned at the center of interaction box during data acquisition stage. https://developerarchive.leapmotion.com/documentation/ csharp/devguide/Leap_Coordinate_Mapping.html.

Hand tremor data of right hand of five subjects were collected by data acquisition software. As it is shown in Fig. 3, after the subject locates their hand at the exact position they can monitor tremor signal on the screen. The flow of the tremor signal on X, Y, Z, and mixed channels can be observed on the graphical interface. The mixed channel is calculated from X, Y, and Z channels and equals to the overall displacement amount of the hand tremor. Data acquisition interface and other related software modules are developed in Java with Open Cezeri Library (OCL) [19]. Data recording should only start if user's tremors data becomes consistent and reliable enough. Usually, about 5 seconds of preparation time seems adequate. The initial data segment of channels related to the preparation stage can be seen in Fig. 3. During the acquisition phase subjects are not allowed to talk because speaking may deteriorate the signal quality.

It should be noted that leap motion device generates X, Y, and Z values by default, but we do not use the raw data since we may capture different signalsfor even the same user. To overcome this problem, we calculate the displacement amount by taking the difference of consecutive data points. This approach also standardizes the data as in the normalization process. Another significant issue is related to record duration, since meanwhile, this study investigates the

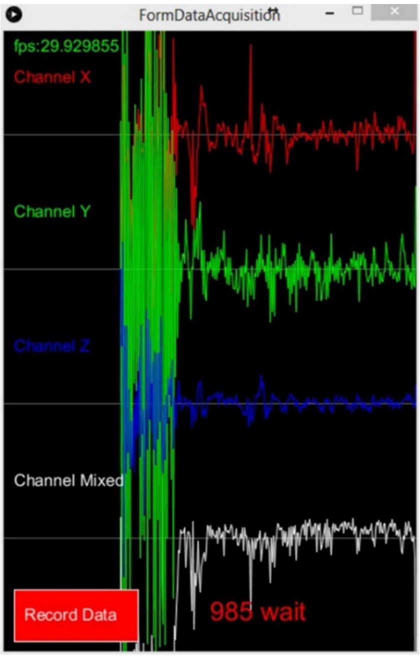

FIGURE 3. Data acquisition interface shows X, Y, Z and mixed channels in different colors. First large deviations in signal indicate preparation stage and are not recorded.

optimal record duration of hand tremor data. As Fig. 3 also indicates that the data is acquired at a rate of about 30 frames per second (fps). Here, the frame corresponds to the instantaneous relative displacement values of X, Y, and Z channels that data acquisition software computes. For that matter, our record length ranges from 8 to 2048 records. Translating from length to time can be computed as in the Eq. 1.

$$\textit{Recording Time}\ (s) = \frac{\textit{Record Length}}{30} \tag{1}$$

Record length vector consists of 8, 16, 32, 64, 128, 256, 512, 1024, and 2048. Every element in the vector is called as a modality. Each subject provides 100 training and 100 testing data for each modality so the training and test set size is 500 in total. The number of subjects is limited to five because it was the first research for biometric recognition and the data acquisition process took a long time due to the large number of modalities. In fact, as a proof of concept, we focused only on applicability and feature extraction. Investigating on the large amount of subjects will be our next objective.

III. MATERIALS AND METHODS

A. FEATURE EXTRACTION

Typical hand tremor signals taken from the first and second subjects are illustrated in Fig. 4 and Fig. 5, respectively. Tremor data is a type of 1024 modal and rows are associated with the X (top), Y, Z, and mixed (bottom) channels, accordingly. As it is seen, time series of each channel indicates a little bit periodicity and signals of two subjects can be differentiated from each other in terms of frequency and amplitude.

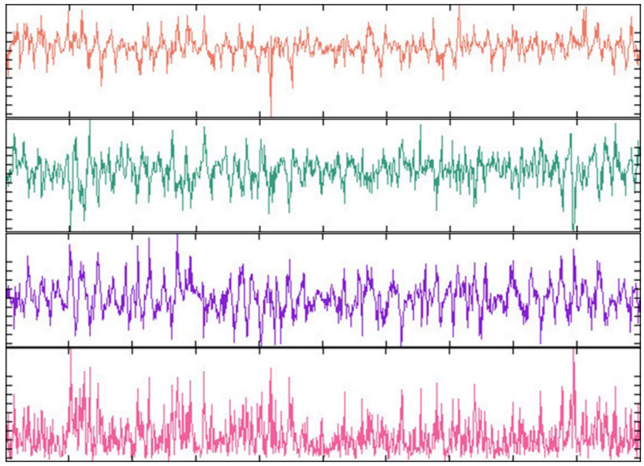

FIGURE 4. Typical hand tremor signals of X, Y, Z and mixed channels of 1024 modal from top to bottom, acquired from subject-1 to be able to assess the signal variation visually.

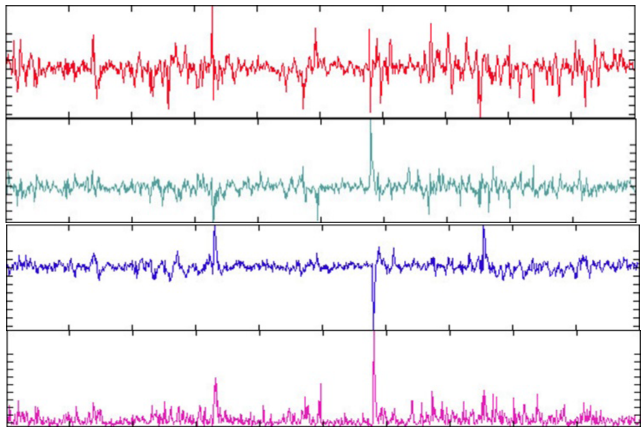

FIGURE 5. Typical hand tremor signals of X, Y, Z and mixed channels of 1024 modal from top to bottom, acquired from subject-2 to be able to assess the signal variation visually.

Since using the raw data as a feature vector, owning its large size may cause dimensionality problem that is not desired in machine learning. Therefore, we adopted feature extraction process on raw data.

The extracted feature should be invariant to altering and fluctuating in time series signal. Therefore, statistical features are worth to be used since they calculate overall signal values. In this context, mean, standard deviation, energy, entropy, and number of peaks values were extracted from the raw data. In the second approach, Local Binary Pattern (LBP) is used as the feature extraction method. 1D-LBP was successfully adopted over time series data in various studies [20], [21]. 1D-LBP tries to reveal the discrimination power of a data segment by taking the difference between center point with the right and left values of the center. All neighbor values are compared with the center value; if it is greater or equal it assigns as one,otherwise, it becomes zero. Next, all neighbor values are combined to form a binary representation of the original signal with respect to the center point.

Then, the binary value is converted to the decimal value as in (2). At this stage, each point on the original signal corresponds to its decimal value (see Fig. 6). By taking histogram, 1D LBP feature vector is formed. Eq. 2 summarizes the whole procedure.

$$N_{1D\_LBP} = \sum_{n=0}^{K-1} F\left(D_n - D_c\right).2^{K-1-n}$$
$$F(t) = \begin{cases} 1 & ift \geq 0 \\ 0 & otherwise \end{cases} \quad (2)$$

Here, K corresponds to the data segment size. In this study, we used 8 for convenience to form uniform LBP from 256 bins. D_n and D_c equal to n^{th} value and the center value of the data segment, respectively. Index value n becomes greater from left to the right as it is shown in Fig. 6. Note that, the higher the index, the lower the weight in Eq. 2.

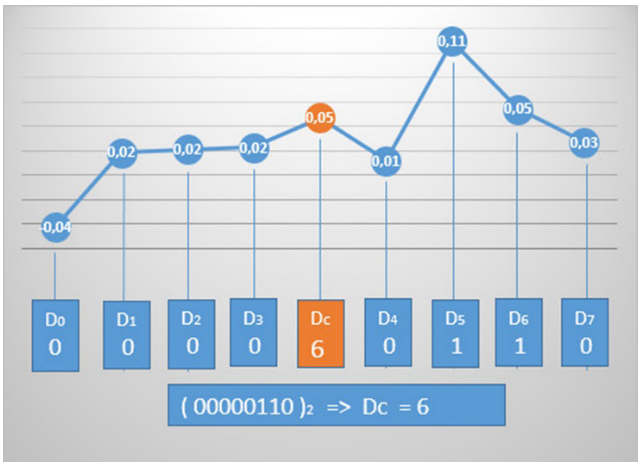

FIGURE 6. Operational logic of 1D-LBP method on a typical data segment.

Frequency components of hand tremor signals can also be utilized to differentiate signals from each other. Thus, we adopted both Fast Fourier Transform (FFT) and Discrete Wavelet Transform(DWT) techniques. It should benoted that outputs of these techniques are not used directly, but statistical and 1D-LBP methods have been applied to extract features, instead. Consequently, we obtained 6 different feature vectors for training and test sets. Those features and lengths are listed in Table 1.

By default, DWT with db3 filter produces 12 decomposition levels (see Fig. 7). Representation power diminishes as it goes down. Hence, the first two levels of decomposition were considered to be adequate and the rest were ignored in this study.

That is why the DWT + 1D-LBP feature vector is twice big as its size counterpart. Notice that the number 59 in the 1D-LBP feature vectors comes from the uniform histogram pattern. Normally, the number of histogram attributes of 8-bit 1-LBP is 256.

TABLE 1. Extracted feature vectors.

Name	Length
Statistical	5
1D_LBP	59
FFT+Statistical	5
FFT+1D_LBP	59
DWT+Statistical	5
DWT+1D_LBP	118

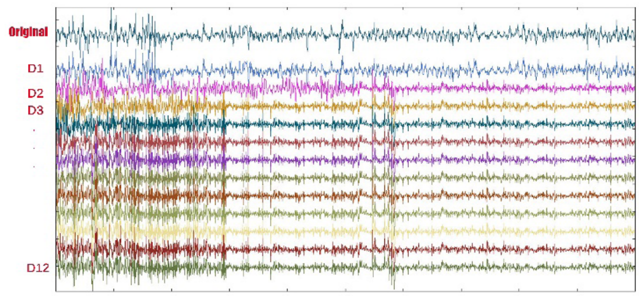

FIGURE 7. DWT decomposition levels of 2048 time interval from D1 to D12 of original signal (top) are shown. Only first two levels are considered due to their information content.

B. CLASSIFICATION

Naïve Bayes and Multi-Layer Perceptron (MLP) are used as classifiers throughout the study. As our aim is to determine the feature vector with the best recognition performance, number of the selected classifier was kept limited. Naïve Bayes represents simple and linear, while MLP represents complex and nonlinear classifiers. The dataset was portioned into two groups as training and testing. There are 500 rows in each cluster, equally distributed for five classes. Here the class label is interpreted as the user or the subject. 10-fold cross-validation was performed on the training set, while the test set was fully isolated. For vectorization, classification, and visualization operations OCL and Waikato environment for knowledge analysis (Weka) data mining software were utilized [19], [22].

IV. EXPERIMENTAL RESULTS

According to Chen *et al.* [18], the frequency range of essential tremor (vibration at hand) is theoretically between 3 and 8 Hz. Considering the requirements of the Nyquist theorem [23], the minimum sampling frequency in our case should be 16 Hz or above. It is clear from Fig. 3, the 30 Hz frequency applied in this study can represent hand tremor without problems.

Another concern is related to the capturing reproducible data from subjects during training and testing phases. That is, deviations at the data points should be small enough inside the class itself, but large between the classes. Fig. 8 depicts the

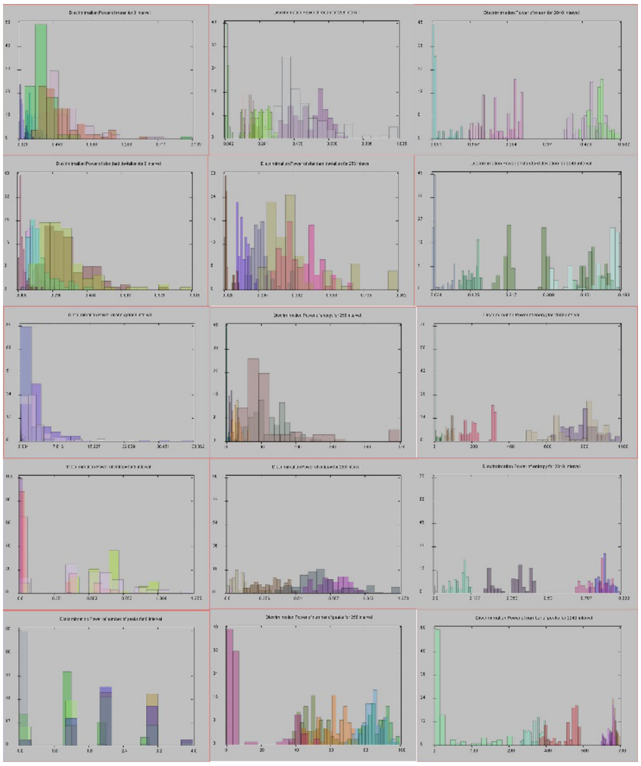

FIGURE 8. Histogram based visual analysis of discrimination power of statistical features for 8, 256 and 2048 time interval modalities plotted via OCL [18].

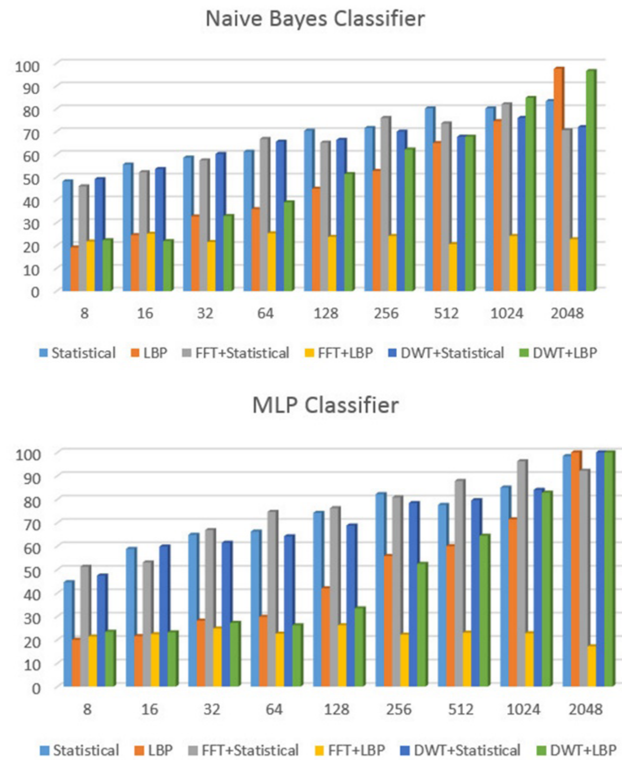

FIGURE 9. Classification performance of Naïve Bayes and MLP on the proposed feature vector along with different time interval modes.

visual analysis of discrimination power of statistical features for 8, 256, and 2048 time interval modalities. As it is seen in Fig. 8, between-class separation becomes more salient when we move towards high interval from low, because almost every histogram of 8 exhibits severe overlapping. On the other hand, rightmost column (2048 interval) shows good between-class separation for almost all cases. Nonetheless, most prominent between-class scatter can be observed in entropy and number of peaks features. In addition to strong between-class separation, the combined within-class scatter is also observed at high time interval modalities. Other features can also be analyzed as in Fig. 8 by means of histogram-based class distribution plot. But in this paper, only statistical features are examined.

As we have mentioned previously, Naïve Bayes and MLP were used as classifiers throughout the study. Fig. 9 shows the test classification performance of the proposed feature vectors along with different time-interval modes of X channel for Naïve Bayes and MLP. Notice that, here, we only printed out X channel plots, due to the reason that the other channels did not exhibit remarkable output. In fact, they could not pass 40% classification accuracy limit. So performance analysis continued only with X channel. Remaining channels, including Y, Z. and mixed, are too poor to show performance plots in this paper.

From Fig. 9, we can figure out that, Naïve Bayes and MLP reveals almost similar results except that MLP outperforms Naïve Bayes in most cases. Therefore we can declare that the hand tremor signal looks like a nonlinear signal rather than a linear signal.

Another interesting point is that as time-interval becomes higher, recognition rate also increases, which in turn implies to get better recognition rate, hand tremor signals should be as high as possible (in our case 2048 is the winner). Essentially, this outcome complies with our previous deductions related to the visual interpretation of class distributions in Fig. 8. Fig. 9 also tells us that features related to LBP always produce poor performance in the range of 8 and 256 acquisition time-intervals. However, from 256 to 2048, feature vectors with LBP start to recover and exhibits better performance. Thus, we can conclude that features with LBP depend highly on data acquisition time. On the other hand, statistically based features behave more robust against low time-interval values, and gradually increases as the time-interval raises, which indicate for relatively short acquisition times they are more suitable and provide greater comfort to subjects. Another interpretation of Fig. 9 is related to the FFT + LBP case. As it is seen in both graphs, applying LBP on FFT yields very poor performance. Even more, it seems invariant to the acquisition time-intervals. Nevertheless, DWT + LBP and FFT + Statistical features contradict this fact. The source of poor performance may, in fact, be based on the similar mathematical foundations of LBP and FFT, as both FFT and LBP reside in the frequency domain. Therefore, taking LBP after FFT is like taking double FFT or double LBP of original signal, which may deteriorate the signal itself.

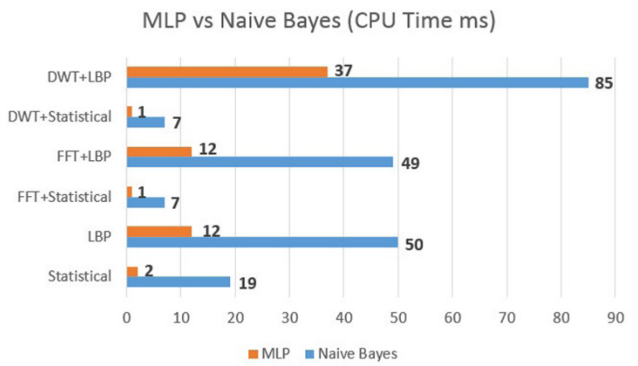

FIGURE 10. **Comparisons of classifiers versus proposed feature vectors in terms of CPU processing time in millisecond.**

DWT could overcome this problem since DWT keeps spatial and/or temporal information also in which signal still resides in spatial or temporal space. That is why DWT + LBP shows an excellent discrimination power.

Finally, a comparison of computation speeds of the proposed attributes can be useful in determining the best feature type. Fig. 10 demonstrates the computing time in a millisecond in the testing stages. It should be noted here we took only testing phase into account, because training is only done once and in real use subjects are usually confronted with test performance. However, this rule may not apply to Naïve Bayes learning algorithm, since it is considered as the lazy learner. Therefore, we sum up both training and testing time intervals to determine Naïve Bayes processing time. CPU processing times of acquisition modalities are very similar to each other. Thus, for the sake of simplicity, we calculated the average value for each modality and prepared Fig. 10, in which one can make a comparison between classifiers with respect to the proposed feature sets in a more elegant manner. Fig. 10 indicates that MLP outperforms Naïve Bayes classifier in terms of processing time for all cases. Indeed, for relatively small feature sets MLP computes faster than Naïve Bayes. On the other hand, in more complex network structures, this gap begins to clog, as in the LBP related feature sets. For example, the ratio is about 10 times for the statistical traits, while it decreases to 2 times for DWT + LBP features. Consequently, DWT + Statistical features should be preferred for a rapid identification system with a high classification performance.

V. CONCLUSION

In the current study, we utilized leap motion device to investigate the feasibility of hand tremor based biometric recognition. We tried to answer the question whether the hand tremor can be used as an efficient and effective biometric identification trait or not. In this context, we gathered spatiotemporal hand tremor data from five volunteers. Leap motion device, by default, provides X, Y, and Z locations. In order to unify the hand position and produce standardized hand tremor signals, we computed displacement amounts from adjacent frames. Moreover, mixed displacement value was also calculated and added to the channel set. Accordingly, we have diversified the data at various time interval mods starting from 8 and extending to 2048. For each modality, we collected 100 observations for training and 100 for testing. Then, we applied statistical, one-dimensional LBP, FFT + Statistical, FFT + LBP, DWT + Statistical, and DWT + LBP feature extraction methods. Naïve Bayes and MLP were chosen as learning algorithms for evaluating the discrimination power of the proposed feature sets. Only channel X could provide promising results and the rest were unsatisfactory. The reason why X dimension produces more reasonable results than others is that tremor in hands usually occurs along the X-axis and therefore leap motion captures more coherent signal on X dimension. Experiments revealed that for channel X, having 100 % classification accuracy rate, LBP, DWT + LBP, and DWT + Statistical feature extraction methods for 2048 mode outperform other approaches if we use MLP classifier. Thus, the applicability of using hand tremor signal for biometric recognition has been verified. This study also revealed that applying DWT on the raw data produces more salient feature than FFT and it is strongly advised not to use LBP after FFT although applying LBP after DWT exhibits good results. In addition to this, we also analyzed the computational efficiency of the classifier used for testing stage and realized that MLP has lower response time. As a future task we plan to utilize hand geometry along with hand tremors data as it is suggested [10] to have a possible effect to improve the discrimination power and provide a better recognition rate for small time-intervals. Additionally, we want to extend the study to cover authentication process as well.

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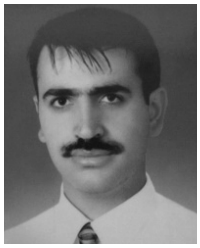

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