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Time and Frequency Domain Feature Extraction Method of Doppler Radar for Hand Gesture Based Human to Machine Interface

Aloysius Adya Pramudita[1, *], Lukas[2], and Edwar[1]

Abstract—In the development of hand gesture based Human to Machine Interface, Doppler response feature extraction method plays an important role in translating hand gesture of certain information. The Doppler response feature extraction method from hand gesture sign was proposed and designed by combining time and frequency domain analysis. The extraction of the Doppler response features at time domain is developed by using cross correlation, and the time domain feature is represented by using peak value of cross correlation result and its time shift. The Doppler response feature of frequency domain is extracted by employing a discriminator filter determined by the frequency spectrum observation of Doppler response. The proposed method was employed as a preprocessing for Continuous Wave (CW) radar output signals, which is able to relieve the pattern classification of Doppler response associated with each hand gesture. The simulation and laboratory experiment using HB 100 Doppler radar were performed to investigate the proposed method. The results show that the combination of all three features was capable of differentiating every type of hand gestures movement.

1. INTRODUCTION

The development of Human to Machine Interface (HMI) needs to accommodate any form of sign used as command interface. With regard to this matter, hand gesture can be represented as a sign of a command to control the system or machine. It encourages the development of the HMI which has capability to interpret the hand gesture sign into signal command in the form of electrical signals. As a result, the development of technology has continued to increase in the last few years to support activities for disabled people [1, 2]. The development of technology also occurs in electronic devices. The interpretation of cues such as movement, eyes, and bioelectric in communication becomes one of the technology features that can be developed for disabled people. A number of researches in the HMI field are also motivated by the needs of disabled people to help them work on various activities independently [3–5].

This research is more focused on interpreting hand gesture motion into information that can be used to communicate with the machine. An important concept that needs to be elaborated on the development of a hand gesture interpreter is motion detector. In the past decades, gestures have been usually identified and judged by wearing sensor gloves [6] to obtain angles and positions of each joint in the gesture. However, it is difficult to use widely due to the cost and inconvenience of wearing the sensor. Therefore, non-contact device is more suitable to be implemented in detecting hand gesture. To the best of the authors' knowledge, there are a few studies conducted in this area. Passive Infrared (PIR) was studied in developing a motion detection method, but this method is only limited to discriminate the presence or absence of movement and combining with other sensors such as seismic sensors which was used to overcome the problem [7]. The use of cameras has also been studied and proposed to conduct motion detection through either image processing or video [8]. Kinect sensors has been proposed to

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* Corresponding author: Aloysius Adya Pramudita (pramuditaadya@telkomuniversity.ac.id).
[1] Telkom University, Indonesia. [2] Atma Jaya Catholic University, Indonesia.

use in body pose detection [9, 10], skeleton tracking technology [11], and other aspects. By using three-dimension video analysis, this method certainly generates large data size (image/video) that gives a consequence of higher computation and memory needs. This method also has limitation on the adequacy of light intensity. The use of radio signals in wireless communications such as Wi-Fi signals has been studied in the development of methods for detecting human movements [12]. However, the use of a Received Signal Strength Indicator (RSSI) as a parameter needs to consider the problem of interference from similar sources, so that this problem needs to be mitigated [13]. For further development of the method, elaborating the concept of passive radar can be conducted as further research.

Development of non-contacting sensors based on radar systems has been done in several fields such as in medical field for detecting a human vital signs (respiration, heartbeat [14–16], structure health monitoring [17], and landslide monitoring [18]. Doppler radar is a radar system that detects the Doppler effect that occur on a target. When the target moves, the reflection of the radar signal generated by the target will experience a Doppler effect which is indicated by a frequency shift. The direction of movement will determine the frequency shift that occurs [19]. The Doppler response is then determined by the parameters of the movement.

Research in the development of Doppler radar as a motion detection has been conducted [20, 21]. An experiment and development of a 2.4 GHz Doppler radar system for detecting small-range motion was performed to overcome the resolution problem in PIR and ultrasonic sensor [20]. In this experiment, a Doppler radar was used to detect a human respiration signature by observing the radar output in time domain. Phase data processing is commonly used in improving the resolution in motion detection. Several methods of handling a distortion that may occur in phase processing has also been studied [21]. Considering motion detection/interpretation purposes, this method potentially provides smaller data, and its operation is independent of light availability. Several previous researches on hand gesture recognition using a radar system were developed based on CW, Frequency Modulated Continuous Wave (FMCW), and Ulta-wideband (UWB) radar. The extended Differentiate and Cross Multiply (DACM) algorithm to solve the null point and codomain restriction issued from traditional Doppler radar sensors [22], which is hand gesture recognition using FMCW millimetre wave, was reported [23]. The complex processing of the radar signal for obtaining the accurate detection result was needed. For example, a neural network was applied to recognize the pattern of radar output from a hand gestures target [24]. Feature extraction method can be used to reduce the complexity of recognition or classification process. With respect to the need of a compact and simple HMI, the Doppler response feature extraction method from CW radar output is proposed in this paper.

A Doppler radar is a radar system that detects a Doppler effect on a target. When the target performs a movement, the reflection of radar signal generated by the target will cause a Doppler effect characterized by a frequency shift in which the occurrence of frequency shift will be determined by its movement. The movement will determine the frequency shift that occurs [10]. The Doppler radar system is potentially elaborated as a concept in motion detector. The studies in implementing Doppler radar for motion detection were conducted previously [11, 12]. Several studies on the Doppler response have been carried out regarding hand gestures interpretation. Convolutional Neural Network has been proposed to process the Doppler radar output for recognizing the hand gesture [24]. Combination of Arcsine algorithm and 2-D Motion algorithm has been demonstrated for reconstructing the hand gesture motion [25]. Analysis of Doppler response features and developing its extraction method were done to enhance hand gesture recognition [26, 27]. Hand movement is commonly used as a sign for non-verbal communication. If each hand gesture is represented by different movements, then the movements with a particular trajectory will provide different Doppler radar responses. Extraction features of the Doppler radar response from a hand gesture are needed in interpreting the hand gesture sign into certain information. In this paper, observations on time and frequency domains are performed to identify the features or parameters of Doppler response of hand gesture. The proposed extraction method of the Doppler response features is designed by combining the time and frequency domain processing. The extraction of the Doppler response feature in the time domain is conducted using cross correlation. Cross correlation is one of the simplest methods for measuring the similarity between two signals. It is employed for extracting the feature in time domain estimating the similarity level of the radar output against reference signals. The Doppler response feature in frequency domain is extracted employing a discriminator filter determined based on the frequency spectrum observation of the Doppler response.

The proposed model is expected to be a preprocessing for the CW radar output signal that is able to relieve the pattern classification of Doppler response associated with each hand gesture. The simulation and laboratory experiment using HB 100 Doppler radar are performed to investigate the proposed method.

The discussion in this paper is organized as follows. Section 1 explains the background and problem addressed related to the development of the proposed method. Furthermore, Section 2, describes the proposed method and the experiment method conducted to investigate the proposed method. Then, Section 3 is the discussion and analysis of the experiment results, and finally, the last section is conclusion.

2. PROPOSED METHOD

2.1. CW Doppler Radar for Human to Machine Interface

In this research a simple Doppler radar using CW radar is elaborated as a hand movement sensor in developing HMI. Every hand gesture that is used as a command sign on HMI is expected to be identified with its features based on its Doppler response. The conceptual illustration of hand gestures sign interpretation employed as an HMI system is shown in Figure 1. A number of hand gesture forms could be selected and set as a gesture of command to the machine or equipment, then HMI uses it to interpret the signal. The model for extracting the Doppler response feature from a motion gesture becomes one of the key parts of the HMI system. The extraction model of the Doppler response feature was expected to ensure that each gesture is successfully interpreted and simplifies the classification process.

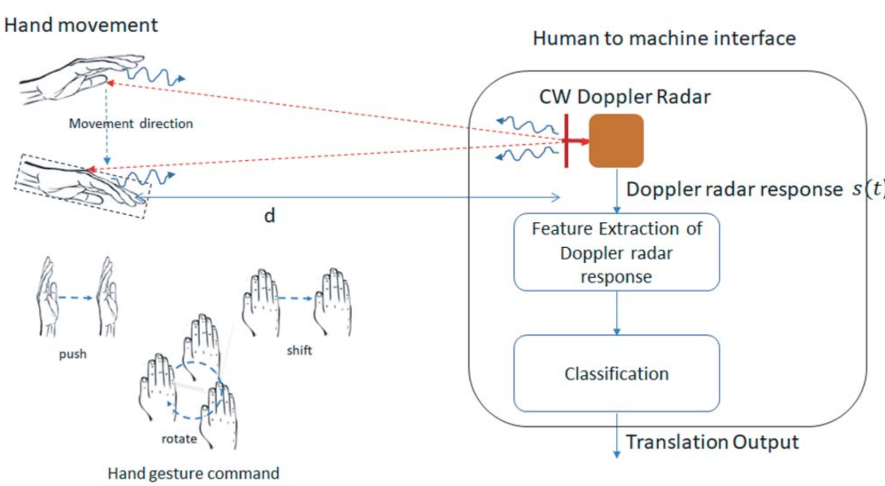


Figure 1. .Illustration of Human to Machine interface based on CW Doppler radar.

The CW radar basically consists of sinusoidal signal generator, power splitter, power amplifier and transmitting antenna at transmitter side and low pass filter, mixer, low noise amplifier, and receiving antenna at receiver side. The block diagram of CW radar system is shown in Figure 2. CW radar system transmitted electromagnetic waves with a single frequency of f_0, and target distance to the radar will affect the phase shift in the reflected wave received by radar. The transmitted signal can be written as Eq. (1) with A_t and θ respectively representing the amplitude and initial phase of X_t. If the distance between target and radar is d_0, then the transmitted waves reflected by the target will arrive at the receiver with phase shift of $4\pi d/\lambda$. λ is the wavelength of transmitted wave form. The received waveform can be written as Eq. (2) with A_r and θ respectively representing the amplitude and initial phase of X_r.

$$X_t(t) = A_t \cos(2\pi f_0 t) \tag{1}$$

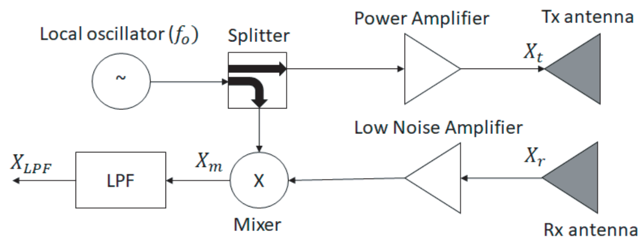


Figure 2. Block Diagram of 10 GHz CW radar system.

$$X_r(t) = A_r \cos\left(2\pi f_0 t + \frac{4\pi d}{\lambda} + \theta\right) \tag{2}$$

The reflected wave is then mixed with the transmitted signal, and the mixer output can be written as Eq. (3) with A_m representing the amplitude of X_m. Furthermore, the phase difference component from the mixer output is selected by using a low-pass filter (LPF), and the LPF output is the dc signal when the target is static. The LPF output is then written as Eq. (4) with A_{LPF} representing the amplitude of X_{LPF}. When there is a movement from the target, the distance between radar and target varies in time until the movement stop. In this research, the LPF output on the CW radar system illustrated in Figure 2 is defined as Doppler response from target movement. To investigate properties of the Doppler radar output regarding the target movement, the LPF output modelling is derived. Basically, the received signal contains multiple reflected waves from the target, thus the LPF output can be estimated as superposition of individual LPF output relating occurred multiple reflections from moving target. The LPF output model is written as Eq. (4). d_0 is the initial distance between radar and target, α the attenuation that may occur when the wave propagates and reflects back to the receiver, and $d_n(t)$ the shifting which is caused by the movement.

$$X_m(t) = A_m \cos\left(4\pi f_0 t + \frac{4\pi d(t)}{\lambda} + \theta\right) + \cos\left(\frac{4\pi d(t)}{\lambda} + \theta\right) \tag{3}$$

$$X_{LPF}(t) = A_{LPF} \cos\left(\frac{4\pi d(t)}{\lambda} + \theta\right) \tag{4}$$

$$X_{LPF}(t) = \sum_{n=1}^{N} A(n) e^{-\alpha(d_0 + d_n(t))} \cos\left(\frac{4\pi(d_0 + d_n(t))}{\lambda} + \theta\right) \tag{5}$$

Referring to Equation (4), it can be concluded that the movement on target will affect the frequency of the LPF output. When the target movement is modelled with a linear function at a constant speed v, $d_n(t)$ can be substituted by $\sqrt{d_0^2 + (vt)^2}$. Figures 3 and 4 show the LPF output of the CW radar system for a target with two different motion functions. Those motion functions represent the linear and exponential shift. To investigate the property of the Doppler response, the observation on time and frequency domains is conducted to the LPF output. Figure 3 shows the LPF output on the time domain, and Figure 4 shows the frequency spectrum of the LPF output. It appears from Figure 3 that the LPF output for linear and exponential motions indicates different Doppler responses.

Cross correlation is a simple method that has been widely used in determining the similarity of two signals [28, 29]. Cross correlation is performed not only for a 1-dimension signal but also for a 2-dimension signal such as image [29]. Considering a number of results on the previous studies, therefore the cross correlation method is employed in the proposed method for extracting the Doppler response features from each hand gesture that is used. The set of reference signals can be composed from the LPF output associated with each hand gesture. Furthermore, the cross correlation is used to measure the similarity between arbitrary sample of Doppler response and existing reference signals. Similarity level can be identified from the peak value of the cross correlation result. Cross correlation can be used also to estimate the time shift of a signal referring to the reference signal. Referring to the two cross correlation features, peak value of cross correlation and its time shift are used as time domain features of hand gesture Doppler response.

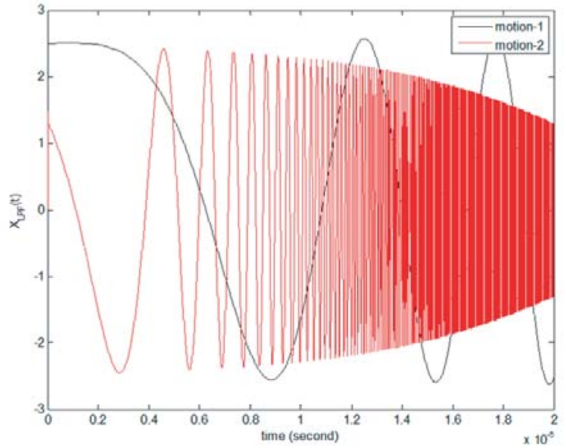


Figure 3. LPF output of 10 GHz CW radar for two different kinds of motions.

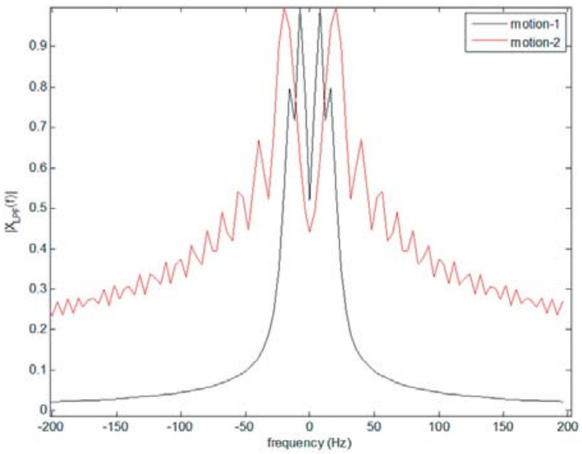


Figure 4. The spectrum of LPF output for two different motions.

Referring to the result in Figure 4, it appears that the two movements have different Doppler responses characterized by the difference in frequency spectrum. Referring to Eq. (5), it can be understood that the hand gestures function influences the frequency component of the LPF output. After observing each spectrum in Figure 4, a discriminator filter can be used to differentiate between gestures. The type and frequency range of the discriminator filter can be determined so that the filter output for each hand gesture can be well differentiated. For example, when we use the high pass filter with cutoff frequency of 50 Hz as a discriminator filter, filter output for motion-1 will be greater than motion-2. However, there is a variation on a type of hand gesture when it is repeated causing variation on its Doppler response. This fact should be considered in the development of the feature extraction model.

2.2. Proposed Method

Considering the observation results that have been obtained in time and frequency domains, the design of proposed feature extraction model consists of two parts. The first part is used to extract the time domain feature, and the second part is used to extract the frequency domain feature. Cross correlation is used for extracting the time domain feature with the peak, and time shift is chosen to represent the time domain feature. A discriminator filter is used to extract the frequency domain feature with the type of filter that could be selected by observing the spectrum of the LPF output of each hand gesture. In this model, we use summation spectrum to obtain the frequency domain feature. The proposed method applied to m type of hand gestures is depicted in Figure 5. The cross correlation between LPF output of nth sample and reference signal for the mth hand gesture can be calculated by using Eq. (6) with T standing for recording period of the radar output, and the time shift (S_{nm}) could be determined from the location of the peak value.

$$X_{Cnm}(s) = \frac{1}{2T} \int_{-T}^{T} X_{LPF_n}(t) X_{ref_m}(t-s) \tag{6}$$

The output of frequency domain feature extraction (X_{df_sum}) can be calculated by using Eq. (7), with $H_d(f)$ and $X_{LPF_n}(f)$ respectively standing for frequency response of discriminator filter and Fourier transform of LPF output. f_L and f_H are respectively the lowest and highest frequencies of the discrimator filter response considered in calculation. The response type (Low Pass, High Pass, and Band Pass) and its cutoff frequency of the discriminator filter can be determined after observing the frequency spectrum of LPF outputs associated with each hand gesture. The selection of filter type and its cutoff frequency are oriented for achieving the ability to differentiate LPF outputs from different

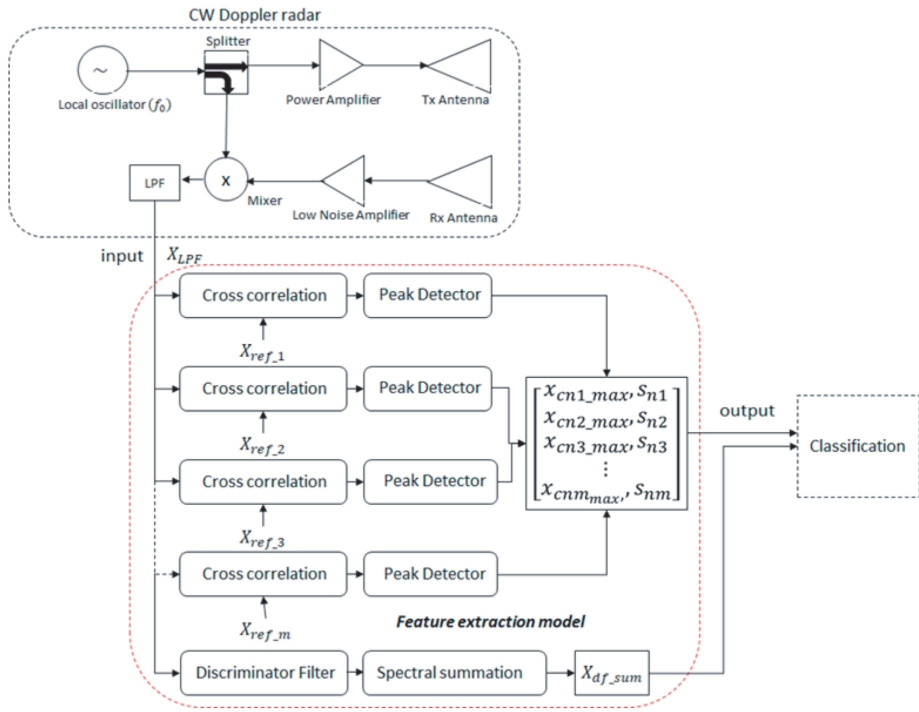


Figure 5. Feature extraction method that proposed for hand gesture Doppler response.

hand gestures.

$$X_{df_{sum}} = \int_{f_L}^{f_H} |X_{LPF_n}(f)H_d(f)|df \tag{7}$$

The feature extraction calculation becomes preprocessing for the hand gesture Doppler response before being recognized or classified into a certain sign. With respect to the proposed feature extraction method depicted in Figure 4, the feature of each hand gesture is represented by three values, i.e., X_{Cnm}, S_{nm}, and $X_d f_{sum}$. The peak value of cross correlation, time shift, and total spectrum of discriminator output are used as input data of classification process.

2.3. Experimental Model

Further investigation is conducted by performing laboratory experiments using the HB 100 as CW module radar working at a frequency of 10 GHz. LPF output from HB 100 is connected to a USB soundcard. The acquisition of LPF output data is carried out using a laptop. The experiment setup is shown in Figure 6.

Hand gesture movements are recorded at a distance (d_0) of 50 cm from the CW radar module. Four different hand gestures are selected as signs that are used in the experimental investigation. The first gesture (hand gesture-1) is pushing hand movements. The second gesture (hand gesture-2) is a shifting movement to the side direction. The third (hand gesture-3) and fourth (hand gesture-4) gestures are rotation movements with clockwise and counter clockwise directions. The measured LPF output is recorded for several times, and some of the results are shown in Figures 7 and 8. Figure 7 shows the sample of measured LPF output from each hand gesture. Figure 8 describes the variation that may occur in the LPF output of hand gesture-1. The background noise that produces by HB100 CW radar module is quite low with its level around −30 dB compared to the LPF output signal. Therefore, it does not give significant effect on recording the LPF output. One of the samples from the number of recorded LPF outputs of each hand gesture then is taken as a reference signal which is used later in the cross correlation calculation process as shown in Figure 5. The reference signal for the first, second, third, and fourth hand gestures are consecutively represented as $X(ref_1)$, $X(ref_2)$, $X(ref_3)$,

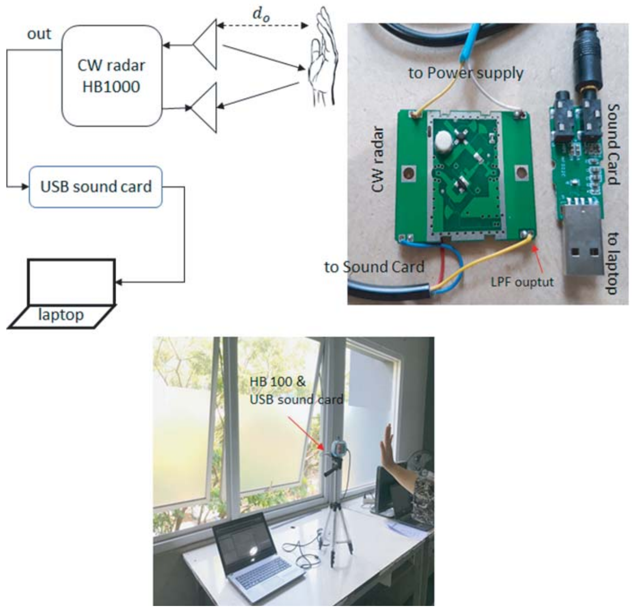


Figure 6. Experiment setup.

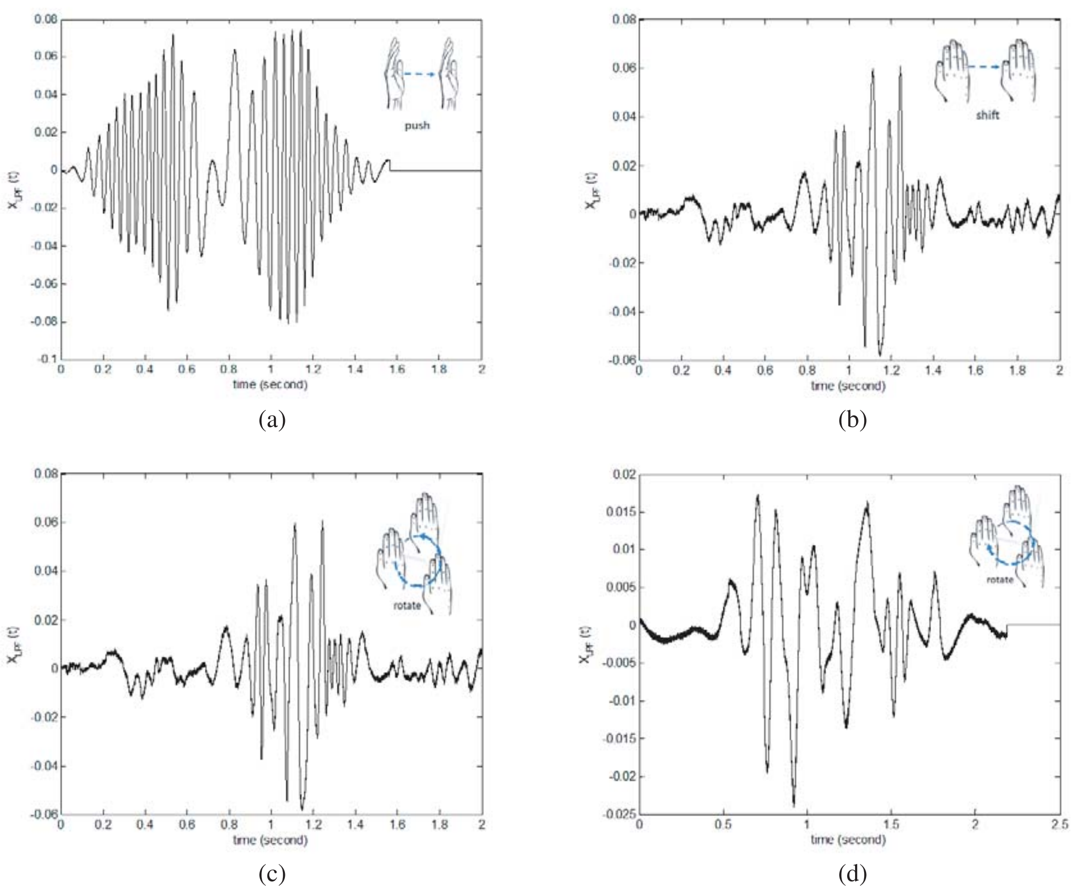


Figure 7. The measured LPF output samples from each hand gestures. (a) Hand gesture-1. (b) Hand gesture-2. (c) Hand gesture-3. (d) Hand gesture-4.

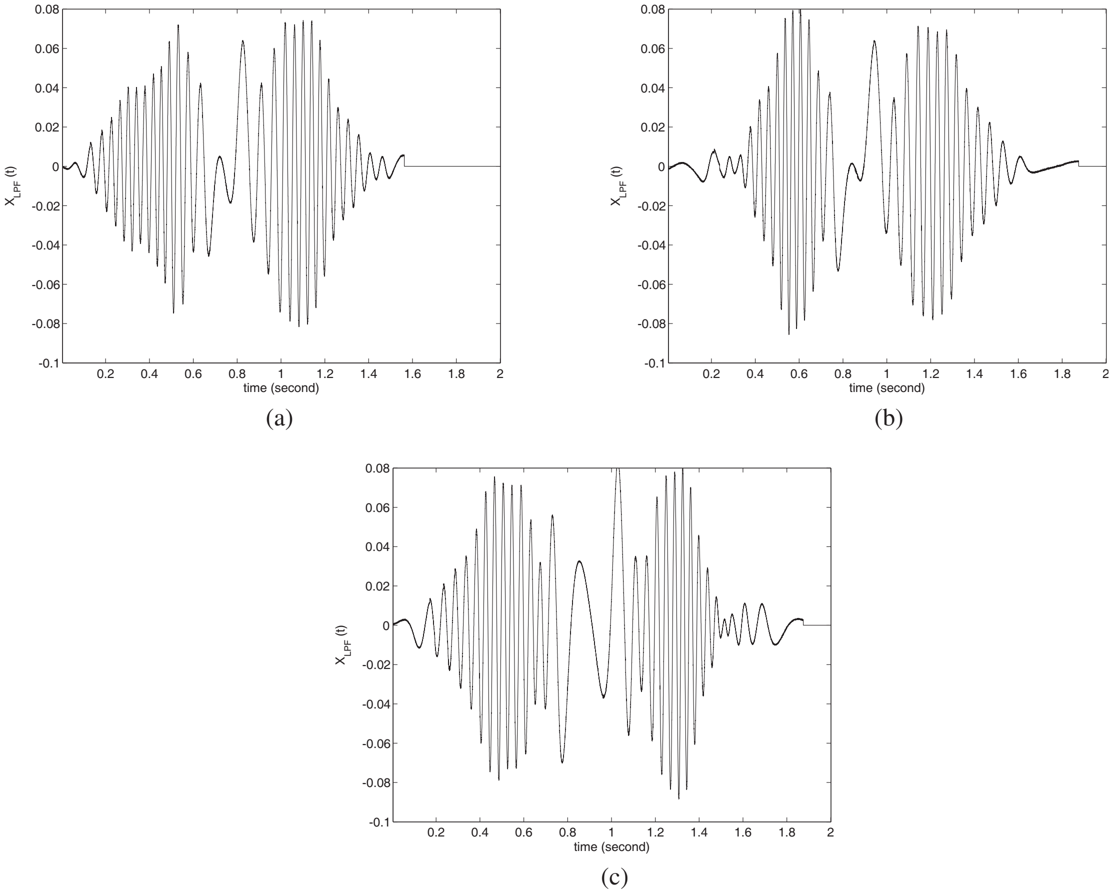


Figure 8. The LPF output samples for hand gesture-1. (a) 1st sample. (b) 2nd sample. (c) 3rd sample.

and $X(ref_4)$. Furthermore, the cross correlation calculations between recorded LPF output represent the Doppler response of a hand gesture, and each signal reference is performed referring to Eq. (7).

The similarity level of two signals could be determined based on the cross correlation peak value obtained by using peak detector. Moreover, cross correlation could be used to determine the relative delay of the similar signal regarding the reference signal. Shown in Figure 7, the LPF output from each hand gesture has a different pattern. Several LPF output samples form hand gesture-1, which are depicted in Figure 8, illustrate the variation that may occur during recoding. Several methods have been studied and applied to classify the signal such as statistical method [30], neural network [31], and Fuzzy logic [32]. To deal with the number of hand gesture signs that used in HMI system, simplicity and low computational cost are more appropriate for this case.

3. RESULT AND ANALYSIS

Figure 9 shows cross correlation result of the LPF output sample recorded for hand gesture-1. With respect to four results in Figure 9, X_{c11}, X_{c12}, X_{c13}, and X_{c14} respectively represent the cross correlation between sample signal for hand gesture-1 and first, second, third, and fourth reference signals. The results show that cross correlations with the first reference signal having the largest peak value are compared to cross correlations with another reference signal. The result indicates that the recorded LPF output is Doppler response from hand gesture-1. The same result can be found for hand gesture-2, hand gesture-3, and hand gesture-4. These results indicate that the peak value of cross correlation result is promising as a feature of Doppler response.

To evaluate the cross correlation performance in extracting the Doppler response feature, several

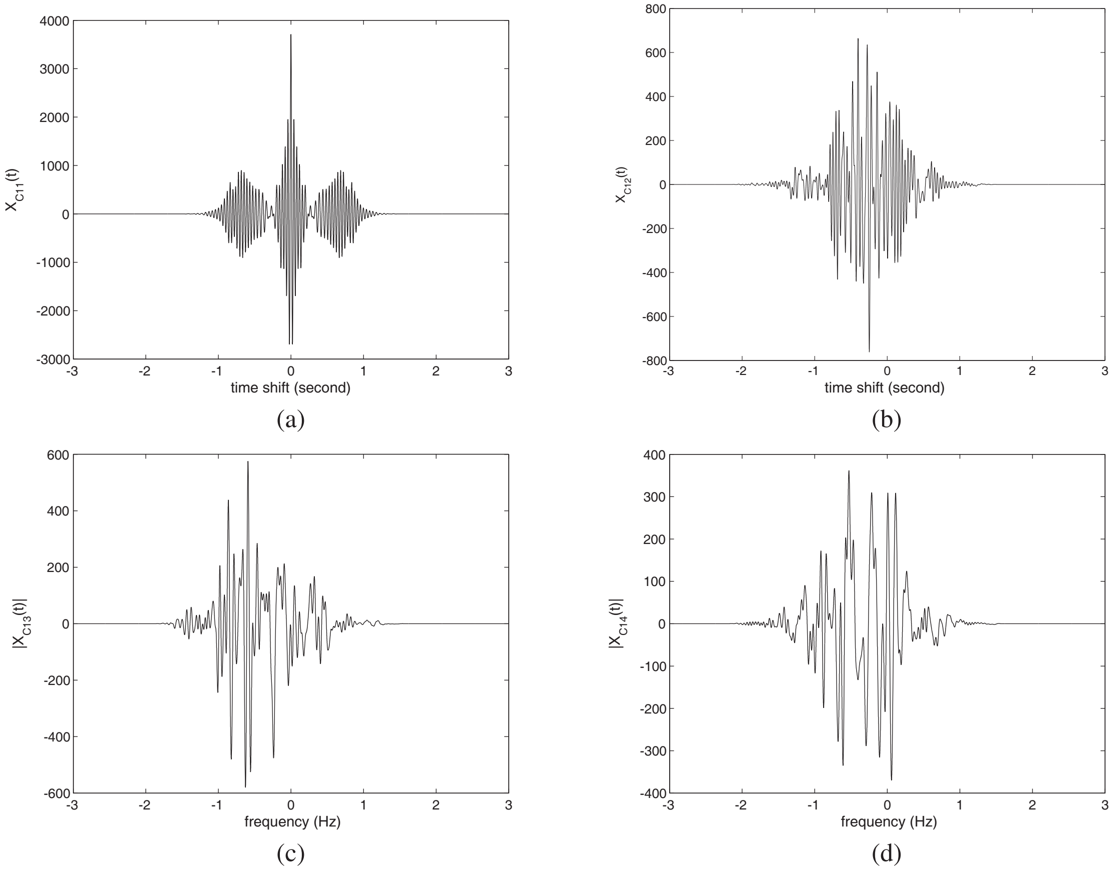


Figure 9. Cross-correlation results between LPF output of hand gesture-1 with references signals.

experiments on each hand gesture are performed by taking several recordings and then processed by using the proposed feature extraction method. The result of 10 times of the experiment performed for hand gesture-1 indicates that the peak value of cross correlation result to the first reference signal has the largest value. The results are shown in Figure 10(a). By using the same number of experiments for hand gesture-2, there are seven experiments produced the largest peak value when LPF output was correlated with the second reference signal, and the result can be seen in Figure 10(b). The result in Figure 10(c) indicates that seven experiments produced the largest peak value when LPF output was correlated with the third reference signal. The result in Figure 10(d) shows that all experiment produced the largest peak value when correlated with the fourth reference signal. The summary of these results is that the similarity level of the Doppler response could be identified by cross correlation method, although the result might not absolutely produce the correct identifier for all hand gesture responses. For example, three samples on hand gesture-2 are stated to have the largest peak value with respect to its correlation with the fourth reference signal. Some variation that might occur with similar hand gesture movements might result in cross correlation with its reference signal lower than the cross correlation with another reference signal. The same result also appears in hand gesture-3 with three samples that are identified with the largest peak on it cross correlation with the fourth reference signal. Furthermore, the experiments are conducted by taking 50 samples, and the success rates in extracting the features are listed in Table 1.

To overcome the problem that may rise in using cross correlation method, the proposed method also elaborates the observation of Doppler response in frequency domain. As demonstrated in the previous section, the Doppler effect could be essentially identified from the frequency domain. Different hand movements are essentially a shift from the initial position with a different movement function, which causes different changes in frequency component of LPF output. Therefore, each different movement could be distinguished from the frequency domain.

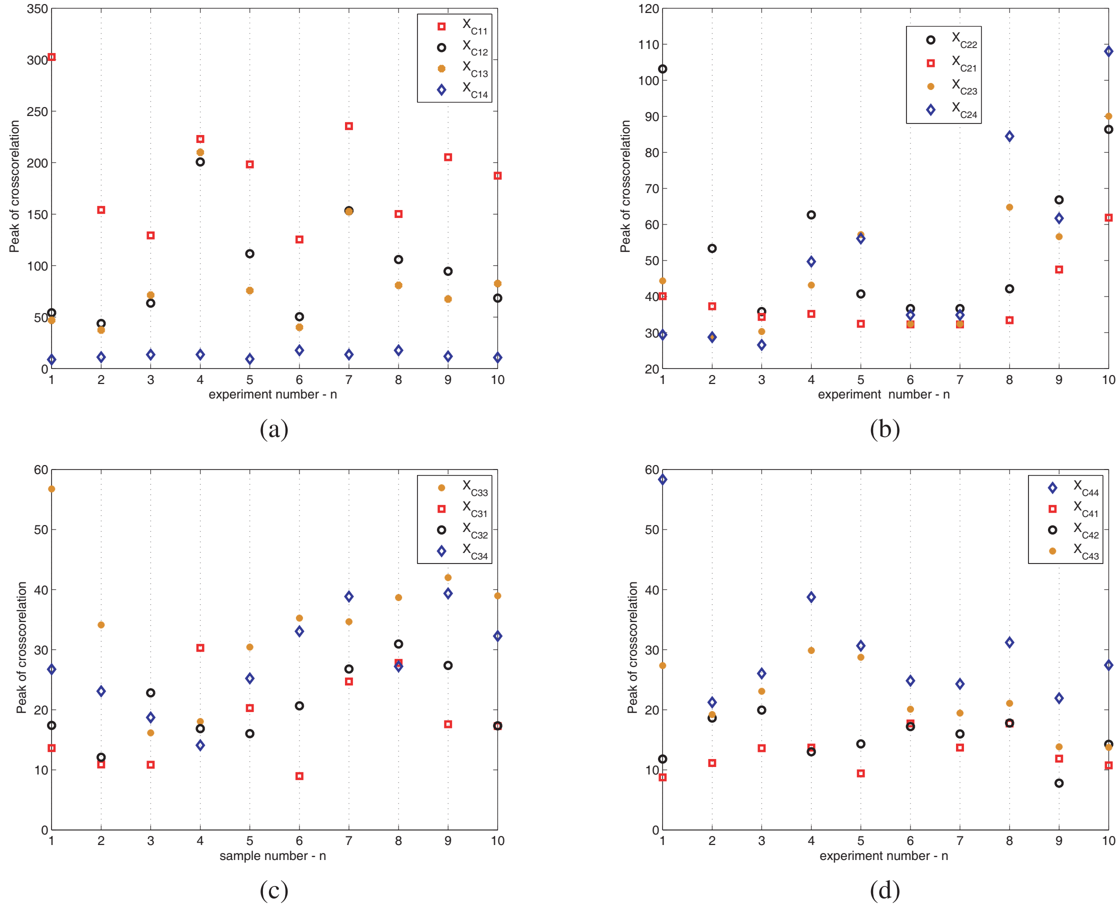
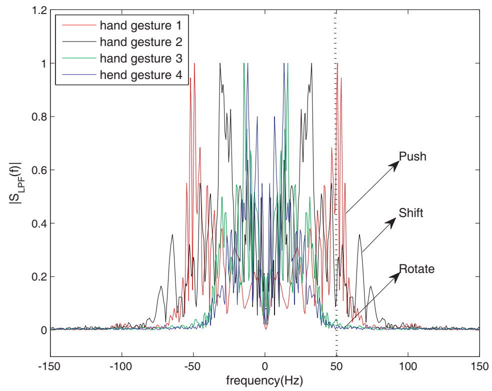


Figure 10. Peak value of cross correlation for Doppler response of hand gestures. (a) Hand gesture-1. (b) Hand gesture-2. (c) Hand gesture-3. (d) Hand gesture-4.

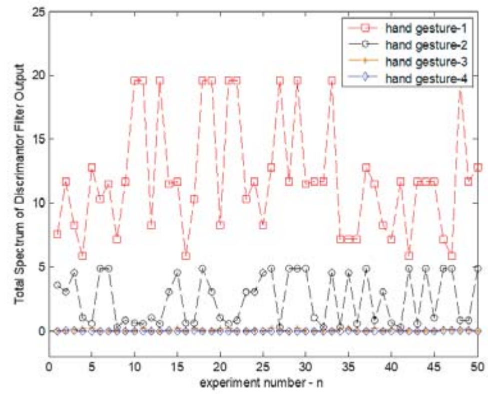
Table 1. Success rate in extracting each feture of hand gesture.

Hand gesture	Peak of cross correlation ($X_{cn,m}$)	Time Shift (S_{nm})	Discriminator filter output ($X_{df_{sum}}$)
Hand gesture-1	100%	100%	100%
Hand gesture-2	73%	100%	100%
Hand gesture-3	73%	100%	100%
Hand gesture-4	100%	100%	168%

The simulation results in Section 2.1 show that the spectra of linear and exponential movements have different frequency spectra. Therefore, the discriminator filter could be used to generate different output values for both movements. The proposed method of observation in frequency domain is also elaborated by applying discriminator filter in which the filter response could be determined based on observation oof the frequency spectrum of LPF output for each hand gesture. Figure 11(a) describes the frequency spectra of LPF output for four hand gestures used in the experiments. Pushing, shifting, and rotating hand movements have different peak spectrum locations, respectively at 50 Hz, 33 Hz, and 13 Hz. Moreover, the filtering of peak spectrum can be applied to differentiate the kind of hand gesture. For example, when the observation is obtained at a frequency range above 50 Hz, the spectrum for pushing, shifting, and rotating could be well differentiated. By applying the high pass filter as a discriminator filter, the three kinds of hand gesture movements could be differentiated. In the proposed



(a)



(b)

Figure 11. The frequency domain features. (a) Spectrum of Doppler response for four different hand gestures. (b) Total spectrum of discriminator filter output for four different hand gestures.

method, high pass filter with the low frequency cut off at 50 Hz is applied as a filter discriminator. To anticipate the fluctuations that might be found in the passband range, the summation of entire spectrum of the discriminator ($X_{df_{sum}}$) filter output is performed. Furthermore, to investigate the performance of proposed method in extracting the frequency domain feature, the experiment is performed by recording 50 samples on each hand gesture. Figure 11(b) shows $X_{df_{sum}}$ of each hand gesture. Hand gesture-1 has $X_{df_{sum}}$ value which is always greater than the other. Hand gesture-2 has $X_{df_{sum}}$ value which is always lower than hand gesture-1 and always higher than hand gesture-3 and hand gesture-4. Hand gesture-3 and 4 have the lowest $X_{df_{sum}}$ and a very similar $X_{df_{sum}}$ value. It can be understood from the fact that hand gesture-3 and hand gesture-4 are the same movement function (rotation in clockwise and counter clockwise) with different directions. These movements have the same relative shift to the radar position; therefore, the LPF output as the Doppler response has relatively same spectrum. For the case of different directional movements, the directional feature could be extracted from the time shift (S_{nm}) of cross correlation peak value. Success rates in extracting each feature of hand gestures are listed in Table 1. The results show that hand gesture-1 could be identified from all defined features. The different hand gesture movements, i.e., pushing, shifting, and rotation, could be well differentiated by using $X_{df_{sum}}$. Considering the results in Table 1, each hand gesture could be identified at least from two features that are defined in the proposed method. Finally, the proposed method is capable of extracting the features of each hand gesture.

4. CONCLUSION

The Doppler radar response feature extraction method from a hand gesture has been proposed in this paper. The proposed method is a part of HMI used for interpreting the hand gesture sign into certain information. The proposed extraction model is designed by combining the feature extraction both on time and frequency domains. The Doppler response feature extraction in the time domain is conducted by using cross correlation, and the time domain features are represented as peak value and time shift of cross correlation result. The Doppler response feature in frequency domain is extracted by employing a discriminator filter determined based on the frequency spectrum observation of the Doppler response. The feature extraction method is proposed as a preprocessing for the CW radar output signal that is able to relieve the pattern classification of Doppler response associated with each hand gesture. The simulation and laboratory experiment using HB 100 Doppler radar are performed to investigate the proposed method. The experiment results show that cross correlation has the lowest success rate of 73% in performing the Doppler response feature extraction. The variation that might occur in performing a type of hand gesture can influence the result. The feature at the frequency domain is represented by the summation of discriminator filter output spectrum. The frequency domain features successfully distinguish each different type of hand gesture. However, this feature cannot distinguish the direction of the movement in which this direction on a similar hand gesture can be distinguished through time shift of cross correlation results. The use of combination of all three features shows the capability to differentiate every type of hand gestures movement.

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