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Discrete Sine Transform Analysis, Discrete Cosine Transform and Discrete Fourier Transform for Introduction to Voice Register

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ABSTRACT

Voice register is a division of human voice area based on sound source, resonant space sensation, shape, color, sound timbre, and high and low tones produced, with the type of voice tested is the female voice register for chest voice, head voice, falsetto and vocalfry. The data used in this study is a set of female voice register audio file recorded with the help of the adobe audition 1.5 application. The audio file extension used in this study is file.wav. The choice of audio.wav file is due to the default audio format in audio processing on the windows operating system. In this study, the percentage of discrete sine transform (DST) transformations true detection rate ranged from 63% to 79%, the percentage of discrete cosine transform (DCT) transformations true detection rate ranged from 61% to 73% and the percentage of discrete fourier transform (DFT) transformation rates of true detection ranged from 58% to 61%. The average DST transformation is true detection rate of 73%, DCT transformation is an average true detection rate of 66% and the average DFT transformation is true detection rate of 59%. The best transformation method for introducing voice registers through female voices is DST and DFT.

Keywords: Discrete sine transform analysis, discrete cosine transform, DCT, discrete fourier transform (DFT), Voice register

INTRODUCTION

A means of communicating among people that is very effective is sound (Fadlisyah & Muhathir, 2015). Besides effective voice is also more familiar to humans in communication. The vibration of an object produces physical phenomena in the form of sound, in the form of analog signals where the amplitude changes over time continuously (Fadlisyah, 2013). Voice recognition has been widely used in various purposes as an applied technique in the field of film processing of digital signal processing (Chakraborty, 2014), as an example of technology in the field of telecommunications which so far has only provided services for sending text data, apparently it has also been able to use voice in serving data transmission. According to (Fadlisyah and Muhathir, 2015) the introduction of voices is the conversion process of sequential words, using algorithms or methods applied to computer programs with the aim of obtaining the characteristics or characteristics of voice patterns which will subsequently be used as patterns of reference.

All general systems that require human interaction in daily activities use sound processing as its main concept (Goyal & Batra, 2017). The words spoken can be accepted and identified with sound processing abilities (Swamy & K, 2013). Automatic speech recognition converts speech signals into word sequences with the help of an algorithm implemented in a computer program (Chauhan, Samal, & Ghoshal, 2015). The aspects of human soundness are used for identification by changing the phrase spoken from an analog to digital format, and extracting unique vocal characteristics such as frequency, pitch, rhythm and tone to form sound samples or speaker models (Parwinder & Rani, 2014).

According to (Fadlisyah & Muhathir, 2015) isolated words, connected words, continuous speech, spontaneous speech are four types of categories in sound processing systems. Isolated words is a sound processing where one word is received at a time and the system waits between the speaker's utterances to be heard, connected words is a connecting system of words that is almost similar to isolated words, but allows separating utterances with a minimum gap between utterances to be turn the same, continuous speech is a continuous sound processing that allows users to speak almost naturally, while the content is computer determined (the basic principle of computer dictation). Spontaneous speech is a spontaneous sound that can be categorized in natural sounds not trained and heard. Spontaneous sound processing systems must be able to handle a variety of natural sound features such as slightly stuttering or "ahs" and "ahs" words.

This voice recognition system should be built with the basic specifications as follows:

1.Using efficient computing, where in the advanced development system hallaklak need, such as introduction of voice voice, head voice, falsetto, and vocalfry and others. In a speech recognition system, the use of computation that is too complex is very influential on the speed of sound recognition performance.

2.In this study the parameters used as a reference to measure the work of the system is the truth detection and false detection.

Complex computing is always involved in various researches on the recognition of sounds that have been done. As is well known, on the basis of recognizing patterns, the accuracy of the system's working instructions can be improved by computations that are complex, but the speed of the performance of the system is affected by complex computing, especially in relation to the pattern recognition with a large number of systems. Saving and reliable computation in sound recognition systems, trying to be discovered by researchers, is because in the future sound recognition systems will be associated with a large number of records as the number of world population increases. However, the researchers at this time still have not found a computation that is so economical and reliable for sound recognition, especially in the application of voice recognition or other systems related to sound. The computational approach that has been applied has less than each other. The challenge of concentration in this study is the choice of efficient and reliable use of computing.

Various kinds of computer technology today are expanding in their use, along with the discovery of various kinds of methods, both in terms of synthetic networks, transformation, distance, and similarity. In this research, the transformer transformation model is compared to the transformation of sinus and transformations of the sinus.

RESEARCH METHODS

Stages of research carried out is to study research first, such as literature studies and conduct consultations with supervisors. The research process will only continue after problems have been discovered and formulate problems to be resolved.

The workflow diagram of the system carried out in this study is illustrated in figure 1.

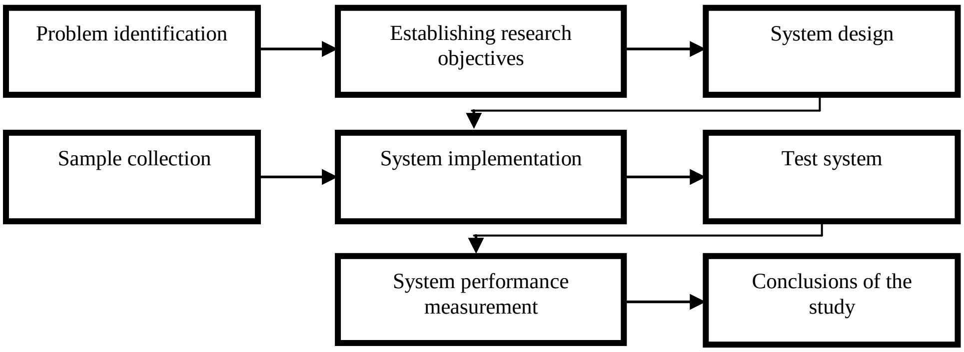


Figure 1. General Research Workflow

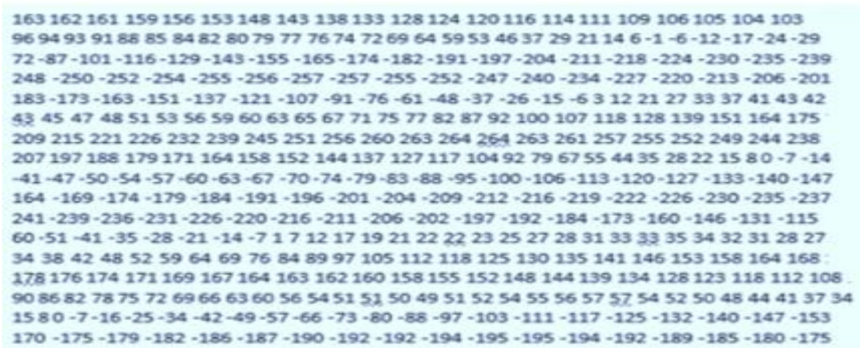
Based on figure 1, it can be explained that the research workflow in general begins with identifying the problems to be further investigated, then setting research objectives so that the scope of research does not come out of the core of the research itself and subsequently design a system that will be able to be used to solve problems has been determined, before implementing the system that has been designed, the process of collecting female voice register voice samples is carried out, then the next step is to implement the system in accordance with the stated research objectives and the processing of female voice register voice samples has been collected then proceed to the testing stage of the system, after the stage system testing is done and there is no error in the transformation work process that has been set then the final stage will be the stage of measuring the performance of the system for each transformation so that the conclusion of this research.

RESULT

Sound Pattern Sampling Results

Each voice register of women has a specific or different sound sampling. In sine transformation, transformations and transformative transformers, sound sampling training must be determined before testing.

Figure 2. shows a sampling of female voice registers with a chest voice model.



163 162 161 159 156 153 148 143 138 133 128 124 120 116 114 111 109 106 105 104 103
96 94 93 91 88 85 84 82 80 79 77 76 74 72 69 64 59 53 46 37 29 21 14 6 -1 -6 -12 -17 -24 -29
72 -87 -101 -116 -129 -143 -155 -165 -174 -182 -191 -197 -204 -211 -218 -224 -230 -235 -239
248 -250 -252 -254 -255 -256 -257 -257 -255 -252 -247 -240 -234 -227 -220 -213 -206 -201
183 -173 -163 -151 -137 -121 -107 -91 -76 -61 -48 -37 -26 -15 -6 3 12 21 27 33 37 41 43 42
43 45 47 48 51 53 56 59 60 63 65 67 71 75 77 82 87 92 100 107 118 128 139 151 164 175
209 215 221 226 232 239 245 251 256 260 263 264 264 263 261 257 255 252 249 244 238
207 197 188 179 171 164 158 152 144 137 127 117 104 92 79 67 55 44 35 28 22 15 8 0 -7 -14
-41 -47 -50 -54 -57 -60 -63 -67 -70 -74 -79 -83 -88 -95 -100 -106 -113 -120 -127 -133 -140 -147
164 -169 -174 -179 -184 -191 -196 -201 -204 -209 -212 -216 -219 -222 -226 -230 -235 -237
241 -239 -236 -231 -226 -220 -216 -211 -206 -202 -197 -192 -184 -173 -160 -146 -131 -115
60 -51 -41 -35 -28 -21 -14 -7 1 7 12 17 19 21 22 22 23 25 27 28 31 33 33 35 34 32 31 28 27
34 38 42 48 52 59 64 69 76 84 89 97 105 112 118 125 130 135 141 146 153 158 164 168
178 176 174 171 169 167 164 163 162 160 158 155 152 148 144 139 134 128 123 118 112 108
90 86 82 78 75 72 69 66 63 60 56 54 51 51 50 49 51 52 54 55 56 57 57 54 52 50 48 44 41 37 34
15 8 0 -7 -16 -25 -34 -42 -49 -57 -66 -73 -80 -88 -97 -103 -111 -117 -125 -132 -140 -147 -153
170 -175 -179 -182 -186 -187 -190 -192 -192 -194 -195 -195 -194 -192 -189 -185 -180 -175

Figure 2. Sound Sampling Value

Figure 2 is the result of sampling the sound register pattern of the voice list with the different frequency values, the values of the frequency contained, as well as the lower number of voice registers then the sound register tone then the voice register number is then the sound register value then the voice register value is lower then the voice register value then the voice register value then the voice register value then the voice register value then the voice register value then the voice register value then the voice register value then the voice register value then the voice register value then the voice register value then the voice register value which is referred to as being transformed into Sinus transformation, the transformation of cosine and transformer fourier.

Transformation Testing

The sound register test with Sine transformation, Cosine transformation andourier transformation is done with 10 times testing, the results of testing the sound register with the help of Sinus transformation, the transformation of Cosine and the transformation ofourier can be seen on tables 1 to table 10.

Table 1. First Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0.68**	0.15	0.10	0.07	**0.45**	0.26	0.12	0.17	**0.42**	0.02	0.02	0.54
HV	0.12	**0.65**	0.05	0.18	0.26	**0.70**	0.03	0.01	0.11	**0.72**	0.02	0.15
FS	0.13	0.16	**0.67**	0.04	0.04	0.23	**0.61**	0.12	0.14	0.15	**0.63**	0.08
VF	0.17	0.11	0.01	**0.71**	0.10	0.08	0.08	**0.74**	0.17	0.03	0.14	**0.66**

In the first test DST was able to recognize the voice registerCV of 68% in CV, HV by 65% in HV, FS by 67% in FS and VF by 71% in VF. On the first test, DST was able to recognize voice registers with an accuracy of 68%.

In the first test, DCT was able to recognize a 45% CV voice register on the CV, 70% HV on the HV, 61% on the FS and 74% on the FS and VF on the VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 63%.

In the first test DFT was able to recognize a CV voice register of 42% in CV, HV by 72% in HV, FS by 63% in FS and VF at 66% in VF. On average in the first test DFT was able to recognize voice registers with an accuracy of 61%.

Table 2. Second Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0,68**	0,02	0,02	0,28	**0,47**	0,19	0,10	0,24	**0,36**	0,35	0,12	0,17
HV	0,11	**0,72**	0,02	0,15	0,12	**0,72**	0,05	0,11	0,26	**0,70**	0,03	0,01
FS	0,14	0,10	**0,68**	0,08	0,13	0,20	**0,63**	0,04	0,04	0,23	**0,61**	0,12
VF	0,17	0,03	0,10	**0,70**	0,17	0,11	0,01	**0,71**	0,10	0,08	0,18	**0,64**

In the second test the DST was able to recognize a CV voice register of 68% in the CV, an HV of 72% in the HV, an FS of 68% in the FS and a VF of 70% in the VF. On average in the first test DST is able to recognize voice registers with an accuracy of 70%.

In the second test, DCT was able to recognize a CV voice register of 47% in the CV, HV by 72% in the HV, FS by 63% in the FS and VF by 71% in the VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 63%.

In the second test DFT was able to recognize a CV voice register of 36% in CV, HV by 70% in HV, FS by 61% in FS and VF by 64% in VF. On average, the first DFT test was able to recognize the voice register with 58% accuracy.

Table 3. Third Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0,71**	0,11	0,12	0,06	**0,42**	0,02	0,02	0,54	**0,47**	0,19	0,10	0,24
HV	0,26	**0,70**	0,03	0,01	0,11	**0,72**	0,02	0,15	0,12	**0,55**	0,05	0,28
FS	0,04	0,10	**0,74**	0,12	0,14	0,15	**0,63**	0,08	0,13	0,20	**0,63**	0,04
VF	0,10	0,08	0,10	**0,72**	0,17	0,03	0,14	**0,66**	0,17	0,11	0,01	**0,71**

In the third test DST was able to recognize a CV voice register of 71% in CV, HV by 70% in HV, FS by 74% in FS and VF by 72% in VF. On average, the first DST test was able to recognize voice registers with an accuracy of 72%.

In the third test, DCT was able to recognize a CV voice register of 42% in CV, HV by 72% in HV, FS by 63% in FS and VF at 66% in VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 61%.

In the third test, DFT was able to recognize a CV voice register of 47% in the CV, HV by 55% in the HV, FS by 63% in the FS and VF by 71% in the VF. On average, the first DFT test was able to recognize voice registers with an accuracy of 59%.

Table 4. Fourth Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0.61**	0.09	0.10	0.20	**0.52**	0.19	0.10	0.19	**0.42**	0.02	0.02	0.54
HV	0.12	**0.55**	0.05	0.28	0.10	**0.70**	0.05	0.15	0.11	**0.72**	0.02	0.15
FS	0.13	0.20	**0.63**	0.04	0.13	0.20	**0.63**	0.04	0.14	0.15	**0.63**	0.08
VF	0.17	0.11	0.01	**0.71**	0.17	0.11	0.01	**0.71**	0.17	0.03	0.14	**0.66**

In the fourth test DST was able to recognize a CV voice register of 61% in CV, HV by 55% in HV, FS by 63% in FS and VF of 71% in VF. On average in the first test DST was able to recognize voice registers with an accuracy of 63%.

In the fourth test, DCT was able to recognize a CV voice register of 52% in the CV, an HV of 70% in the HV, an FS of 63% in the FS and a VF of 71% in the VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 64%.

In the fourth test DFT was able to recognize a CV voice register of 42% in CV, HV by 72% in HV, FS by 63% in FS and VF at 66% in VF. On average in the first test DFT was able to recognize voice registers with an accuracy of 61%.

Table 5. Fifth Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0.56**	0.19	0.10	0.15	**0.71**	0.04	0.12	0.13	**0.42**	0.02	0.02	0.54
HV	0.12	**0.68**	0.05	0.15	0.26	**0.70**	0.03	0.01	0.11	**0.72**	0.02	0.15
FS	0.03	0.03	**0.90**	0.04	0.04	0.08	**0.86**	0.02	0.14	0.15	**0.63**	0.08
VF	0.17	0.11	0.01	**0.71**	0.10	0.08	0.18	**0.64**	0.17	0.03	0.14	**0.66**

In the fifth test DST was able to recognize a CV voice register of 56% in CV, HV by 68% in HV, FS by 90% in FS and VF by 71% in VF. On average in the first test DST was able to recognize voice registers with an accuracy of 71%.

In the fifth test, DCT was able to recognize a CV voice register of 71% in CV, HV by 70% in HV, FS by 86% in FS and VF of 64% in VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 73%.

In the fifth test DFT was able to recognize a CV voice register of 42% in the CV, HV by 72% in the HV, FS by 63% in the FS and VF at 66% in the VF. On average in the first test DFT was able to recognize voice registers with an accuracy of 61%.

Table 6. Sixth Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0,59**	0,12	0,12	0,17	**0,53**	0,23	0,12	0,12	**0,47**	0,19	0,10	0,24
HV	0,07	**0,89**	0,03	0,01	0,11	**0,81**	0,02	0,06	0,12	**0,55**	0,05	0,28
FS	0,04	0,09	**0,75**	0,12	0,14	0,15	**0,63**	0,08	0,13	0,20	**0,63**	0,04
VF	0,01	0,05	0,06	**0,88**	0,17	0,03	0,14	**0,66**	0,17	0,11	0,01	**0,71**

In the sixth test DST was able to recognize a CV voice register of 59% in the CV, HV by 89% in the HV, FS by 75% in the FS and VF by 88% in the VF. On average in the first test DST was able to recognize voice registers with an accuracy of 78%.

In the sixth test DCT was able to recognize a CV voice register of 53% in the CV, HV at 81% in the HV, FS at 63% in the FS and VF at 66% in the VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 66%.

In the sixth DFT test was able to recognize a CV voice register of 47% in the CV, HV by 55% in the HV, FS by 63% in the FS and VF by 71% in the VF. On average, the first DFT test was able to recognize voice registers with an accuracy of 59%.

Table 7. Seventh Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0,63**	0,02	0,02	0,33	**0,69**	0,09	0,10	0,12	**0,36**	0,35	0,12	0,17
HV	0,08	**0,86**	0,02	0,04	0,12	**0,55**	0,05	0,28	0,26	**0,70**	0,03	0,01
FS	0,14	0,02	**0,76**	0,08	0,05	0,02	**0,89**	0,04	0,04	0,23	**0,61**	0,12
VF	0,10	0,03	0,02	**0,85**	0,17	0,11	0,01	**0,71**	0,10	0,08	0,18	**0,64**

In the seventh test DST was able to recognize a CV voice register of 63% in CV, HV by 86% in HV, FS by 76% in FS and VF by 85% in VF. On average in the first test DST was able to recognize voice registers with an accuracy of 78%.

In the seventh test DCT was able to recognize a CV voice register of 69% in the CV, HV by 55% in the HV, FS by 89% in the FS and VF by 71% in the VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 71%.

In the seventh test DFT was able to recognize a CV voice register of 36% in CV, HV by 70% in HV, FS by 61% in FS and VF by 64% in VF. On average, the first DFT test was able to recognize the voice register with 58% accuracy.

Table 8. Eighth Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0,78**	0,02	0,02	0,18	**0,47**	0,19	0,10	0,24	**0,36**	0,35	0,12	0,17
HV	0,11	**0,74**	0,02	0,13	0,12	**0,55**	0,05	0,28	0,26	**0,70**	0,03	0,01
FS	0,01	0,02	**0,92**	0,05	0,13	0,20	**0,63**	0,04	0,04	0,23	**0,61**	0,12
VF	0,17	0,03	0,14	**0,66**	0,17	0,11	0,01	**0,71**	0,10	0,08	0,18	**0,64**

In the eighth test DST was able to recognize a CV voice register of 78% in CV, HV by 74% in HV, FS by 92% in FS and VF at 66% in VF. On average in the first test DST was able to recognize voice registers with an accuracy of 78%.

In the eighth test DCT was able to recognize a CV voice register of 47% in the CV, HV by 55% in the HV, FS by 63% in the FS and VF by 71% in the VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 59%.

In the eighth test DFT was able to recognize a CV voice register of 36% in CV, HV by 70% in HV, FS by 61% in FS and VF by 64% in VF. On average, the first DFT test was able to recognize the voice register with 58% accuracy.

Table 9. Ninth Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0,55**	0,19	0,10	0,16	**0,47**	0,24	0,12	0,17	**0,42**	0,02	0,02	0,54
HV	0,12	**0,75**	0,05	0,08	0,26	**0,70**	0,03	0,01	0,11	**0,72**	0,02	0,15
FS	0,02	0,03	**0,92**	0,03	0,02	0,04	**0,90**	0,04	0,14	0,15	**0,63**	0,08
VF	0,16	0,11	0,01	**0,72**	0,10	0,08	0,18	**0,64**	0,17	0,03	0,14	**0,66**

In the ninth test, DST was able to recognize a CV voice register of 55% in the CV, an HV of 75% in the HV, an FS of 92% in the FS and a VF of 72% in the VF. On the first test, DST was able to recognize voice registers with an accuracy of 74%.

In the ninth test, the DCT was able to recognize a CV voice register of 47% in the CV, an HV of 70% in the HV, an FS of 90% in the FS and a VF of 64% in the VF. On the first test, DCT was able to recognize voice registers with an accuracy of 68%.

In the ninth test DFT was able to recognize a CV voice register of 42% in CV, HV by 72% in HV, FS by 63% in FS and VF at 66% in VF. On average in the first test DFT was able to recognize voice registers with an accuracy of 61%.

Table 10. Tenth Test Results

	DST				DCT				DFT			
	CV	HV	FS	VF	CV	HV	FS	VF	CV	HV	FS	VF
CV	**0,69**	0,02	0,02	0,27	**0,47**	**0,47**	**0,47**	**0,47**	**0,36**	0,35	0,12	0,17
HV	0,11	**0,73**	0,02	0,14	0,12	**0,55**	0,05	0,28	0,26	**0,70**	0,03	0,01
FS	0,02	0,01	**0,95**	0,02	0,05	0,03	**0,89**	0,03	0,04	0,23	**0,61**	0,12
VF	0,13	0,03	0,14	**0,70**	0,17	0,11	0,01	**0,71**	0,10	0,08	0,18	**0,64**

In the tenth test DST was able to recognize a CV voice register of 69% in the CV, HV by 73% in the HV, FS by 95% in the FS and VF by 70% in the VF. On average in the first test DST was able to recognize voice registers with an accuracy of 77%.

In the tenth test DCT was able to recognize a CV voice register of 47% in the CV, HV by 55% in the HV, FS by 89% in the FS and VF by 71% in the VF. On average in the first test DCT was able to recognize voice registers with an accuracy of 66%.

In the tenth test DFT was able to recognize a CV voice register of 36% in CV, HV by 70% in HV, FS by 61% in FS and VF by 64% in VF. On average, the first DFT test was able to recognize the voice register with 58% accuracy.

Based on the results of ten testing trials, the results for each test with DST, DCT and DFT transformations have different levels of accuracy. For more details, see figures 3, 4 and 5.

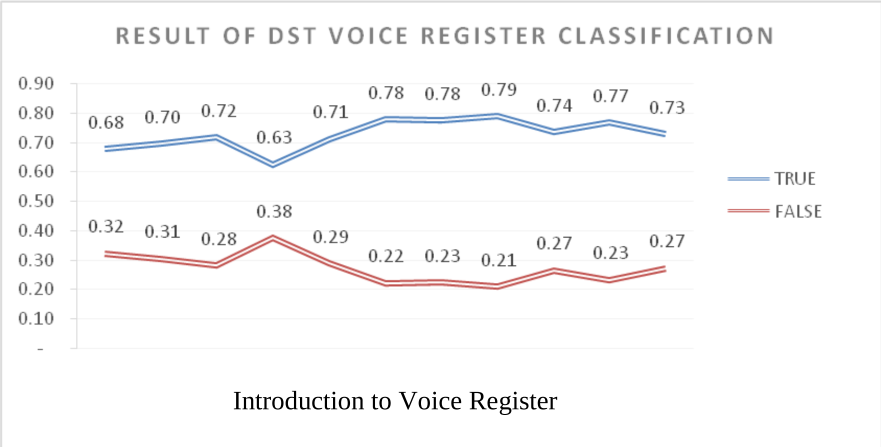


Figure 3. DST Test Results

In the ten DST tests for the introduction of voice registers through female voices, the percentage of DST transformation rates of true detection ranged from 63% to 79%, with an average true detection rate of 73%.

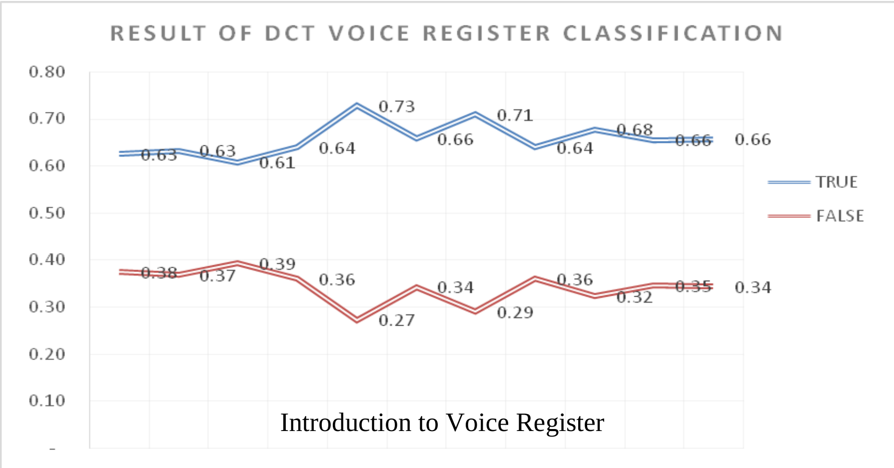


Figure 4. DCT Test Results

In the ten DCT tests for the introduction of voice registers through female voices, the percentage of DCT transformation rates of true detection ranged from 61% to 73%, with an average true detection rate of 66%.

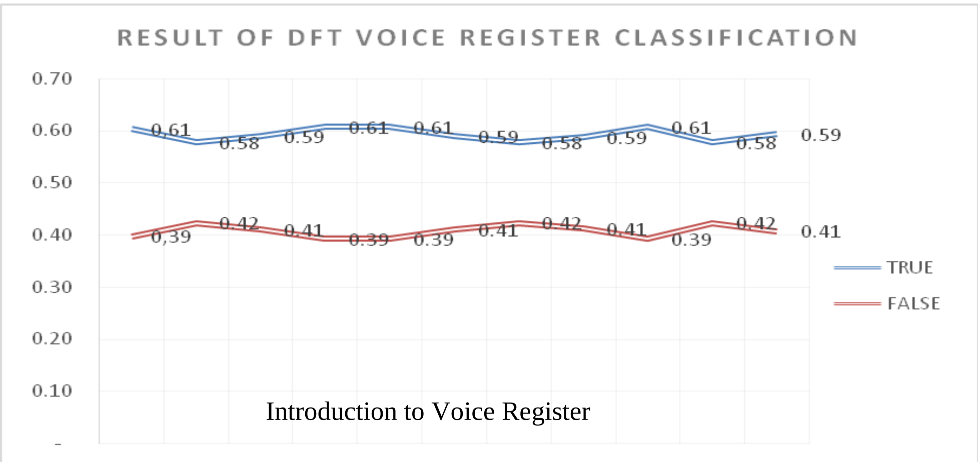


Figure 5. DFT Test Results

In the ten DFT tests for the introduction of voice registers through female voices, the percentage of DFT transformation rates of true detection ranges from 58% to 61%, with an average true detection rate of 59%.

CONCLUSION AND SUGGESTION

CONCLUSION

The results of the study showed that based on ten performance tests each of the transformation methods for the introduction of the invoice register through women was as follows:

1.The percentage of DST transformation rate detection range from 63% to 79%, the percentage of DCT transformation rate detection ranges from 61% to 73% and the percentage of DFT transformation rate detection rate ranges from 58% to 61%.

2.DST transformation average 73% detection rate, DCT transformation average 66% detection rate and 59% average DFT transformation rate.

3.The best transformation method for introducing invoice registers through women is discrete sine transform (DST) and less good is discrete fourier transform (DFT).

Based on the results of research that has been done, the level of system detection is greatly affected by the number of training samples. Observation of sampling patterns of reference for testing, and the level of success of the system in the sound sampling process. Sounds can be recognized by the system if the sampling process of the external signal is similar to the pattern of sampling process.

Previous voice register research only uses discrete fourier transform by transforming values together with the sine and cosine models, while this study developed the voice register signal method by being able to be transformed with the sine transformation and cosine transformation models independently. It turns out that transforming using the DST, DCT and DFT methods individually produces a better level of true detection than using the concurrent method.

SUGGESTION

To improve the quality of the transformation process, both discrete sine transform (DST), discrete cosine transform (DCT) and discrete fourier transform (DFT) can add sound filtering approach either low past filter or high past filter and band past filter before the voice register is transformed to each transform. The addition of the approach will certainly affect the speed of computing in the introduction of the invoice register.

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