Vol.4,No.1, July, 2015
36 - 43,ISSN:0975-5446] [VNSGU JOURNAL OF SCIENCE AND TECHNOLOGY]

Analysis Of Orthogonal Moments For Recognition Of Handwritten MODI Numerals

KULKARNI S.A
VIS Lab
Dr. BAM University,
Aurangabad,(MS)
sankalpsadanand.georai@gmail.com,

BORDE P.L.
VIS Lab
Dr. BAM University,
Aurangabad,(MS)
borde.prashantkumar@gmail.com

MANZA R.R.
BMIP Lab
Dr. BAM University,
Aurangabad,(MS)
manzaramesh@gmail.com

YANNAWAR P.L
VIS Lab
Dr. BAM University,
Aurangabad,(MS)
pravinyannawar@gmail.com

Abstract**:**

Handwritten automatic character recognition has attracted many researchers all over the world to contribute automatic character recognition domain. Shape identification and feature extraction are very important parts of any character recognition system and success of method is highly dependent on selection of features. However feature extraction is the most important step in defining the shape of the character as precisely and as uniquely as possible and achieved success by using invariance property, irrespective of position and orientation. Zernike moments describes shape, identify rotation invariant due to its Orthogonality property. 'MODI' is an ancient script of India with cursive and complex representation of characters. The work described in this paper presents efficiency of *Zernike* moments over Hu's moment for recognition of handwritten 'MODI' numerals.

Keywords: MODI Script, OCR, Feature Extraction, Hu's 7 Moments, Zernike Moments,

1. Introduction:

India is known for its rich cultural heritage. India is a country where we found large diversity in culture, religion and language. India speaks 780 languages out of which 220 languages have been disappeared in last 50 years and another 150 could vanish in next half century [1]. The language is a medium of communication between two individuals which has two forms oral and written. The written language is best known as '*LIPI*'. Every language has its own character set, structure of representation and rules, but aim was same, that is '*Communication*'. Historically, the medium of communication is one of the sign to show the progress of a society.

In this paper we focused on recognition of numerals, from '*MODI*' Script using orthogonal moments. '*MODI*', is an ancient script as compare to other Indian ancient languages. *MODI* script is a cursive form of '*Marathi*'. '*Marathi'* is primary language spoken in the state of Maharashtra in western India.

There are several theories about the origin of this script. In 12th Century MODI was developed by '*Hemadpant*' or '*Hemadri*', (a well-known administrator in the kingdom of '*Mahadev Yadav*' and '*Ramdev Yadav*'. *Raja Ramdevrai* was the last king of '*Yadav Empire*' at *Devgiri* from 1187 to 1318. *MODI* was brought by '*Hemandpant*' from *Sri Lanka* [2,3].
It is a popular notion that only "*Marathi is written in MODI*". The historical evidences, says that The MODI alphabet was invented during the 17th century to write the '*MARATHI*' language of Maharashtra and it was frequently and popularly used for only writing purpose all over the Maharashtra in the era of '*Peshwe*' (Pune) and '*Chatrapati Shivaji Maharaj*' [4,5,6].

Optical character recognition (OCR) is an important research area under pattern recognition. OCR effectively developed for the recognition of printed characters of non-Indian Languages like English. Very strong efforts are going on for the development of OCR in Indian languages especially '*Devanagari*', but very fewer efforts have been done on 'MODI' [7,8].
The MODI script includes of 10 distinctive numerals, as numerals in English and '*Devanagari*'. The numerals themselves are full of moulds or curves (cursive script). This is due to the influence of '*Devanagari*' and writing need not to lift '*Boru*' (*a Bamboo Pen*) too often. No punctuation marks or conjuncts are used in this script. It does not have any marks to indicate the termination of a sentence and the perpendicular stroke is not used. Figure 1 shows numerals of MODI script.

MODI Numerals										
English Numerals	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**

Figure 1: Numerals written in MODI Script

In this paper an experimental approach has been devised to compare and evaluate the performance of Hu's invariant features and Zernike moments on 'MODI' numerals. This paper is organized in four sections section first describes the general background about 'MODI' script, section 2 describes about methodology and feature extraction, experimental results are discussed in section 3 and conclusion has been given in section 4.

2. Methodology and Feature Extraction:

Document has been scanned to produce an image. OCR systems then recognize the characters present in the document image. This is known as offline approach for OCR. Many OCR systems have been developed for different languages. The paper describes the efforts made towards the development of an OCR system for recognition of 'MODI' numerals.

The objective of this research paper is to recognize 'MODI' numeral using Hu seven moment invariant and Zernike moment Features. The set of handwritten 'MODI' numerals were formed. The numeral database is made up-of images of handwritten MODI numerals. This data set was divided in principal of 70-30 ratio and 70% samples were used for training purpose and 30% samples were used for testing. Figure 2 shows schematic representation of steps involved in general recognition system.

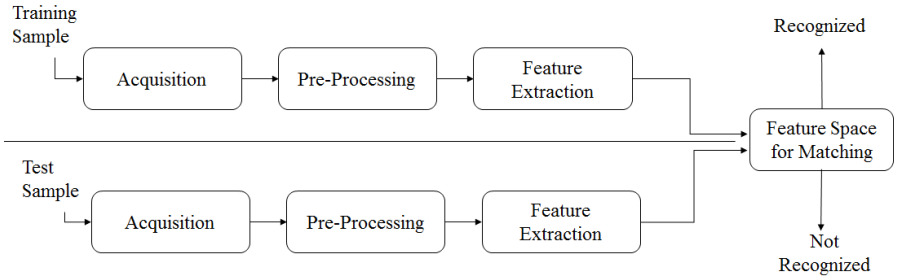

Figure 2: General overview of recognition system

2.1 Data acquisition

It is first step in training and testing; it acquires the data from the user and formulated set of training samples and testing samples. Each subject is provided a sheet of paper for writing numerals. Each subject was asked to write 10 repetitions of numerals. All samples were written by blue ink pen. This input data is sampled in to numeral set.

2.2 Pre-Processing

Each numeral from the data set was pre-processed so as to obtain good discriminating features and to be used at the time of recognition of numerals. The preprocessing includes foreground and background separation of numerals so that foreground information will contain information about the shape of numerals. Morphological operation such as 'opening' and 'closing' were performed. The 'Top Hat' transform were used for extracting small elements and details of numeral and further subtracted from original representation of numerals.

Table 1: Training Sample set of 'MODI' Numerals (Sample size 70%, Known Set)

Sample numerals	Zero	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
No of occurrences in Known set	7	7	7	7	7	7	7	7	7	7

Table 2: Test sample set of 'MODI' Numerals (Sample size 30%, Un-known set)

Sample numerals	Zero	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
No of occurrences in Unknown set	3	3	3	3	3	3	3	3	3	3

2.3 Feature Extraction

The preprocessed numeral data set was sent to feature extraction process where Hu's seven moments and Zernike moments were calculated.

2.4 Hu's Seven Moments

Moment based features are a widely used tool for character recognition. The moment invariants under translation, scaling and rotation, is first introduced by HU in 1962 [9]. Hu formulated seven moments describing, ϕ_1- ϕ_6 are defined as absolute orthogonal invariants moments independent of position, size and orientation and ϕ_7 is skew orthogonal invariant. These features are capable of recognizing properties of character [10].

Hu's seven invariant moments are defined as (1)

$$\phi_1 = n_{20} + n_{02}$$

$$\phi_2 = (n_{20} - n_{02})^2 + 4n_{11}^2$$

$$\phi_3 = (n_{30} - 3n_{12})^2 + (3n_{21} - \mu_{03})^2$$

$$\phi_4 = (n_{30} - 3n_{12})^2 + (n_{21} + \mu_{03})^2$$

$$\phi_5 = (n_{30} - 3n_{12})(n_{30} + n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2] + (3n_{21} - n_{03})(n_{21} + n_{03}[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2]$$

$$\phi_6 = (n_{20} - 3n_{02})[(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2] + 4n_{11}(n_{30} + n_{12})(n_{21} + n_{03})$$

$$\phi_7 = (3n_{21} - n_{03})(n_{30} + n_{12})[(n_{30} + n_{12})^2 - 3(n_{21} + n_{03})^2] - (n_{30} - 3n_{12})(n_{21} + n_{03})[3(n_{30} + n_{12})^2 - (n_{21} + n_{03})^2]$$

After preprocessing feature for each sample have been extracted and stored in to feature matrix known as 'Training Matrix'. Extracted features of training set and test were shown in Table 3 and 4 respectively. The Moment 1- Moment 6 are moments independent of position, size and Moment 7 represents is skew orthogonal invariant moment.

This training matrix will be loaded on feature space where test sample will be matched with the training sample.

Table 3: Hu's invariant seven moments for training set

Known Set	Moment 1	Moment 2	Moment 3	Moment 4	Moment 5	Moment 6	Moment 7
1	0.439297	3.158586	4.012586	5.351023	-10.1121	-6.93292	10.29011
2	0.382928	3.595967	3.834408	5.128674	-9.64348	-7.06116	-10.034
3	0.37414	2.657597	3.404188	4.168286	-8.36224	-5.57721	-7.99057
4	0.374284	2.952558	4.064879	5.004821	-9.53989	8.785265	-11.0414
5	0.333618	2.485306	2.767584	4.434869	8.600354	5.737029	-8.05288
6	0.356483	2.586913	3.862189	4.387529	8.591275	-5.71788	8.770516
7	0.363878	2.733977	4.270367	4.6337	-9.10186	6.004951	-9.65836
8	0.47957	3.622837	2.330934	2.712687	-5.44017	-5.59186	-5.34107
9	0.497947	2.960142	2.590292	2.804096	-5.52694	-4.78791	-5.9778
:	:	:	:	:	:	:	:

Table 4: Hu's seven invariant moments for test set

Unknown Set	Moment 1	Moment 2	Moment 3	Moment 4	Moment 5	Moment 6	Moment 7
1	0.387275	2.307326	3.17545	4.259291	-8.13904	5.689312	-8.11593
2	0.379495	2.161759	3.292866	4.931223	-9.05	-7.21844	9.801051
3	0.390281	2.129297	4.12504	4.254466	-9.35688	5.338704	-8.44749
4	0.53094	2.584335	2.576851	3.154369	-6.08301	-5.0265	6.319333
5	0.541137	2.791727	2.673677	3.010969	-5.86601	-4.51149	-6.47575
6	0.528966	3.175982	2.48736	3.228653	-6.08882	5.627216	-7.08898
7	0.433472	1.881233	1.679941	3.289701	5.820306	4.24049	-6.13503
8	0.496608	2.229467	2.209507	4.24421	9.232714	5.748193	7.471133
9	0.402505	1.739009	1.407491	2.894235	-5.05415	-3.80841	5.739697
:	:	:	:	:	:	:	:

2.5 Zernike Moments

The Zernike polynomials were first proposed in 1934 by Fruits Zernike [11] and According to C. Teh and R. T. Chin [12] and Sundus Y. Hasan [13] Zernike moments are constructed using a set of complex polynomials which form a complete orthogonal set on the unit disk with $(x^2 + y^2) = 1$.

$$Z_{mn} = \frac{m+1}{\pi} \int_x \int_y I(x,y)[V_{mn}(x,y)]dxdy \quad (2)$$

Where m and n define the order of moment and $I(x,y)$ the gray level of a pixel of image I on which the moment is calculated. The Zernike polynomials $V_{mn}(x,y)$ are expected in polar coordinates as follows:

$$V_{mn}(r,\theta) = R_{mn}(r)e^{-jn\theta} \quad (3)$$

Where, $R_{mn}(r)$ is called as orthogonal radial polynomial.

$$R_{mn}(r) = \sum_{s=0}^{\frac{m-|n|}{2}} (-1)^s \frac{(m-s)!}{s!\left[\frac{m+|n|}{2}-s\right]!\left[\frac{m-|n|}{2}-s\right]!} r^{m-2s} \quad (4)$$

Moments Z_{mn} are invariant under rotation and scale changes.

Zernike Moments are the pure statistical measure of pixel distribution around center of gravity of characters and allow capturing information just at single boundary point. They can capture some of the global properties missing from the pure boundary-based representations like the overall image orientation [14]. A. Khotanzad [15] stated that Zernike moment features perform well in the presence of a moderate level of noise in the image. Zernike moments were used for recognition of handwritten characters of various scripts like Amitabh Wahi [9] for *Tamil* script, Jyotsnarani Tripathy[14] for *Oriya* Alphabets, Mustapha Oujaoura [16] for isolated *Arabic* characters, K.V. Kale [17] for *Devanagari* compound characters, Fataneh Alavipouz [18] for *Farsi* characters. In this paper we focused on the recognition of MODI numerals. Table 5 shoes calculated Zernike moment feature up to 9th order for sample figure and Zernike feature matrix in table 6 and 7.

Table 5: Zernike moment feature up to 9th order

Order	One	Two	Three	Four	Five	Six	Seven	Eight	Nine
Character									
Moment in character									

Table 6: Zernike moment features for training set

Known Set	Moment 1	Moment 2	Moment 3	Moment 4	Moment 5	Moment 6	Moment 7	Moment 8	Moment 9
1	53322.64	121.7217	-74066.2	1481.323	212.0719	-1535.74	-36528.9	-5185.22	-800.895
2	49294.11	-1266.11	-63547.8	-375.652	323.5623	-851.935	-46475.3	-635.96	-14.2356
3	48092.17	-1596.11	-62890.8	-1847.22	-985.192	-1618.91	-38918.5	1152.894	-1561.09
4	45896.15	-2006.54	-62571.8	-1345.87	703.5545	683.5055	-36179.2	2224.702	-1463.05
5	45803.84	-4439.96	-56455.3	-604.397	1968.58	-26.4453	-45929.5	178.6441	-906.199
6	46429.63	-1582.23	-60513.3	-726.836	-410.965	755.7271	-40777.8	-1090.52	-1773.75
7	44825.35	-1167.92	-60067.4	1030.914	-188.358	-330.664	-37607.5	-4097.22	-1606.35
8	50364.9	-2676.14	-80992	1612.514	13753.8	-231.175	6494.894	-8779.76	4018.426
9	48349.36	-4653.37	-82895.9	2920.175	14634.18	1098.684	15429.96	-11378.3	3208.953
:	:	:	:	:	:	:	:	:	:

Table 7: Zernike moment features for test set

Unknown Set	Moment 1	Moment 2	Moment 3	Moment 4	Moment 5	Moment 6	Moment 7	Moment 8	Moment 9
1	48650.8	-1120.81	-67239.4	-1831.47	51.90191	1384.498	-32903.6	544.1293	-852.105
2	47282.71	-1626.01	-64656.9	-2827.65	967.931	1153.349	-33237.5	3976.857	-1383.42
3	49388.96	-1304.88	-68211.1	-3715.61	775.8612	-565.823	-32360.2	3877.331	-876.332
4	49965.1	-5893.27	-86784.9	4831.817	15178.24	3659.857	16232	-15651.9	2563.062
5	57778.97	-5182.62	-95118	2753.735	17563.01	967.2171	15202.92	-13331	3875.949
6	56173.1	-2982.99	-90803.8	3061.323	14079.3	-293.222	7028.28	-12055	4393.604
7	43088.02	1923.122	-69706.2	-7747.75	-4192.69	-8418.99	14710.3	24625.47	-425.281
8	52035.39	216.0475	-83802.2	-6704.84	-444.446	-7280.27	15660.38	21300.46	538.981
9	48650.8	-1120.81	-67239.4	-1831.47	51.90191	1384.498	-32903.6	544.1293	-852.105
:	:	:	:	:	:	:	:	:	:

3. Experimental results:

The recognition of samples was done by using Hu's seven invariant features and Zernike moment. These features were calculated for all sample of training set and stored for recognition purpose. Similarly Hu's seven invariant features and Zernike features for test set was also formed and stored.

This feature vector of training sample using Hu' seven invariant moments was loaded and test sample feature were checked for recognition '*Euclidean*' distance classifier. The 'Euclidean' distance provides information between each pair (one vector from test set and other vector from training set).

The distance matrix of training sample and test sample using Hu's seven invariant moments was shown in table 5.

Table 5: Distance Matrix of test set and training set based on HU's seven moments

Sample character	 Zero	 One	 Two	 Three	 Four	 Five	 Six	 Seven	 Eight	 Nine
Unknown/Test set Fig. No.	1 to 3	4 to 6	7 to 9	10 to 12	13 to 15	16 to 18	19 to 21	22 to 24	25 to 27	28 to 30
Expected Match in Known set/Training set (Must be in between)	1 to 7	8 to 14	15 to 21	22 to 28	29 to 35	36 to 42	43 to 49	50 to 56	57 to 63	64 to 70
Result for Unknown set (Fig No) Matched in Known set (fig no)	7,1,7	20,14,34	29,17,16	26,28,55	35,29,27	63,41,26	43,47,46	54,51,51	62,61,61	49,44,42
Hit	3	1	2	2	3	1	3	3	3	0
Miss	0	2	1	1	0	2	0	0	0	3
Hit %	100	33.33	66.66	66.66	100	33.33	100	100	100	0

Table 5 shows that, total 30 test sample features were checked with 70 training sample. The total correctly recognized sample were 21 and 9 were not recognized, they are misclassified. The overall recognition using Hu's seven invariant moments will be 70%. In order to measure the performance of Zernike features on same set of training and test the distance matrix was calculated as shown in table 6.

Table 6: Distance matrix of test set and training set based on Zernike features

Sample character	 Zero	 One	 Two	 Three	 Four	 Five	 Six	 Seven	 Eight	 Nine
Unknown/Test set Fig. No.	1 to 3	4 to 6	7 to 9	10 to 12	13 to 15	16 to 18	19 to 21	22 to 24	25 to 27	28 to 30
Expected Match in Known set/Training set (Must be in between)	1 to 7	8 to 14	15 to 21	22 to 28	29 to 35	36 to 42	43 to 49	50 to 56	57 to 63	64 to 70
Result for Unknown set (Fig No) Matched in Known set (fig no)	4,4,4	9,14,14	19,21,68	27,23,12	31,31,34	41,41,40	43,65,48	56,52,54	62,63,60	70,49,70
Hit	3	3	2	2	3	3	2	3	3	2
Miss	0	0	1	1	0	0	1	0	0	1
Hit %	100	100	66.66	66.66	100	100	66.66	100	100	66.66

.

Table 6 shows that out of 30 test samples 26 where recognized as correct samples over training matrix of 70 samples, whereas only 04 samples were not recognized correctly. The overall recognition rate of Zernike moment using Zernike feature is 86.66%. The results were

clearly indicates that Zernike feature has increased recognition rate of system. Table 7 shows the performance of recognition system based on Hu's seven invariant moments and Zernike moments.

Table 7: Performance of Features used in recognition of MODI Numerals

Training set of 70 Sample	Hu's seven invariant features			Zernike features		
	TP	TN	RR	TP	TN	RR
Total 30 Test Sample	21	09	70.00%	26	04	86.66%

TP: Total True Positive, TN: Total True Negative

4. Conclusion

This piece of work mainly focused on the feature extraction of Hu's seven invariant moments and Zernike moments for the recognition of MODI numerals. The Zernike moments are found to be more reliable and accurate features for recognition of handwritten MODI numerals as compared to Hu's seven invariant moments. The method of recognizing handwritten MODI numerals using Zernike Moments are found better as compare to the methods discussed in [3,4,5,19,20,21]. This approach can be used widely for recognition of handwritten MODI numeral.

References

1. David Lalmalsawma, 2013, "India speaks 780 languages, 220 lost in last 50 years– survey", available at "http://blogs.reuters.com/india/2013/09/07/india-speaks-780-languages-220-lost-in-last-50-years-survey", India Insights, Reuters, Edition US, Accessed: Jan 8, 2015
2. Savant M.Y., 2005, "Marathi MODI Script: Origin, Evolution and Significance", 'Kruti Rakshan', vol 1 no 1, Neha Paliwal ed(s), No. 5, Dr. Rajendra Prasad Road New Delhi 110 001, Mission Director National Mission for Manuscripts, page 16.
3. Rakesh A. Ramraje, 2013, "History of MODI script in Maharashtra", Global Online Electronic International Interdisciplinary Research Journal (GOEIIRJ), Vol II, Issue 1, pp. 54-58
4. Ramteke A. S., Katkar G.S. 2013, "Recognition of Off-line MODI Script- A structure Similarity Approach", International Journal ICT and management, Volume 1, Issue 1, ISSN 2026-6839, pp.12-15
5. Besekar D. N., Ramteke R. J., 2012, "Feature Extraction Algorithm for Handwritten Numerals Recognition of MODI Script using Zoning-based Approach", International Journal of Systems, Algorithms & Applications, Volume 2, Issue ICRASE12, ISSN Online: 2277-2677, pp.1-4
6. Besekar D. N., Ramteke R. J, 2013, "Study for Theoretical Analysis of Handwritten MODI Script – A Recognition Perspective", International Journal of Computer Applications, vol. 64, no. 3, pp.45-49
7. Naren Ranadive, 2014, Randives Indian Antiquities and Inscriptions, "The Origin and Development of Indian Writing System – MODI Script of Maharashtra", available at www.narendranath.webs.com, Accessed: Jan 8, 2015
8. Reza Kasyauqi Sabhara, Chin-Poo Lee, Kian-Ming Lim, 2013, "Comparative study of Hu Moments and Zernike Moments in Object Recognition", Smart Computing Review, vol. 3, no. 3, pp 166-173.
9. Amitabh Wahi, S.Sundaramurthy, P.Poovizhi, 2014, "Handwritten Tamil Character Recognition Using Zernike Moments and Legendre Polynomial", Advances in Intelligent Systems and Computing, Vol. 325, pp.595-603
10. Ming-Kuei Hu, 1962, "Visual Pattern Recognition by Moment Invariants", IRE Transactions on Information Theory, pp.179-187

11. F. Zernike. 1934, Beugungstheorie des Schneidenverfahrens und seiner verbesserten Form, der Phasenkontrastmethode (Diffraction theory of the cut procedure and its improved form, the phase contrast method). Physica, 1:pp. 689-704.
12. C. Teh and R. T. Chin, 1988, "On image analysis by the method of moments". IEEE Trans. on Pattern Analysis and Machine Intelligence, 10(4):pp. 496-513
13. Sundus Y. Hasan, 2012, "Study of Zernike moments using analytical Zernike polynomials", Pelagia Research Library, Advances in Applied Science Research, 3 (1): pp. 583-590
14. Jyotsnarani Tripathy, 2010, "Reconstruction of Oriya Alphabets Using Zernike Moments", International Journal of Computer Applications (0975– 8887), Volume 8– No.8, ISBN: 978-93-80746-07-5, pp. 26-32
15. A. Khotanzad and Y. H. Hongs,1990, "Invariant image recognition by zernike moments," IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 12, pp. 489–497.
16. Mustapha Oujaoura, Rachid El Ayachi, Mohamed Fakir, Belaid Bouikhalene, Brahim Minaoui, 2012, "Zernike moments and neural networks for recognition of isolated Arabic characters", International Journal of Computer Engineering Science (IJCES), Volume 2 Issue 3 (March 2012) ISSN : 2250:3439, pp.17-25
17. K.V. Kale, P.D. Deshmukh, S.V. Chavan, M.M. Kazi , Y.S. Rode, 2014 "Zernike Moment Feature Extraction for Handwritten Devanagari (Marathi) Compound Character Recognition", (IJARAI) International Journal of Advanced Research in Artificial Intelligence, Vol. 3, No.1, pp.68-76
18. Fataneh Alavipouz and Ali Broumandnia, 2014, "Farsi Character Recognition Using New Hybrid Feature Extraction Methods", International Journal of Computer Science, Engineering and Information Technology (IJCSEIT), Vol. 4,No. 1, pp.15-25.
19. Ramteke A. S., Katkar G.S. 2012, "Recognition of Off-line MODI Script", International Journal of Research in Engineering, IT and Social Science (IJREISS), Volume 2, Issue 11, ISSN 2250-0588, pp.102-109
20. Besekar D. N, 2012, "Special Approach for Recognition of Handwritten MODI Script's Vowels", International Journal of Computer Applications (IJCA), MAHA-2012, pp. 48-52.
21. Besekar D. N, 2011, "Recognition of numerals of MODI script using morphological approach", International Referred Research Journal, Shodh Samiksha Aur Mulyamapan, ISSN 0974-2832, vol. 3, Issue -27, pp. 63-66.