Estimation of Informative Features in the Analysis of 2D Images of Bone Objects in Forensic

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***Abstract*—In this paper we propose an approach to solving the problems of extracting and evaluating information features from 2D images of bone fractures and bone objects for further successful classifying fractures. As parameters or features, the textural characteristics of Haralick, local binary patterns of pixels for 2D images, Gabor filters, Laws energy texture characteristics for 2D images are considered. The analysis carried out on basis of information content estimation to select the features that are most suitable for solving the problem of bone fractures classification. This paper also describes the experiments and experimental data.**

***Keywords*—bone objects, texture features, Haralick, local binary patterns**

I. Introduction

Bone fractures are becoming more common in our country. The majority of authors are only concerned about whether the bone is broken or not, with very few concentrating on the classification of bone fractures. There are different feature extraction methods that may be used to diagnose bone fractures. Textural parameters of grayscale digital images with different modality are used as features [1-3]. The grayscale representation is important because it preserves the structure, not the color, of the objects. The color of the object may change depending on the lighting, over time, due to other factors. There are a lot of imaging methods used in forensic and some of them are laser methods, photogrammetry, CT scaning, magnetic resonance imaging, multimodal imaging extends the applications of 3D digital imaging more by combining data acquired from different methods to form a single coupled model. There are only some papers devoted to the texture analysis of 2D images of bone objects for providing a preliminary decision support system. The main task of this paper estimate the possibility of using texture features in developing models that can automatically detect and classify fractures in human bones by decision support system.

II. Data preparation

The original images obtained from a camera with different resolutions contain the following elements: background, measurement tools and areas of interest (example in Fig. 1). For example Fig. 2 and Fig. 3 illustrate areas of interest on base images that have been selected. As you can see selected rectangular fragments containing 100 % of the fracture surface. The images have been converted to grayscale representation because the color of an object essentially depends on its illumination and changes the texture of the objects surface areas of interest [4-17].

Fig. 1. Example of a base image.

All available original images were divided into two groups. The first group for analysis was formed such that selected areas of interest included not only images of fractures but also bone fragments without damage.

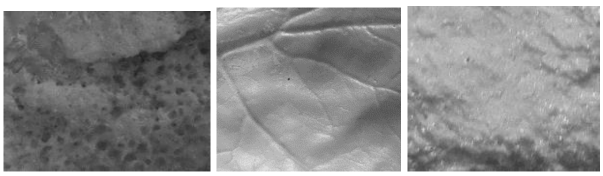

Fig. 2. Example of a base images from first group.

The second group for analysis contained only images of bone fragments with fractures (skull injuries).

III. Feature Engineering and analysis

The following groups of textural features were studied to distinguish between the types of bone damage from the first group:

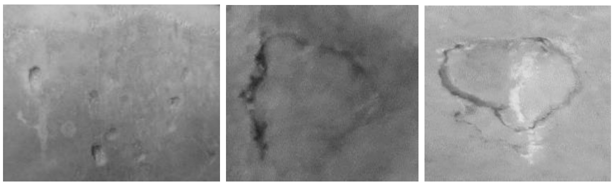

Fig. 3. Example of a base images from second group.

- 13 features of Haralik based on adjacency matrices of brightness values [18-19];
- local binary pixel images (LBP) [19];
- Gabor filters [21];
- energy texture characteristics of Laws [21-22].

The following variants of LBP signs were used:

- radius=3, number of patterns=24;
- radius=5, number of patterns=40;
- radius=7, number of patterns=56.

The LBP name of a feature contains its parameters: lbp_r<radius>_h<template_index>. After calculating the features in each pixel, a histogram of their results was compiled. This histogram is the result as a set of features. A total of 26 results of LBP histograms within a radius of 3 were collected; 42 LBP histogram within a radius values of 5; 58 LBP histogram measurements within a radius of 7.

The Gabor filters were applied under the following parametes: sizes of filter cores are 15, 21 and 31; rotation angles are 0°, 22°, 24°, 67°, 90°, 112°, 135°, 157°.

The name of the filter characterizes its parameters: ks_<kernel size>_th_<rotation angle>. As an estimation, the average value of the matrix obtained by filtering the image is used.

The following textural energy characteristics of Laws were used: L_NL_N, E_NE_N, S_NS_N, L_NE_N, E_NS_N, L_NS_N where N are the dimensions of the base vector, the values of which can be taken from the pair [3, 5, 7]. As an estimation for Laws as well as for Gabor filters the average value of the matrix obtained by filtering the image is used.

There are at least two important reasons to get rid of unimportant features. The first one: the more data, the higher the computational complexity. If we work with train datasets, the size of the data is not a problem, but, for loaded production systems, hundreds of extra features will be quite tangible. The second reason is that some algorithms take non-informative features as a signal and overfit. There is statistical approaches for feature estimation but we used other one selection from modeling. The main idea is to use some model as an feature importance estimator: for example, we can use linear model with Lasso regularization or some tree based models (which have natural ability to compute feature importance). Then, based on received importance/weights we can choose some threshold and take features, that have importance above this value.

We estimate over 180 textural features. For estimation the information content of features used mathematical apparatus based on the statistical procedures ANOVA. ANalysis Of VAriance (ANOVA) - is a statistical model and estimation procedures used to analyze the differences among means. ANOVA based on the law of total variance. In its simplest form, ANOVA provides a statistical test of whether two or more population means are equal, and therefore generalizes the t-test beyond two means. In other words, the ANOVA is used to test the difference between two or more means - based on F-statistic [29] - class of statistical tests that calculate the ratio between values of the variance, such as the variance from two different samples, or the explained and unexplained variance using a statistical test; Recursive Feature Elimination (RFE) [23] based on L1 norm or Linear Support Vector Machines (SVMs) [24]. SVMs are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. The support vector clustering algorithm, applies the statistics of support vectors, developed in the support vector machines algorithm, to categorize unlabeled data. These data sets require unsupervised learning approaches, which attempt to find natural clustering of the data to groups and, then, to map new data according to these clusters.

The goal of Recursive Feature Elimination (RFE) is to select features by recursively considering smaller sets of features. The estimator is trained on an initial set of features, and the information content of each feature is determined by the coefficients of the model. Then the least informative ones are removed from the current feature set. This procedure is repeated recursively to reduce the set of features until the desired number of the most informative features is reached.

Linear models with L1 norm have sparse solutions: many of their coefficients have equal chances. When the goal is to reduce the data size for another use by the classifier, the non-zero coefficients are removed. The linear classifier SVM with the parameter C=0.01 was used as estimator.

The Extremely Randomized Trees (ExtraTrees) model implements a collection of trees that fit a set of randomized

TABLE I. 20 THE MOST INFORMATIVE FEATURES FOR IDENTIFYING SURFACE DAMAGE AND BONE FRACTURES

№	Names of Features	Total score
1	lbp_r3_h6	0.026883
2	lbp_r5_h7	0.026713
3	lbp_r3_h5	0.023050
4	lbp_r7_h0	0.020107
5	lbp_r5_h29	0.020078
6	lbp_r3_h17	0.019377
7	lbp_r7_h9	0.018229
8	lbp_r7_h7	0.017201
9	lbp_r5_h30	0.016604
10	lbp_r3_h18	0.015955
11	lbp_r5_h6	0.015771
12	lbp_r7_h29	0.014985
13	lbp_r7_h27	0.014879
14	lbp_r7_h8	0.014655
15	lbp_r3_h23	0.014529
16	lbp_r3_h4	0.013667
17	lbp_r7_h31	0.013111
18	lbp_r7_h6	0.013103
19	lbp_r3_h19	0.013058
20	lbp_r7_h28	0.012983

TABLE II. THE MOST INFORMATIVE FEATURES IDENTIFIED AT THE 1ST GROUP

ANOVA		**Linear SVM L1**		**Extra Trees**		**Random Forest**		**Combined Score**	
Feature	***Score***	***Feature***	***Score***	***Feature***	***Score***	***Feature***	***Score***	***Feature***	***Score***
lbp_r3_h17	13.64	L7E7	0.0010	lbp_r3_h5	0.028	lbp_r7_h7	0.037	lbp_r5_h7	2.47
lbp_r3_h18	12.06	Variance	0.0010	lbp_r3_h6	0.028	lbp_r7_h0	0.034	lbp_r3_h5	2.37
lbp_r7_h47	11.98	L7S7	0.0023	lbp_r5_h7	0.024	lbp_r3_h5	0.032	lbp_r3_h18	2.33
lbp_r5_h29	11.97	—	—	lbp_r3_h18	0.019	lbp_r7_h6	0.031	lbp_r7_h9	2.26
lbp_r3_h23	11.39	—	—	lbp_r3_h17	0.018	lbp_r3_h18	0.03	lbp_r3_h6	2.23
lbp_r5_h33	10.96	—	—	lbp_r7_h0	0.017	lbp_r5_h9	0.029	lbp_r7_h7	2.22
lbp_r7_h9	10.72	—	—	lbp_r7_h31	0.016	lbp_r7_h9	0.028	lbp_r3_h17	2.20
lbp_r3_h6	10.29	—	—	lbp_r3_h23	0.015	lbp_r5_h7	0.027	lbp_r7_h0	2.10
lbp_r3_h5	10.26	—	—	lbp_r7_h47	0.015	lbp_r3_h6	0.027	lbp_r5_h9	2.04
lbp_r5_h7	10.09	—	—	lbp_r5_h6	0.015	lbp_r5_h6	0.026	lbp_r7_h6	1.85

solutions on different subsamples of datasets and uses averaging to determine the accuracy of predictions and control overfitting. ExtraTrees at each level of the tree selects the criteria randomly [25].The random forest construction method implements a set of randomly constructed solutions. The random forest at each level of the tree selects the base criteria of the Gini criterion [26-27].

In the last two methods, 1000 trees were built. When comparing the data, both methods identified 55 features, but their originality was somewhat different, as shown in Table 1.

The results of the selection of the most informative features for surface damage and bone fractures are presented for the first group for analysis at the Table 1 or Table 2 and

TABLE III. THE MOST INFORMATIVE FEATURES IDENTIFIED AT THE 2ND GROUP

ANOVA		**Linear SVM L1**		**Extra Trees**		**Random Forest**		**Combined Score**	
Feature	***Score***	***Feature***	***Score***	***Feature***	***Score***	***Feature***	***Score***	***Feature***	***Score***
lbp_r5_h33	24.57	L7E7	0.0040	Correlation	0.013	lbp_r7_h5	0.0185	lbp_r5_h34	2.78
lbp_r5_h34	23.73	L5L5	0.0009	lbp_r5_h30	0.013	L7L7	0.0183	lbp_r7_h50	2.58
lbp_r7_h50	23.38	L7S7	0.0007	lbp_r5_h31	0.012	lbp_r5_h6	0.0182	lbp_r5_h33	2.55
lbp_r3_h17	22.63	L7L7	0.0006	lbp_r5_h29	0.012	lbp_r5_h34	0.0181	lbp_r3_h18	2.55
lbp_r3_h18	22.33	—	—	lbp_r7_h45	0.011	DifferenceVariance	0.0181	lbp_r5_h6	2.50
lbp_r7_h51	22.18	—	—	lbp_r5_h34	0.011	Correlation	0.0179	lbp_r7_h5	2.43
lbp_r5_h6	21.59	—	—	lbp_r3_h18	0.011	lbp_r7_h50	0.0173	lbp_r3_h19	2.28
lbp_r5_h30	21.55	—	—	SumAverage	0.010	lbp_r5_h33	0.0166	lbp_r7_h51	2.28
lbp_r5_h35	21.08	—	—	SumVariance	0.010	Variance	0.0156	lbp_r3_h17	2.25
lbp_r7_h48	20.91	—	—	MeasofCorrelation	0.010	MeasofCorrelation	0.0155	Correlation	2.25

Fig. 4. On this research set of 27 images of 13 bone objects, the most informative features are the LBP type with different radii. The results of the selection of the most informative features of superficial injuries and bone fractures are presented for the second group for analysis at the Table 3 and Fig. 5. A total of 181 features were studied using the tools described above (ANOVA, Linear SVMs, ExtraTrees, Random forests). For example, see Table 3, which present the most informative features for the second gtoup of images for analysis.

On the set of 45 images of 6 bone objects, the most informative features were LBP-type features with different

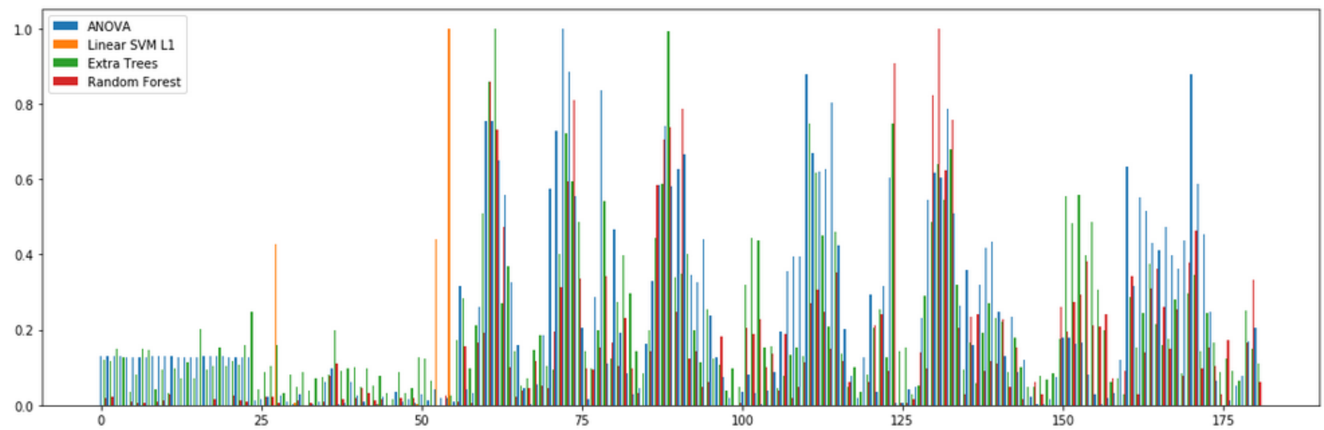

Fig. 4. Total normalized estimates of the information content for all features of fractures and bones for the first group for analysis

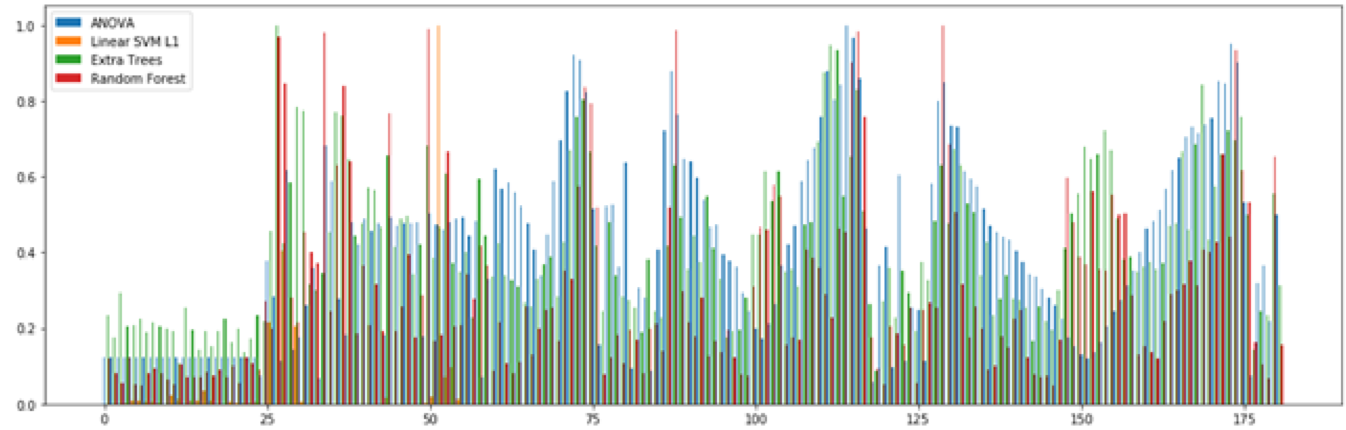

Fig. 5. Total normalized estimates of the information content for all features of fractures and bones for the first group for analysis

radii and the Haralik Correlation texture characteristic. The results of the selection of the most informative features are presented.

The selected features make it possible to classify and quantify damage to bone objects based on their images, see Table 1. Testing of the software implementation of the method for automated selecting features of 2D high-resolution images of bone objects useful for identifying damage was performed successfully on 72 images of 19 bone objects.

IV. Conclusion

The paper presents an experimental software package for 2D high-resolution bone image processing in part of selecting the most informative features for further classification. A complex algorithmic solution is proposed, which makes it possible to automate the feature selection for further bone image classification and analysis. As we see in paper the selected features can be useful for classification of bone images and have good practical prospects.

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