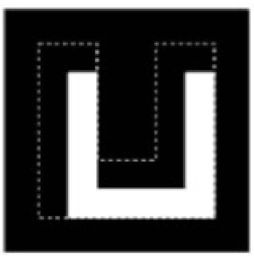
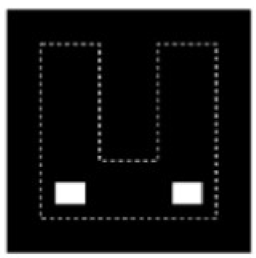
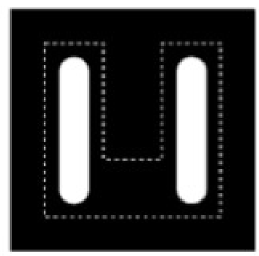
DIP_HW9

December 5, 2019

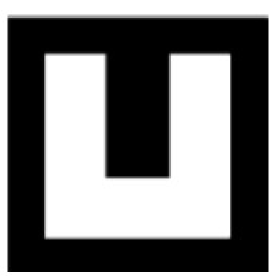
1 Digital Image Processing - HW9 - 98722278 - Mohammad Doosti Lakhani

In this notebook, I have solved the assignment's problems which are as follows:

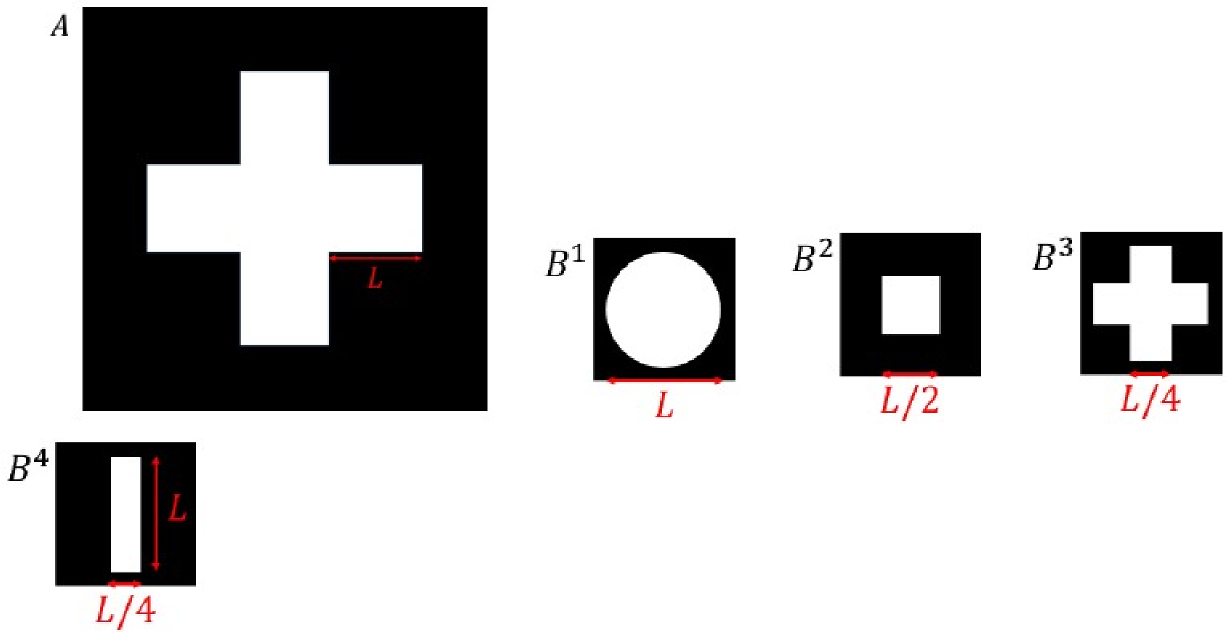
1. Consider this image and determine the type of morphological operation and structural element by defining its center:

A.  B.  C.  D.


2. Given the sets as below images, draw the result of the given morphological operations:



q1 im1




```
1. (A  B4)  B2
2. (A  B1)  B3
3. (A  B4)  B2
4. (A  B2)  B3
```

3. Do this tasks for this question:

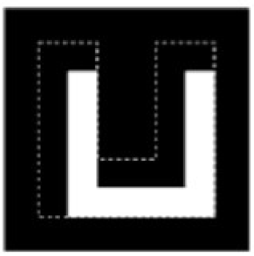
    1. **Hit-or-Miss** operation has been explained in section 9.4 in the book (Gonsalez), explain it.
    2. Read this paper and compare **LBP** and **Soft LBP**.

4. Train and evalute a model for Farsi handwritten digit recognition

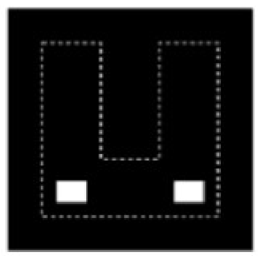
    1. Use this dataset https://github.com/amir-saniyan/HodaDatasetReader
    2. Use Feature extraction such a texture
    3. Use **SVM** and **kNN** for learning process as mandatory classifiers
    4. Other classifiers (optional)
    5. Evalute model using confustion matrix and average accuracy
    6. Compare results w.r.t. different features (optional)

q1 im1

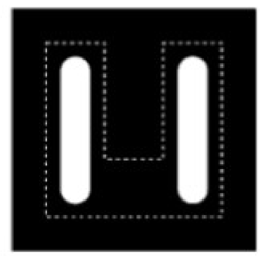
1.1 1 Consider this image and determine the type of morphological operation and structural element by defining its center:



1.

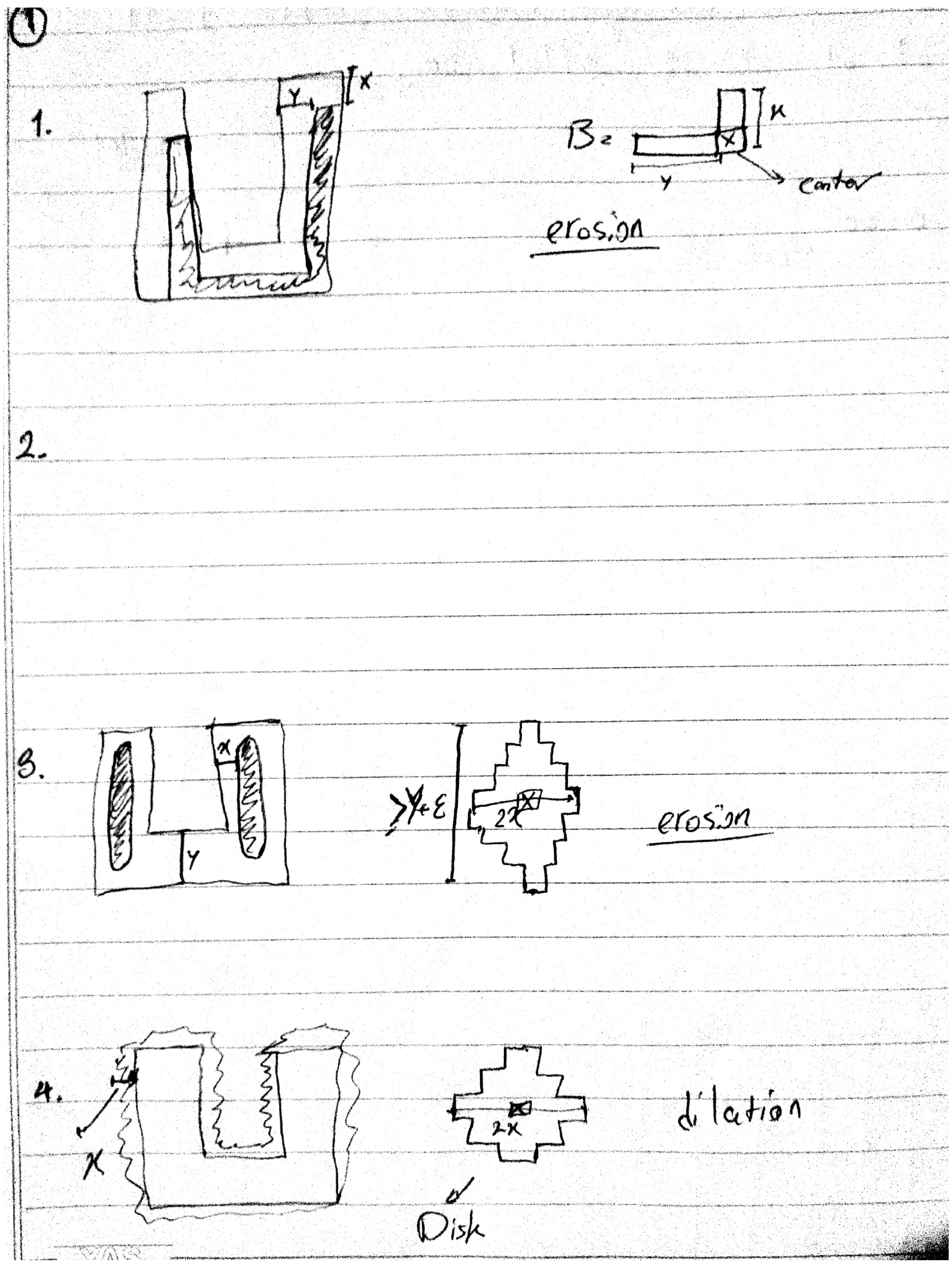


2.



3.

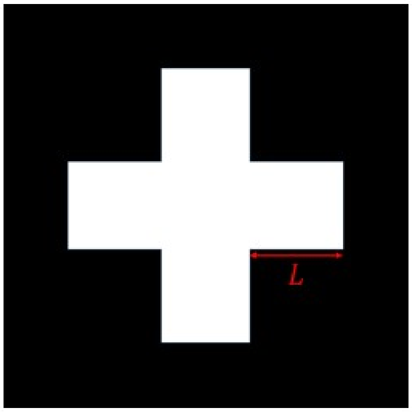
4.



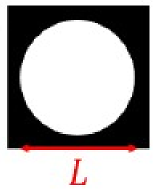
answer of question 1

1.2 2 Given the sets as below images, draw the result of the given morphological operations:

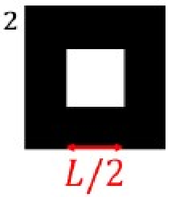
A



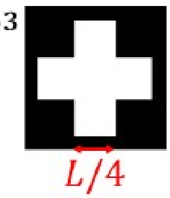
B^1



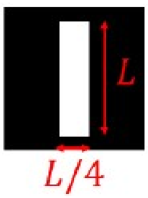
B^2



B^3



B^4



1. (A B4) B2
2. (A B1) B3
3. (A B4) B2
4. (A B2) B3

1.3 3 Do this tasks for this question:

1. **Hit-or-Miss** operation has been explained in section 9.4 in the book (Gonzales), explain it.
2. Read this paper and compare **LBP** and **Soft LBP**.

1.3.1 3. A Hit-or-Miss Operator

First thing we need to know is that HOM is used for basic shape detection which works on binary images where 1s indicate foreground and 0s for background.

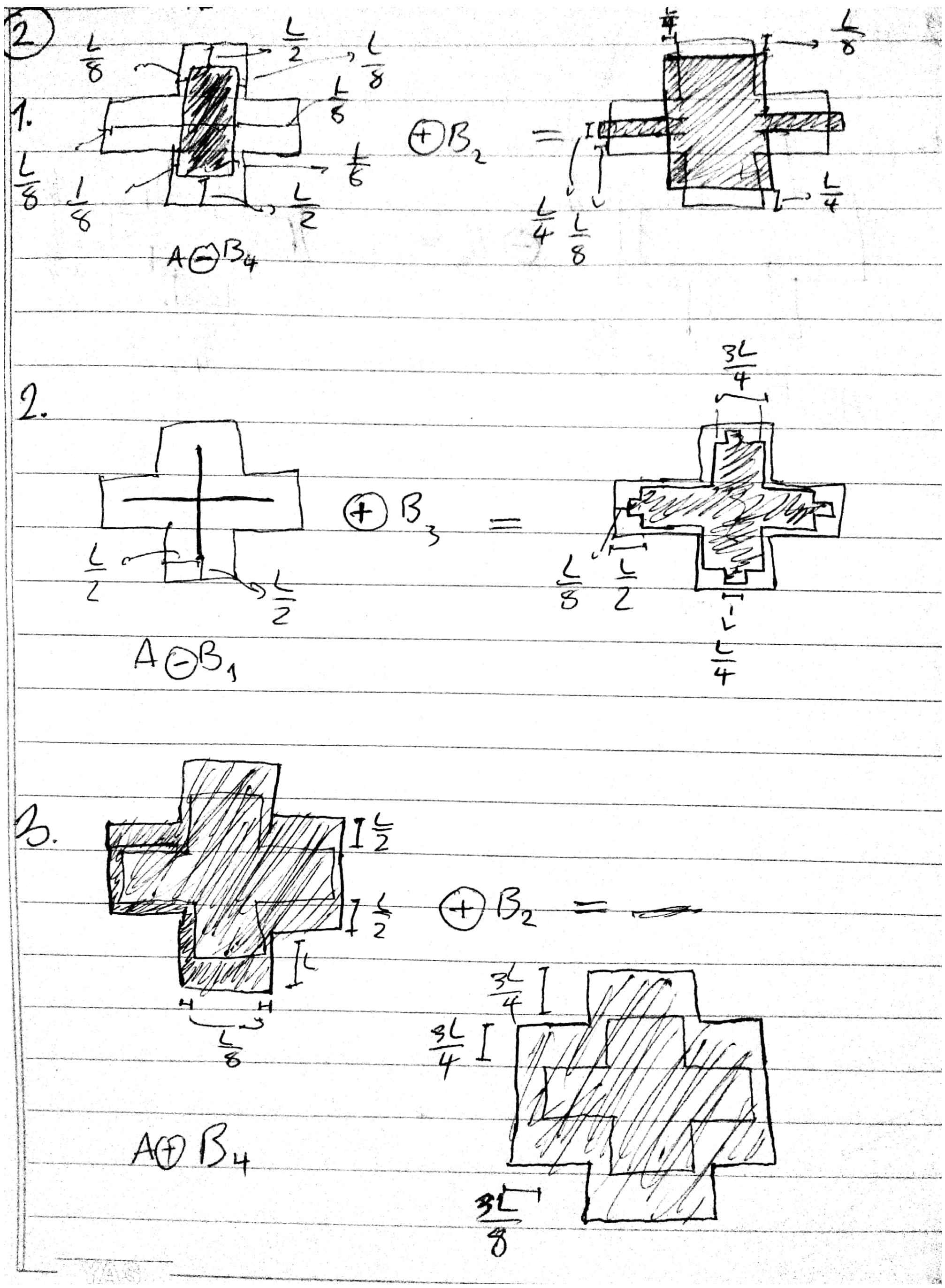
HOM uses two structural elements, one for foreground and one for background.

Here is the matchematical definition of it:

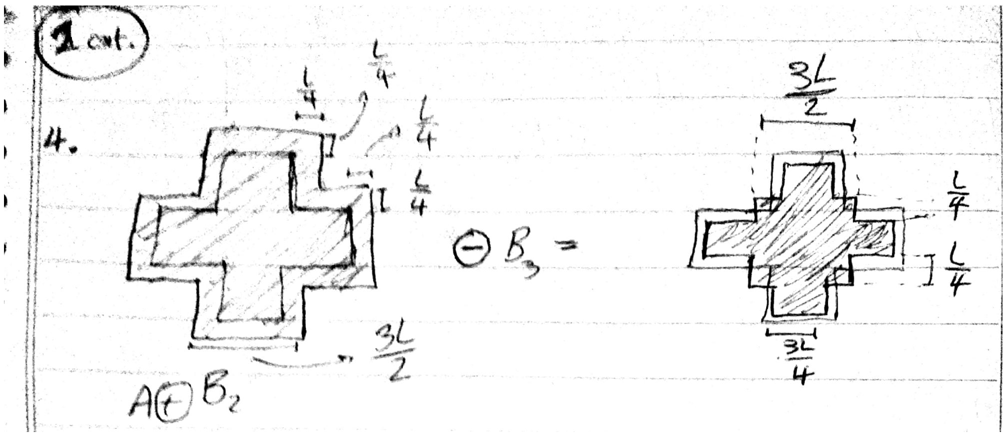
Intuitively, it says that foreground and background structural elements must match simultaneously. But we also can represent same operation using only one structural element, here is the matchematical definition:

In this situation, structural element **B** consisits of both foreground and background pixels and that is why we need to do the operation simultaneously. In simple words, in erosion we just check for foreground elements but in this operation, we match foreground pixels of structural element with foreground pixels of image and **at the same time** wew also match background pixels of structural element with background pixels of image.

As a simple example, let's say we want to find a dot in image. We need that it means that a single foreground pixel should be surrended by many background pixels in all directions. So



answer1 to question 2



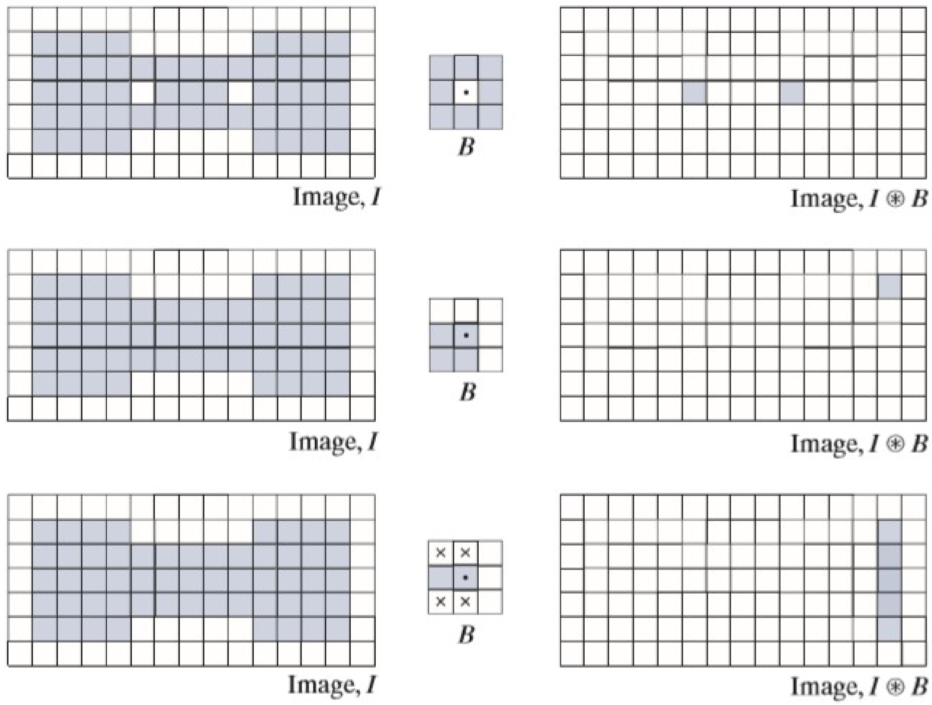
answer2 to question 2

$$I \circledast B_{1,2} = \left\{ z \middle| (B_1)_z \subseteq A \text{ and } (B_2)_z \subseteq A^c \right\}$$
$$= (A \ominus B_1) \cap \left(A^c \ominus B_2\right)$$

HOM formula

$$I \circledast B = \left\{ z \middle| (B)_z \subseteq I \right\}$$

HOM formula 2



HOM examples

same structural element will be used and only would match when a single foreground pixel get surrended by background pixels.

Here is 3 examples of this operation:

1.3.2 3.B Compare Soft LBP and LBP

Soft LBP's major charactrestic is rebustness against noises and continuous output w.r.t. inputs which also can work well on degraded images.

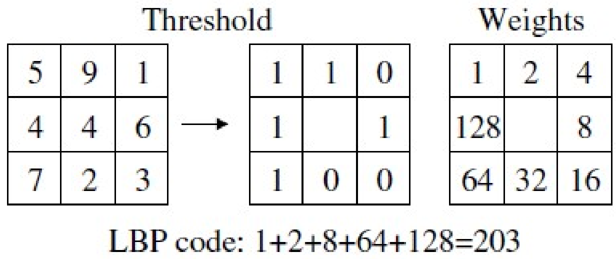
So let's first talk about LBP itself and what makes it special. It is fast and invariant to gray-scale intensity changes which makes it tolerant against illumination changes which can be used for texture classification, face analysis, etc.

The possible problem of basic LBP could be the fixed thresholding regarding neighboring pixels where could make it very sensitive to noises.

Basic LBP compare pixels in a 3x3 window and mark lower ones zero and vice versa. Finally, summing up by weighting to power of 2 would be our desired output. This operation and its thresholding window can be represented using below depictions where P is number of sampling points on a circle of radius of R:

Where the problem is the thresholding function which is as follow:

So as we knew it from the begining the goal is to increase robustness via fuzzy membership function and here is the new defined functions where the parameter D controls the amount of fuzzification:



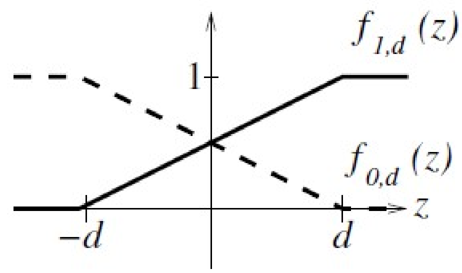
fixed thresold

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} s(g_c - g_p)2^P,$$

basic LBP

$$f_{1,d}(z) = \begin{cases} 0, & z < -d \\ 0.5 + 0.5\frac{z}{d}, & -d \leq z \leq d \\ 1, & z > d. \end{cases}$$

$$f_{0,d}(z) = 1 - f_{1,d}(z).$$



To build the histogram, now each pixel instead of contributing to only one bin where happens in basic LBP, now contributes to all bins regarding the membership function where sums up to 1 over all bins:

By using this membership functions, soft LBP looses one of the upsides of the basic LBP which is invariance to gray-level illumination. But the upside effect is that small changes introduces small effects too. On top of that, another issue affecting Soft LBP is that this method is computationally expensive because the contribution of the each pixel need to be computed w.r.t. all 2ˆP bins.

These result comparsion could be great to finish explanation.

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases}$$

basic LBP Thresholding

$$SLBP(x,y,i) = \prod_{p=0}^{P-1}[b_p(i)f_{1,d}(g_c - g_p) + (1-b_p(i))f_{0,d}(g_c - g_p)],$$

pixel in bin of histogram in soft LBP

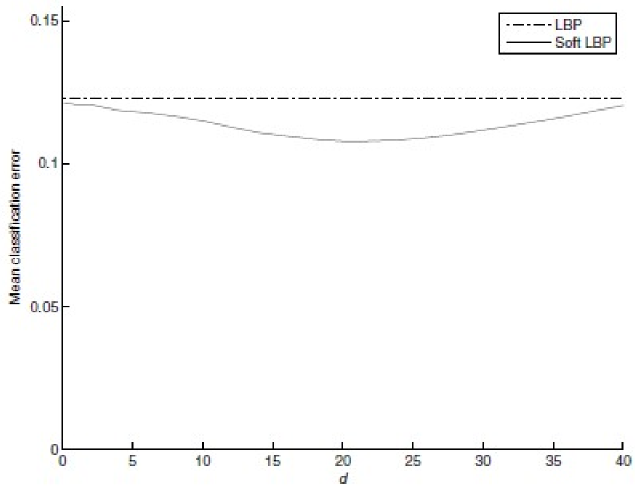


Fig. 5. Mean classification error over all test images.

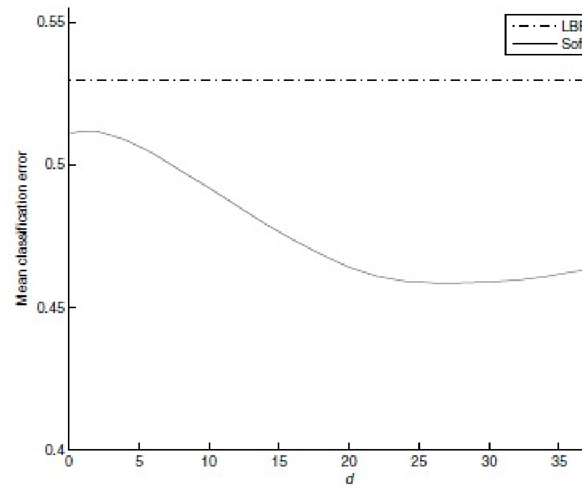


Fig. 6. Mean classification error over test images v tive noise.

1.4 4 Train and evalute a model for Farsi handwritten digit recognition

1. Use this dataset https://github.com/amir-saniyan/HodaDatasetReader
2. Use Features such a texture and geometry
3. Use **SVM** and **kNN** for learning process as mandatory classifiers
4. Evalute model using confustion matrix and average accuracy
5. Compare results w.r.t. different features (optional)

In [1]:
```
!git clone https://github.com/amir-saniyan/HodaDatasetReader.git
```

```
Cloning into 'HodaDatasetReader'...
remote: Enumerating objects: 24, done.
remote: Total 24 (delta 0), reused 0 (delta 0), pack-reused 24
Unpacking objects: 100% (24/24), done.
```

In [ ]:
```
import numpy as np
from matplotlib import pyplot as plt

from HodaDatasetReader.HodaDatasetReader import read_hoda_cdb, read_hoda_dataset
```

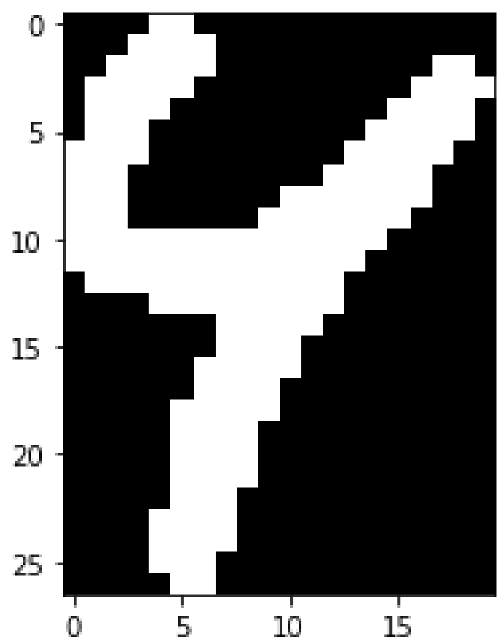
```python
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import LinearSVC, SVC
from sklearn.ensemble import AdaBoostClassifier, RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix

from skimage.feature import local_binary_pattern
import cv2

import pickle
```

1.4.1 4.A Use this dataset HodaDataset

```python
In [ ]: train_images, train_labels = read_hoda_cdb('./HodaDatasetReader/DigitDB/Train 60000.cdb
        test_images, test_labels = read_hoda_cdb('./HodaDatasetReader/DigitDB/Test 20000.cdb')
```

```python
In [ ]: plt.imshow(train_images[0], cmap='gray')
        print(train_labels[0])
```

6



1.4.2 4.B Feature Extraction

1. Geometry
2. Texture

4.B.a Geometry

```
In [ ]: def extract_geometrical_features(images):
            features = np.zeros((len(images), 5))

            for i in range(len(images)):

                try:
                    im, contour, hierarchy = cv2.findContours(train_images[i], 1, 2)
                    contour = contour[0]
                    area = cv2.contourArea(contour)
                    perimeter = cv2.arcLength(contour, True)
                    convex_hull = cv2.convexHull(contour)
                    convex_hull_area = cv2.contourArea(convex_hull)
                    rect = cv2.minAreaRect(contour)
                    _,_, w, h = cv2.boundingRect(contour)

                    compactness = 4*np.pi*area/(perimeter**2)
                    solidity = area / convex_hull_area
                    eccentricity = rect[1][1] / rect[1][0]
                    aspect_ratio = float(w)/float(h)
                    extent = area / (w*h)
                except:
                    pass

                features[i, 0] = compactness
                features[i, 1] = solidity
                features[i, 2] = eccentricity
                features[i, 3] = aspect_ratio
                features[i, 4] = extent

            return features
```

```
In [ ]: extract_geometrical_features(train_images[0:1])
```

```
Out[ ]: array([[0.17906382, 0.46539792, 0.57727276, 0.74074074, 0.24907407]])
```

```
In [ ]: geometrical_features_train = extract_geometrical_features(train_images)
        geometrical_features_test = extract_geometrical_features(test_images)
```

4.B.b Texture Note as the size of images are not same, we need to find the maximum sized image and extend all other images to that size after extracting features. `find_max_size` can do this.

```
In [ ]: def find_max_size(images):
            return np.max([image.shape[0]*image.shape[1] for image in images])
        max_len = np.max([find_max_size(train_images), find_max_size(test_images)])
        max_len
```

```
Out[ ]: 2560
```

In [16]:
```
resized = cv2.resize(train_images[70], (32, 32), interpolation = cv2.INTER_AREA)
winSize = (16,16)
blockSize = (16,16)
blockStride = (8,8)
cellSize = (8,8)
nbins = 9
derivAperture = 1
winSigma = 4.
histogramNormType = 0
L2HysThreshold = 2.0000000000000001e-01
gammaCorrection = 0
nlevels = 64
hog = cv2.HOGDescriptor(winSize,blockSize,blockStride,cellSize,nbins,derivAperture,wi
                        histogramNormType,L2HysThreshold,gammaCorrection,nlevels)
h = hog.compute(resized)
h = h.reshape(1, -1)
```

Out[16]: (324, 1)

In [ ]:
```
def extract_textural_features(images, max_size, mode='lbp', feature_size=324):
    if mode=='lbp':
        # the reason of 16777215 magic number is that after calculating LBP, most of t
        # it's have been used to extend all LBP transform of images to same size
        features = np.ones((len(images), max_size)) * 16777215
        radius = 3
        n_points = 8 * radius
        for i in range(len(images)):
            features[i, :images[i].shape[0]*images[i].shape[1]] = local_binary_pattern
        return features
    elif mode=='hog':
        features = np.zeros((len(images), 324))  # for 32x32 image with this config re
        for idx, img in enumerate(images):
            img = cv2.resize(img, (32, 32), interpolation = cv2.INTER_AREA)
            winSize = (16,16)
            blockSize = (16,16)
            blockStride = (8,8)
            cellSize = (8,8)
            nbins = 9
            derivAperture = 1
            winSigma = 4.
            histogramNormType = 0
            L2HysThreshold = 2.0000000000000001e-01
            gammaCorrection = 0
            nlevels = 64
            hog = cv2.HOGDescriptor(winSize,blockSize,blockStride,cellSize,nbins,deriv
                                    histogramNormType,L2HysThreshold,gammaCorrection,n
            h = hog.compute(img)
            h = h.reshape(1, -1)
```

```
                features[idx,:] = h
            return features.astype(np.float16)
        else:
            pass
```

In [ ]:
```
extract_textural_features(train_images[2:3], max_len)
```

Out[ ]:
```
array([[16777215., 16646145., 14614529., ..., 16777215., 16777215.,
        16777215.]])
```

In [25]:
```
extract_textural_features(train_images[2:3], None, 'hog').shape
```

Out[25]:
```
(1, 324)
```

In [ ]:
```
# LBP
textural_features_train = extract_textural_features(train_images, max_len)
textural_features_test = extract_textural_features(test_images, max_len)
textural_features_train = textural_features_train.astype(np.uint32)
textural_features_test = textural_features_test.astype(np.uint32)

# HOG
textural_features_hog_train = extract_textural_features(train_images, None, 'hog')
textural_features_hog_test = extract_textural_features(test_images, None, 'hog')
```

1.4.3 4.C Training

1. kNN
    1. Geometrical Features
    2. LBP Textural Features
    3. HOG Textural Features
2. Linear SVC
    1. Geometrical Features
    2. LBP Textural Features
    3. HOG Textural Features
3. Naive Bayes
    1. Geometrical Features
    2. LBP Textural Features
    3. HOG Textural Features
4. AdaBoost
    1. Geometrical Features
    2. LBP Textural Features
    3. HOG Textural Features
5. Random Forest
    1. Geometrical Features
    2. LBP Textural Features
    3. HOG Textural Features

4.C.a kNN Training

1. Geometric
2. LBP Textural
3. HOG Textural

4.C.a.i Geometric kNN

```
In [ ]: knn_geo = KNeighborsClassifier(n_neighbors=5, weights='distance')
        knn_geo.fit(geometrical_features_train, train_labels)
```

```
Out[ ]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                             metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                             weights='distance')
```

4.C.a.ii LBP Textural kNN

```
In [ ]: knn_tex = KNeighborsClassifier(n_neighbors=5, weights='distance')
        knn_tex.fit(textural_features_train, train_labels)
```

```
Out[ ]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                             metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                             weights='distance')
```

4.C.a.iii HOG Textural kNN

```
In [33]: knn_tex_hog = KNeighborsClassifier(n_neighbors=5, weights='distance')
         knn_tex_hog.fit(textural_features_hog_train, train_labels)
```

```
Out[33]: KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                              metric_params=None, n_jobs=None, n_neighbors=5, p=2,
                              weights='distance')
```

```
In [ ]: pickle.dump(knn_geo, open('knn_geo.model', 'wb'))
        pickle.dump(knn_tex, open('knn_tex.model', 'wb'))
```

4.C.b Linear SVC Training

1. Geometric
2. LBP Textural
3. HOG Textural

4.C.b.i Geometrical Linear SVC

```
In [ ]: linear_svc_geo = LinearSVC(max_iter=20000)
        linear_svc_geo.fit(geometrical_features_train, train_labels)
```

```
Out[ ]: LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,
                  intercept_scaling=1, loss='squared_hinge', max_iter=20000,
                  multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
                  verbose=0)
```

4.C.b.ii LBP Textural Linear SVC

```
In [ ]: linear_svc_tex = LinearSVC(max_iter=500, tol=1e-4)
        linear_svc_tex.fit(textural_features_train, train_labels)
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/svm/base.py:929: ConvergenceWarning: Liblinear :
  "the number of iterations.", ConvergenceWarning)
```

```
Out[ ]: LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,
                  intercept_scaling=1, loss='squared_hinge', max_iter=500,
                  multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
                  verbose=0)
```

4.C.b.iii HOG Textural Linear SVC

```
In [37]: linear_svc_tex_hog = LinearSVC(max_iter=500)
         linear_svc_tex_hog.fit(textural_features_hog_train, train_labels)
```

```
Out[37]: LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True,
                   intercept_scaling=1, loss='squared_hinge', max_iter=500,
                   multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,
                   verbose=0)
```

4.C.d Naive Bayes Training

1. Geometric
2. LBP Textural
3. HOG Textural

4.C.d.i Geometrical Naive Bayes

```
In [ ]: gnb_geo = GaussianNB()
        gnb_geo.fit(geometrical_features_train, train_labels)
```

```
Out[ ]: GaussianNB(priors=None, var_smoothing=1e-09)
```

4.C.d.ii LBP Textural Naive Bayes

```
In [ ]: gnb_tex = GaussianNB()
        gnb_tex.fit(textural_features_train, train_labels)
```

```
Out[ ]: GaussianNB(priors=None, var_smoothing=1e-09)
```

4.C.d.iii HOG Textural Naive Bayes

```
In [39]: gnb_tex_hog = GaussianNB()
         gnb_tex_hog.fit(textural_features_hog_train, train_labels)
```

```
Out[39]: GaussianNB(priors=None, var_smoothing=1e-09)
```

4.C.e AdaBoost Training

1. Geometric
2. LBP Textural
3. HOG Textural

4.C.e.i Geometrical AdaBoost

```
In [ ]: adaboost_geo = AdaBoostClassifier(n_estimators=100)  # using decision tree depth=1
        adaboost_geo.fit(geometrical_features_train, train_labels)
```

```
Out[ ]: AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None, learning_rate=1.0,
                           n_estimators=100, random_state=None)
```

4.C.e.ii LBP Textural AdaBoost

```
In [ ]: adaboost_tex = AdaBoostClassifier(n_estimators=100)  # using decision tree depth=1
        adaboost_tex.fit(textural_features_train, train_labels)
```

```
Out[ ]: AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None, learning_rate=1.0,
                           n_estimators=100, random_state=None)
```

4.C.e.iii HOG Textural AdaBoost

```
In [41]: adaboost_tex_hog = AdaBoostClassifier(n_estimators=100)  # using decision tree depth=
         adaboost_tex_hog.fit(textural_features_hog_train, train_labels)
```

```
Out[41]: AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None, learning_rate=1.0,
                            n_estimators=100, random_state=None)
```

4.C.f RandomForest Training

1. Geometric
2. HOG Textural

4.C.f.i Geometrical Random Forest

```
In [ ]: randomforest_geo = RandomForestClassifier(min_samples_leaf=5, n_estimators=100)
        randomforest_geo.fit(geometrical_features_train, train_labels)
```

```
Out[ ]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                               max_depth=None, max_features='auto', max_leaf_nodes=None,
                               min_impurity_decrease=0.0, min_impurity_split=None,
                               min_samples_leaf=5, min_samples_split=2,
                               min_weight_fraction_leaf=0.0, n_estimators=100,
                               n_jobs=None, oob_score=False, random_state=None,
                               verbose=0, warm_start=False)
```

4.C.f.ii HOG Textural Random Forest

```
In [43]: randomforest_tex_hog = RandomForestClassifier(n_estimators=100)  # using decision tre
         randomforest_tex_hog.fit(textural_features_hog_train, train_labels)
```

```
Out[43]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                                max_depth=None, max_features='auto', max_leaf_nodes=None,
                                min_impurity_decrease=0.0, min_impurity_split=None,
                                min_samples_leaf=1, min_samples_split=2,
                                min_weight_fraction_leaf=0.0, n_estimators=100,
                                n_jobs=None, oob_score=False, random_state=None,
                                verbose=0, warm_start=False)
```

1.4.4 4.D Evalutation

1. kNN
2. Linear SVC
3. RBF SVC
4. Naive Bayes
5. AdaBoost
6. Random Forest

```
In [ ]: def draw_confusion_matrix(y_true, y_pred, classes=None, normalize=True, title=None, cma
            acc = np.sum(y_true == y_pred) / len(y_true)
            print('Accuracy = {}'.format(acc))

            cm = confusion_matrix(y_true, y_pred)
            if normalize:
                cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
            print('Confusion Matrix = \n{}'.format(np.round(cm, 3)))

            if classes is None:
                classes = [str(i) for i in range(len(np.unique(y_true)))]

            if not title:
                if normalize:
                    title = 'Normalized confusion matrix'
                else:
                    title = 'Confusion matrix, without normalization'

            fig, ax = plt.subplots()
            im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
            ax.figure.colorbar(im, ax=ax)
            # We want to show all ticks...
            ax.set(xticks=np.arange(cm.shape[1]),
                   yticks=np.arange(cm.shape[0]),
                   # ... and label them with the respective list entries
                   xticklabels=classes, yticklabels=classes,
                   title=title,
```

```
                   ylabel='True label',
                   xlabel='Predicted label')

            # Rotate the tick labels and set their alignment.
            plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
                     rotation_mode="anchor")

            # Loop over data dimensions and create text annotations.
            fmt = '.2f' if normalize else 'd'
            thresh = cm.max() / 2.
            for i in range(cm.shape[0]):
                for j in range(cm.shape[1]):
                    ax.text(j, i, format(cm[i, j], fmt),
                            ha="center", va="center",
                            color="white" if cm[i, j] > thresh else "black")
            fig.tight_layout()
            plt.show()
            return ax
```

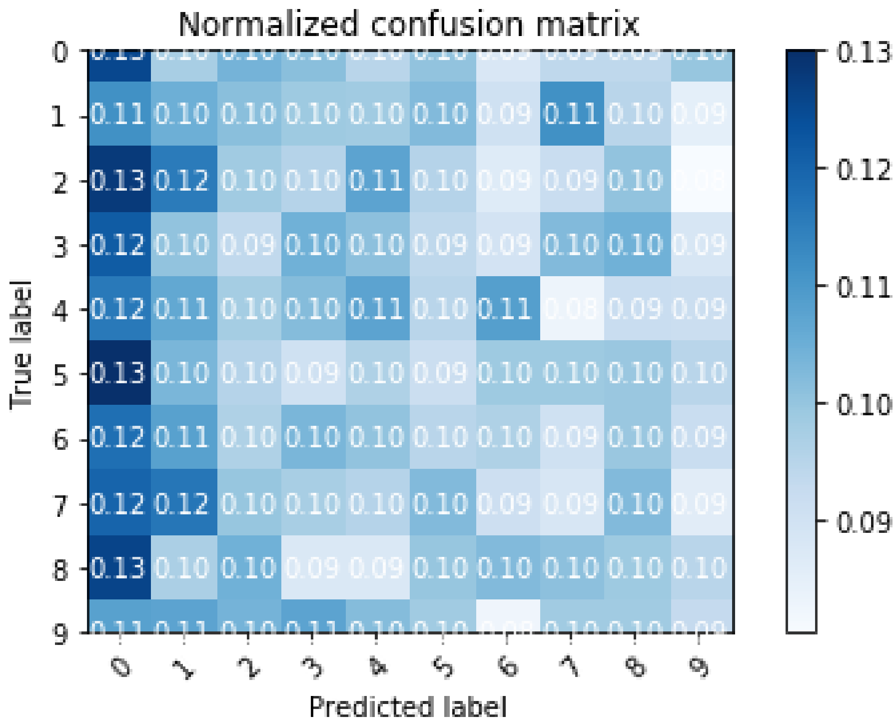
4.D.a kNN Evaluation

1. Geometrical
2. LBP Textural
3. HOG Textural

4.D.a.i Geometric kNN

```
In [ ]: pred = knn_geo.predict(geometrical_features_test)
        draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.10095
Confusion Matrix =
[[0.126 0.098 0.104 0.102 0.095 0.1   0.088 0.094 0.094 0.1  ]
 [0.112 0.105 0.102 0.099 0.098 0.102 0.09  0.112 0.095 0.085]
 [0.128 0.116 0.098 0.096 0.108 0.096 0.086 0.092 0.1   0.08 ]
 [0.122 0.1   0.094 0.104 0.101 0.094 0.09  0.102 0.104 0.088]
 [0.116 0.106 0.098 0.102 0.108 0.095 0.108 0.083 0.092 0.092]
 [0.13  0.104 0.096 0.09  0.096 0.092 0.099 0.099 0.1   0.095]
 [0.118 0.108 0.096 0.104 0.1   0.095 0.096 0.09  0.1   0.092]
 [0.12  0.116 0.1   0.098 0.096 0.102 0.091 0.088 0.102 0.086]
 [0.126 0.097 0.104 0.088 0.088 0.1   0.102 0.101 0.099 0.095]
 [0.108 0.108 0.104 0.108 0.102 0.098 0.082 0.098 0.098 0.093]]
```

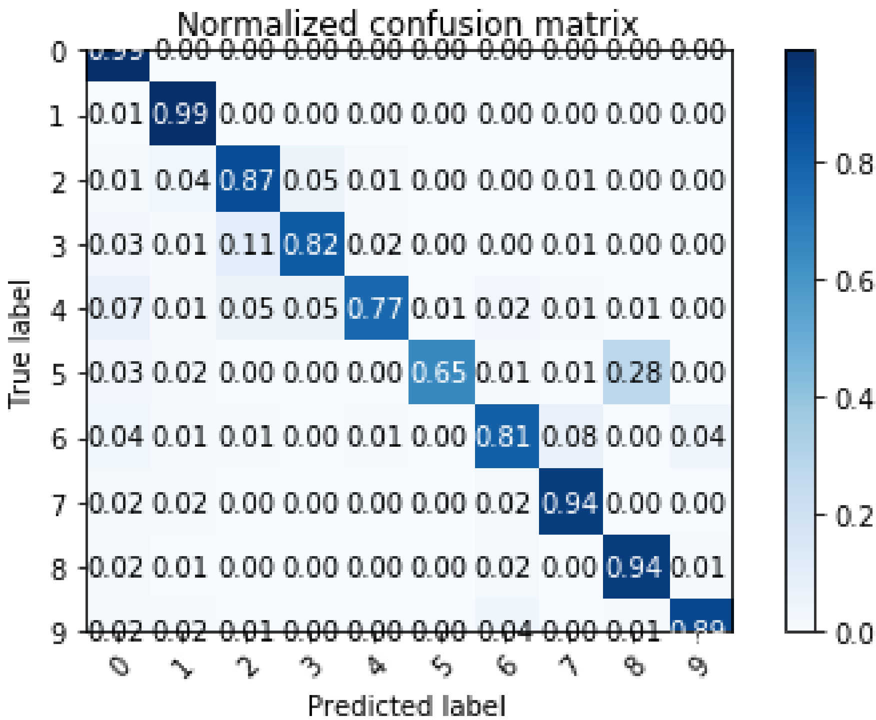


Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff5cb693da0>

4.D.a.ii LBP Textural kNN

In [ ]:
```
# takes about 100 mins!!!
pred = knn_tex.predict(textural_features_test)
draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.8665
Confusion Matrix =
[[0.988 0.004 0.    0.    0.    0.004 0.    0.002 0.    0.001]
 [0.006 0.988 0.002 0.    0.    0.    0.002 0.    0.    0.002]
 [0.015 0.036 0.874 0.051 0.01  0.    0.004 0.007 0.    0.002]
 [0.025 0.014 0.106 0.821 0.023 0.    0.002 0.006 0.002 0.   ]
 [0.07  0.01  0.05  0.052 0.77  0.006 0.024 0.008 0.006 0.001]
 [0.028 0.022 0.002 0.001 0.002 0.652 0.011 0.006 0.276 0.002]
 [0.038 0.008 0.014 0.002 0.008 0.003 0.806 0.076 0.004 0.041]
 [0.02  0.016 0.002 0.    0.    0.    0.022 0.935 0.    0.004]
 [0.02  0.007 0.001 0.    0.    0.    0.022 0.002 0.939 0.01 ]
 [0.022 0.02  0.007 0.    0.    0.002 0.043 0.003 0.009 0.892]]
```

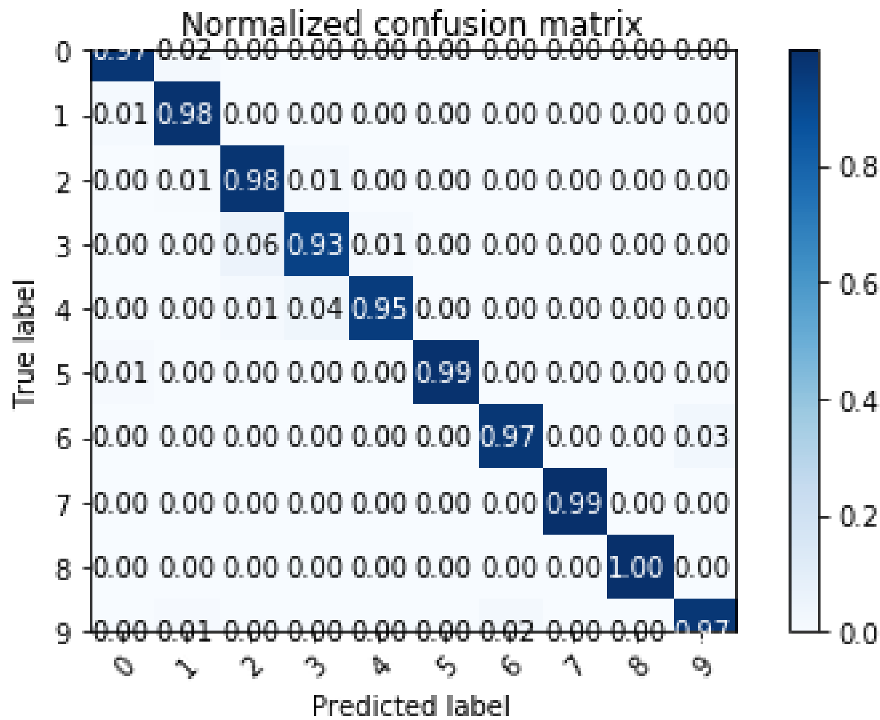


Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd45d24b320>

4.D.a.iii HOG Textural kNN

In [35]:
```
pred = knn_tex_hog.predict(textural_features_hog_test)
draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.97215
Confusion Matrix =
[[0.971 0.023 0.    0.    0.    0.004 0.    0.001 0.    0.   ]
 [0.014 0.982 0.002 0.    0.    0.    0.    0.    0.    0.   ]
 [0.    0.006 0.977 0.014 0.002 0.    0.    0.    0.    0.001]
 [0.    0.    0.056 0.928 0.013 0.002 0.    0.    0.    0.   ]
 [0.    0.    0.014 0.037 0.949 0.    0.    0.    0.    0.   ]
 [0.008 0.002 0.002 0.    0.    0.986 0.    0.    0.002 0.   ]
 [0.    0.    0.    0.    0.001 0.002 0.966 0.    0.    0.03 ]
 [0.    0.002 0.    0.    0.    0.    0.002 0.994 0.    0.   ]
 [0.    0.002 0.    0.    0.    0.    0.    0.    0.998 0.   ]
 [0.001 0.009 0.001 0.    0.    0.001 0.017 0.    0.001 0.97 ]]
```




```
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7fef8f16a588>
```

4.D.b Linear SVC Evaluation

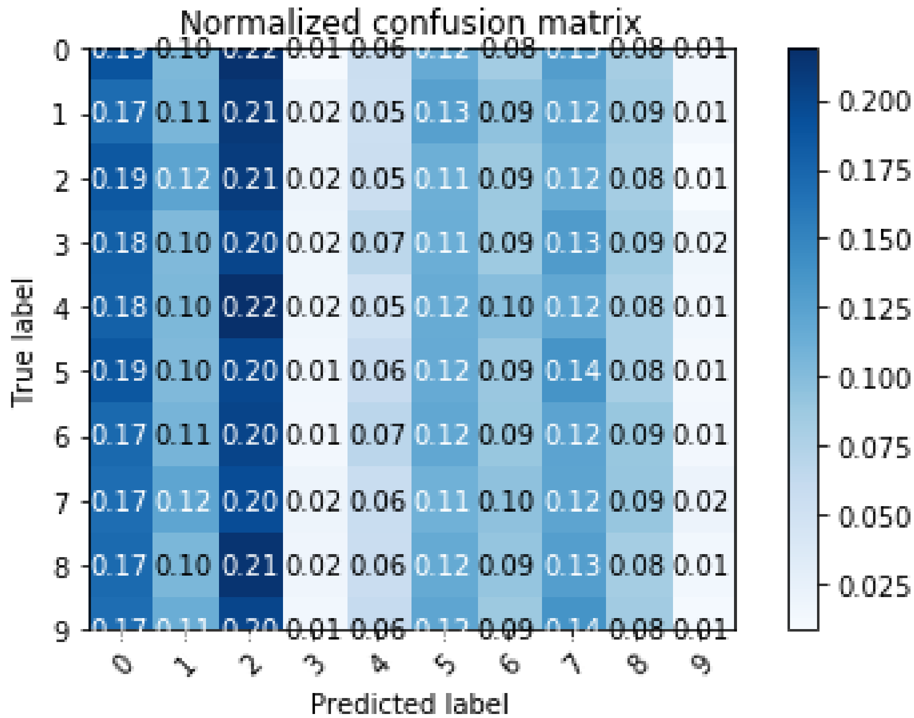
1. Geometrical
2. LBP Textural
3. HOG Textural

4.D.b.i Geometrical Linear SVC

```
In [ ]: pred = linear_svc_geo.predict(geometrical_features_test)
        draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.09935
Confusion Matrix =
[[0.189 0.104 0.216 0.011 0.055 0.116 0.084 0.128 0.082 0.014]
 [0.17  0.106 0.21  0.018 0.054 0.126 0.094 0.122 0.086 0.014]
 [0.186 0.122 0.208 0.018 0.054 0.112 0.088 0.118 0.083 0.008]
 [0.18  0.102 0.2   0.016 0.068 0.113 0.087 0.13  0.086 0.016]
 [0.179 0.104 0.218 0.016 0.051 0.116 0.099 0.12  0.082 0.015]
 [0.187 0.102 0.2   0.015 0.06  0.116 0.09  0.136 0.081 0.013]
 [0.172 0.107 0.202 0.014 0.068 0.12  0.09  0.123 0.09  0.014]
 [0.169 0.121 0.195 0.018 0.057 0.111 0.095 0.122 0.091 0.02 ]
 [0.172 0.104 0.215 0.018 0.056 0.118 0.092 0.128 0.083 0.015]
```

```
 [0.168 0.114 0.201 0.014 0.06  0.121 0.088 0.138 0.084 0.011]]
```

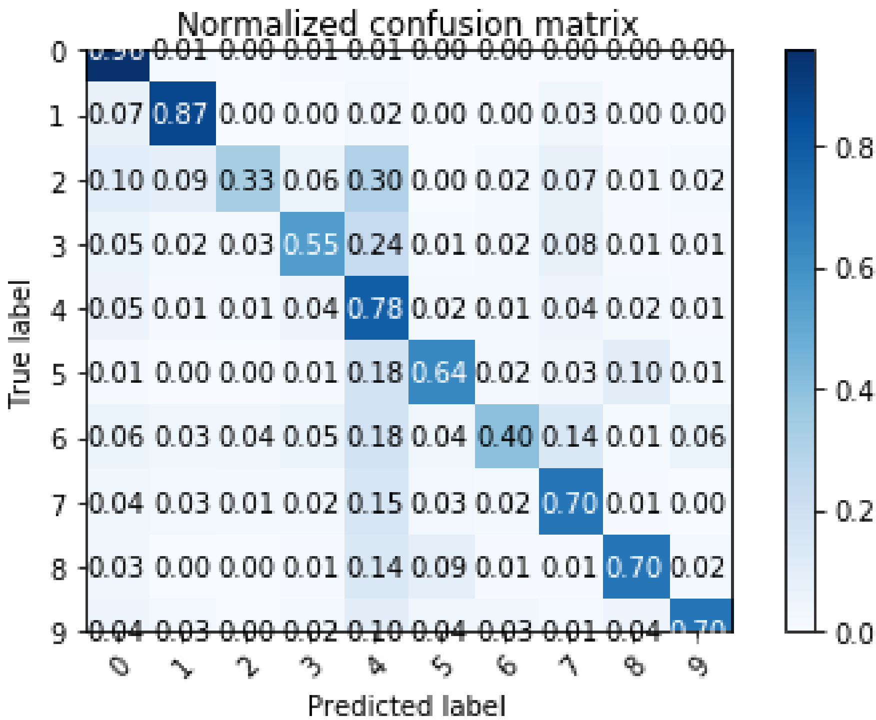


Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff5cb01e3c8>

4.D.b.ii LBP Textural Linear SVC

In [ ]:
```
# note that because of colab's 12 hours time limitation SVC failed to converge so this
pred = linear_svc_tex.predict(textural_features_test)
draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.66145
Confusion Matrix =
[[0.957 0.014 0.    0.008 0.012 0.001 0.002 0.001 0.002 0.003]
 [0.07  0.868 0.004 0.001 0.016 0.001 0.003 0.034 0.002 0.002]
 [0.104 0.088 0.327 0.06  0.304 0.003 0.018 0.072 0.006 0.019]
 [0.05  0.02  0.026 0.548 0.237 0.012 0.016 0.076 0.006 0.008]
 [0.054 0.01  0.012 0.038 0.784 0.016 0.015 0.042 0.02  0.008]
 [0.006 0.001 0.001 0.006 0.178 0.639 0.023 0.03  0.1   0.014]
 [0.056 0.034 0.035 0.05  0.176 0.036 0.399 0.136 0.014 0.063]
 [0.036 0.026 0.015 0.022 0.151 0.028 0.019 0.696 0.006 0.003]
 [0.03  0.002 0.    0.007 0.141 0.09  0.006 0.007 0.7   0.016]
 [0.043 0.026 0.002 0.016 0.095 0.036 0.033 0.013 0.039 0.696]]
```

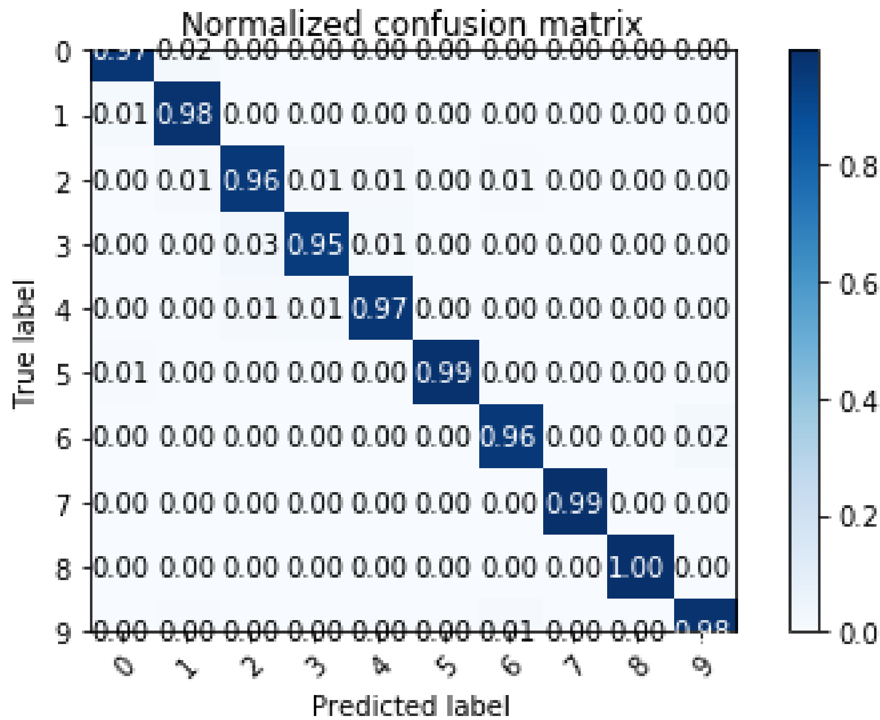


Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd45a5f4fd0>

4.D.b.iii HOG Textural Linear SVC

In [38]:
```
pred = linear_svc_tex_hog.predict(textural_features_hog_test)
draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.9765
Confusion Matrix =
[[0.971 0.022 0.    0.    0.002 0.004 0.001 0.001 0.    0.   ]
 [0.012 0.982 0.    0.    0.002 0.002 0.002 0.    0.    0.   ]
 [0.    0.011 0.964 0.008 0.008 0.    0.006 0.002 0.    0.002]
 [0.    0.    0.028 0.953 0.015 0.002 0.    0.    0.    0.002]
 [0.    0.001 0.008 0.013 0.973 0.002 0.001 0.    0.    0.002]
 [0.006 0.002 0.    0.    0.002 0.988 0.    0.    0.    0.   ]
 [0.    0.003 0.002 0.002 0.003 0.002 0.962 0.001 0.002 0.022]
 [0.    0.002 0.002 0.    0.    0.    0.003 0.992 0.    0.   ]
 [0.    0.001 0.    0.    0.    0.    0.    0.    0.997 0.   ]
 [0.    0.004 0.001 0.002 0.002 0.001 0.008 0.    0.    0.982]]
```



Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7fef8f000e48>

4.E.d Naive Bayes Evalution

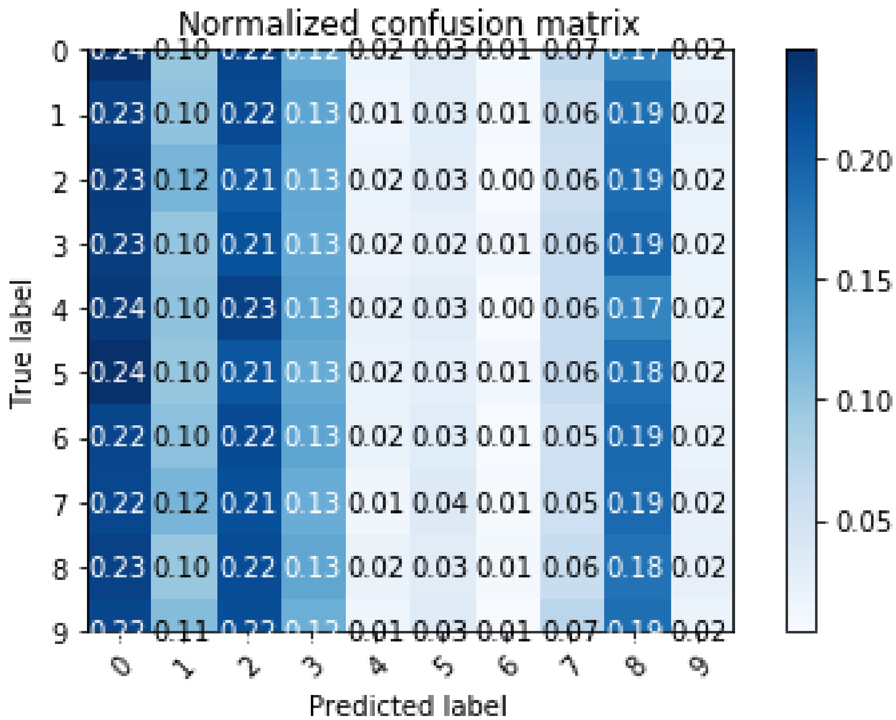
1. Geometric
2. LBP Textural
3. HOG Textural

4.E.d.i Geometrical Naive Bayes

```
In [ ]: pred = gnb_geo.predict(geometrical_features_test)
        draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.0984
Confusion Matrix =
[[0.242 0.098 0.223 0.124 0.017 0.031 0.008 0.066 0.17  0.019]
 [0.229 0.101 0.221 0.133 0.015 0.03  0.006 0.058 0.186 0.022]
 [0.233 0.116 0.206 0.131 0.018 0.029 0.004 0.056 0.188 0.019]
 [0.232 0.099 0.213 0.13  0.018 0.024 0.012 0.061 0.194 0.019]
 [0.236 0.102 0.228 0.134 0.021 0.031 0.004 0.062 0.166 0.017]
 [0.244 0.098 0.21  0.126 0.02  0.026 0.01  0.062 0.185 0.018]
 [0.224 0.104 0.218 0.134 0.02  0.032 0.006 0.052 0.192 0.02 ]
 [0.222 0.116 0.215 0.126 0.013 0.036 0.007 0.054 0.19  0.022]
 [0.228 0.098 0.218 0.132 0.02  0.031 0.008 0.06  0.182 0.023]
```

```
[0.223 0.109 0.217 0.124 0.014 0.032 0.006 0.072 0.186 0.016]]
```

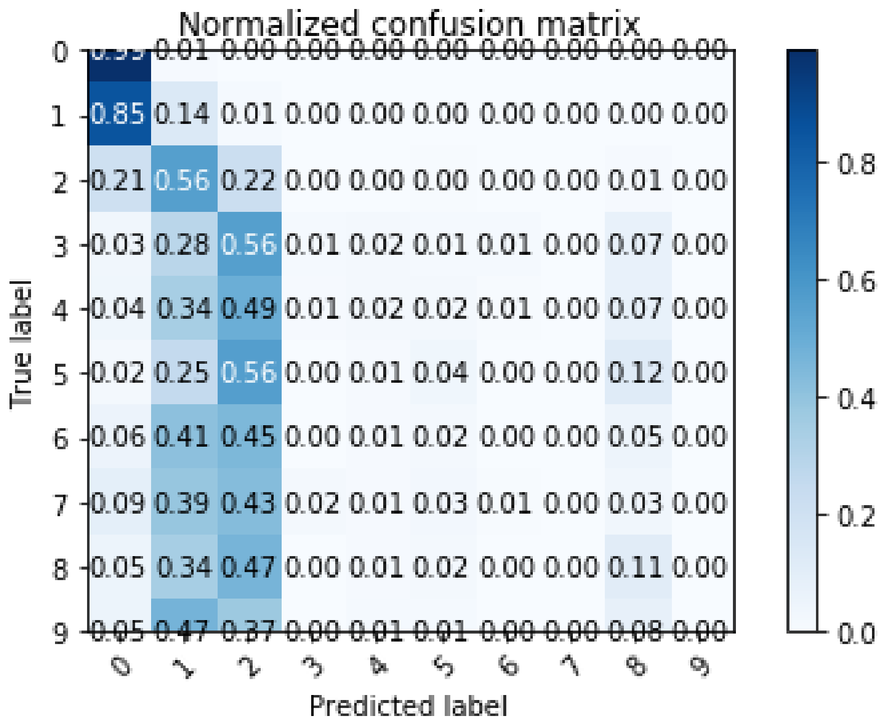


Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd45a454940>

4.E.d.ii LBP Textural Naive Bayes

In [ ]:
```
pred = gnb_tex.predict(textural_features_test)
draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.1524
Confusion Matrix =
[[0.988 0.01  0.002 0.    0.    0.    0.    0.    0.    0.   ]
 [0.849 0.136 0.014 0.    0.    0.    0.    0.    0.    0.   ]
 [0.206 0.556 0.219 0.    0.002 0.004 0.002 0.    0.011 0.   ]
 [0.032 0.282 0.556 0.012 0.018 0.015 0.012 0.001 0.071 0.   ]
 [0.038 0.342 0.492 0.01  0.016 0.021 0.008 0.    0.074 0.   ]
 [0.016 0.254 0.562 0.002 0.008 0.037 0.002 0.    0.12  0.   ]
 [0.055 0.41  0.451 0.004 0.01  0.016 0.002 0.    0.048 0.004]
 [0.09  0.387 0.43  0.016 0.01  0.026 0.006 0.002 0.034 0.   ]
 [0.053 0.342 0.466 0.    0.012 0.018 0.    0.    0.109 0.   ]
 [0.051 0.467 0.371 0.    0.014 0.014 0.002 0.    0.079 0.002]]
```

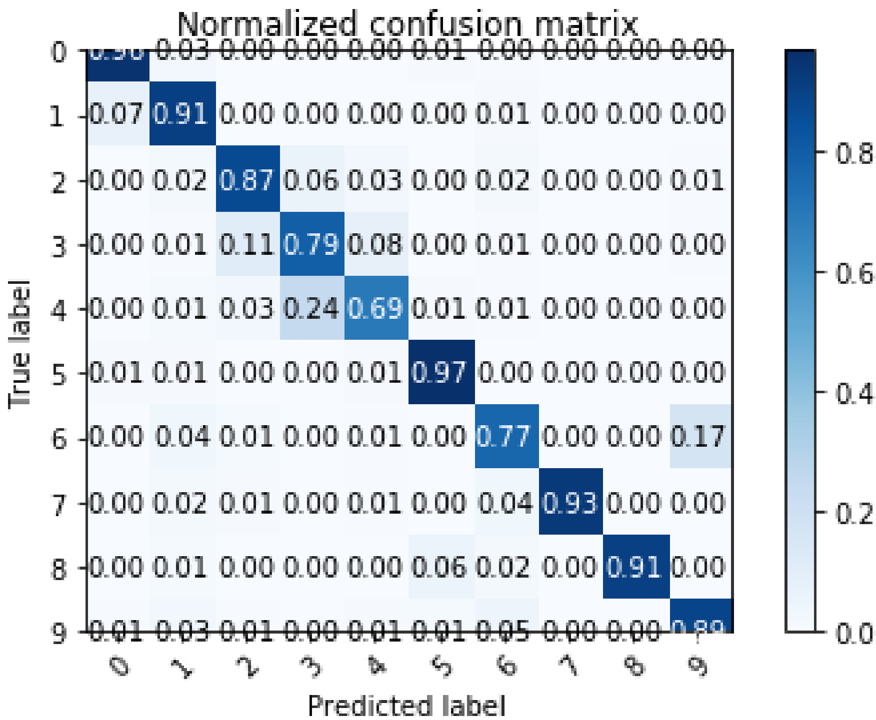


```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd45a2d06d8>
```

4.E.d.iii HOG Textural Naive Bayes

```
In [40]: pred = gnb_tex_hog.predict(textural_features_hog_test)
         draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.8686
Confusion Matrix =
[[0.956 0.027 0.    0.    0.003 0.009 0.004 0.    0.    0.   ]
 [0.07  0.911 0.004 0.    0.002 0.001 0.011 0.    0.    0.002]
 [0.    0.018 0.868 0.062 0.026 0.    0.018 0.002 0.    0.006]
 [0.    0.005 0.113 0.794 0.077 0.    0.008 0.    0.    0.004]
 [0.003 0.012 0.028 0.242 0.694 0.01  0.008 0.    0.    0.002]
 [0.01  0.01  0.    0.    0.01  0.968 0.002 0.    0.    0.   ]
 [0.001 0.036 0.014 0.    0.008 0.004 0.766 0.    0.    0.172]
 [0.001 0.016 0.008 0.    0.006 0.    0.036 0.932 0.    0.   ]
 [0.    0.012 0.    0.    0.002 0.058 0.022 0.    0.906 0.   ]
 [0.006 0.028 0.006 0.    0.01  0.012 0.047 0.    0.002 0.89 ]]
```




```
Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7fef8c69fc50>
```

4.C.e AdaBoost Evaluation

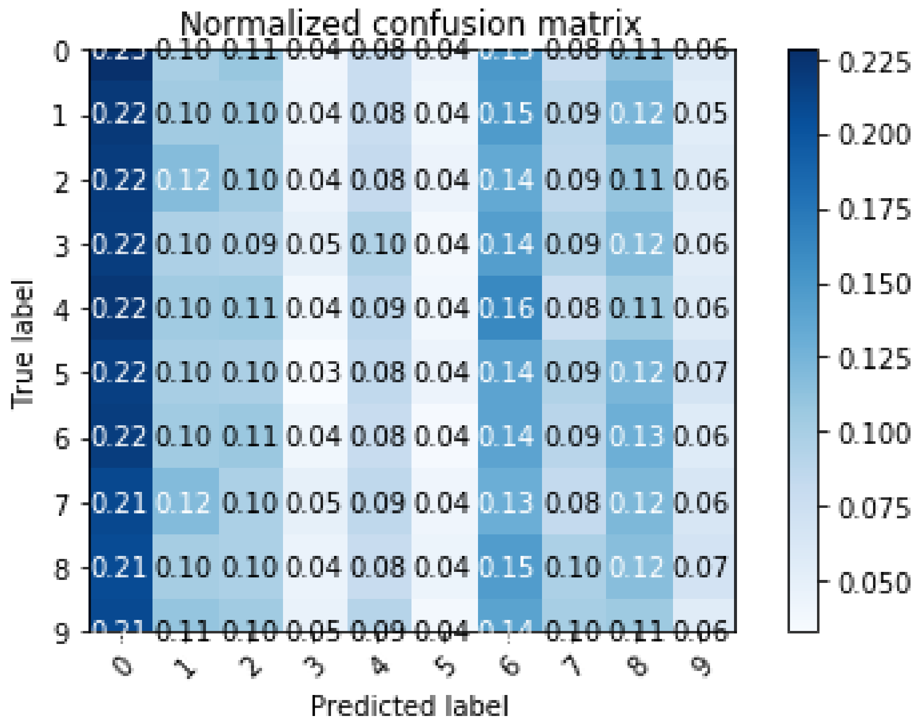
1. Geometric
2. LBP Textural
3. HOG Textural

4.E.e.i Geometrical AdaBoost

```
In [ ]: pred = adaboost_geo.predict(geometrical_features_test)
        draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.101
Confusion Matrix =
[[0.228 0.1   0.108 0.041 0.078 0.044 0.149 0.08  0.114 0.058]
 [0.22  0.104 0.104 0.042 0.078 0.04  0.146 0.088 0.124 0.054]
 [0.218 0.118 0.104 0.044 0.082 0.044 0.135 0.086 0.11  0.058]
 [0.218 0.096 0.094 0.049 0.096 0.037 0.144 0.094 0.118 0.055]
 [0.222 0.104 0.106 0.038 0.088 0.039 0.162 0.077 0.106 0.058]
 [0.216 0.1   0.098 0.033 0.084 0.044 0.139 0.094 0.123 0.068]
 [0.218 0.104 0.107 0.04  0.08  0.035 0.139 0.09  0.129 0.057]
 [0.209 0.119 0.097 0.049 0.086 0.041 0.13  0.083 0.122 0.064]
 [0.207 0.102 0.097 0.044 0.079 0.044 0.146 0.097 0.116 0.068]
```

```
 [0.208 0.11  0.104 0.046 0.091 0.038 0.14  0.1   0.106 0.056]]
```

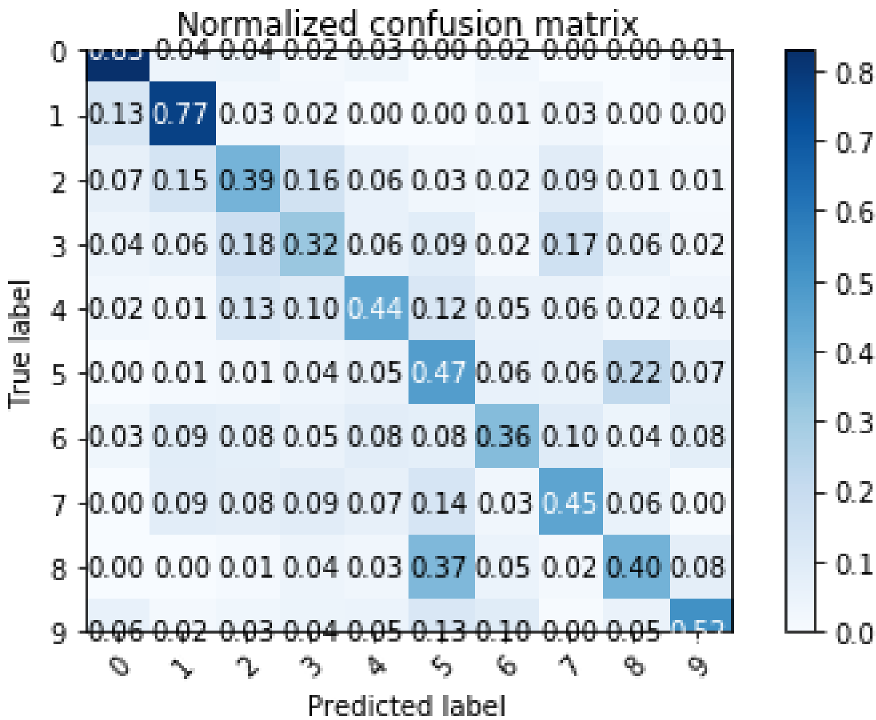


```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd45a0c5358>
```

4.E.e.ii LBP Textural AdaBoost

```
In [ ]: pred = adaboost_tex.predict(textural_features_test)
        draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.495
Confusion Matrix =
[[0.828 0.04  0.044 0.017 0.03  0.002 0.024 0.001 0.    0.014]
 [0.13  0.772 0.025 0.021 0.002 0.002 0.015 0.028 0.    0.004]
 [0.068 0.146 0.394 0.162 0.062 0.026 0.023 0.093 0.014 0.012]
 [0.04  0.056 0.176 0.318 0.062 0.09  0.016 0.168 0.058 0.017]
 [0.023 0.014 0.128 0.104 0.438 0.125 0.054 0.055 0.024 0.035]
 [0.001 0.012 0.014 0.036 0.052 0.475 0.062 0.056 0.22  0.072]
 [0.032 0.088 0.076 0.054 0.084 0.078 0.362 0.098 0.044 0.084]
 [0.    0.087 0.08  0.092 0.066 0.138 0.027 0.448 0.058 0.004]
 [0.    0.003 0.01  0.04  0.029 0.373 0.051 0.019 0.396 0.078]
 [0.062 0.018 0.031 0.044 0.049 0.126 0.096 0.004 0.053 0.518]]
```

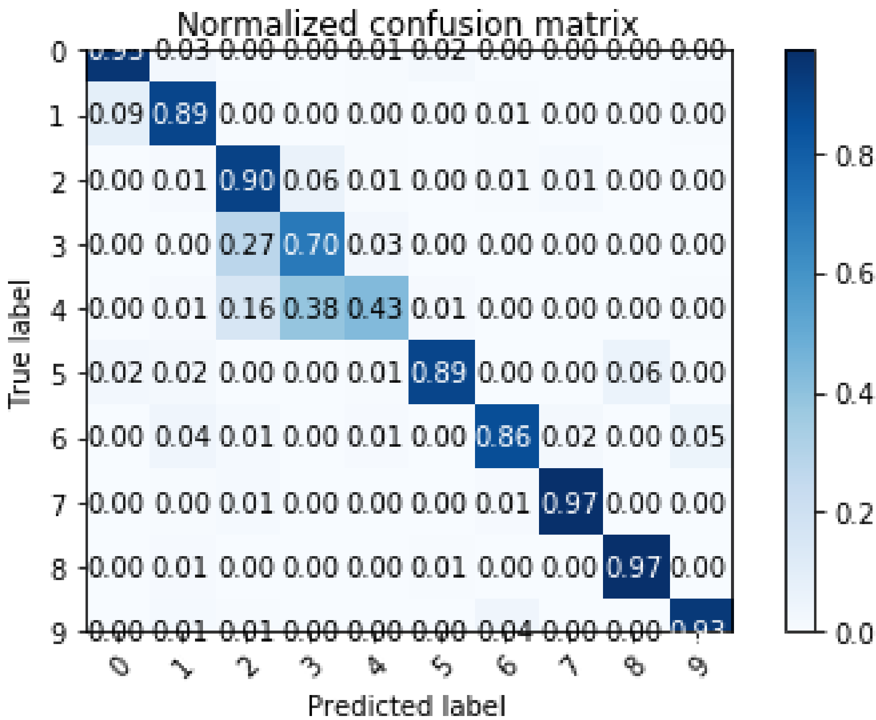



```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd459f914a8>
```

4.E.e.iii HOG Textural AdaBoost

```
In [42]: pred = adaboost_tex_hog.predict(textural_features_hog_test)
         draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.84905
Confusion Matrix =
[[0.947 0.025 0.    0.    0.006 0.019 0.    0.    0.    0.002]
 [0.09  0.889 0.004 0.    0.004 0.    0.007 0.    0.    0.004]
 [0.    0.008 0.902 0.062 0.006 0.    0.006 0.012 0.    0.003]
 [0.    0.    0.274 0.696 0.025 0.    0.002 0.    0.    0.   ]
 [0.002 0.008 0.158 0.384 0.431 0.01  0.002 0.    0.    0.004]
 [0.023 0.018 0.    0.    0.007 0.891 0.001 0.    0.058 0.   ]
 [0.    0.042 0.014 0.    0.01  0.002 0.858 0.02  0.    0.052]
 [0.001 0.004 0.012 0.003 0.    0.    0.009 0.97  0.    0.   ]
 [0.    0.011 0.    0.    0.003 0.008 0.003 0.    0.972 0.004]
 [0.002 0.014 0.006 0.    0.002 0.001 0.04  0.    0.    0.934]]
```



Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x7fef8c5600b8>

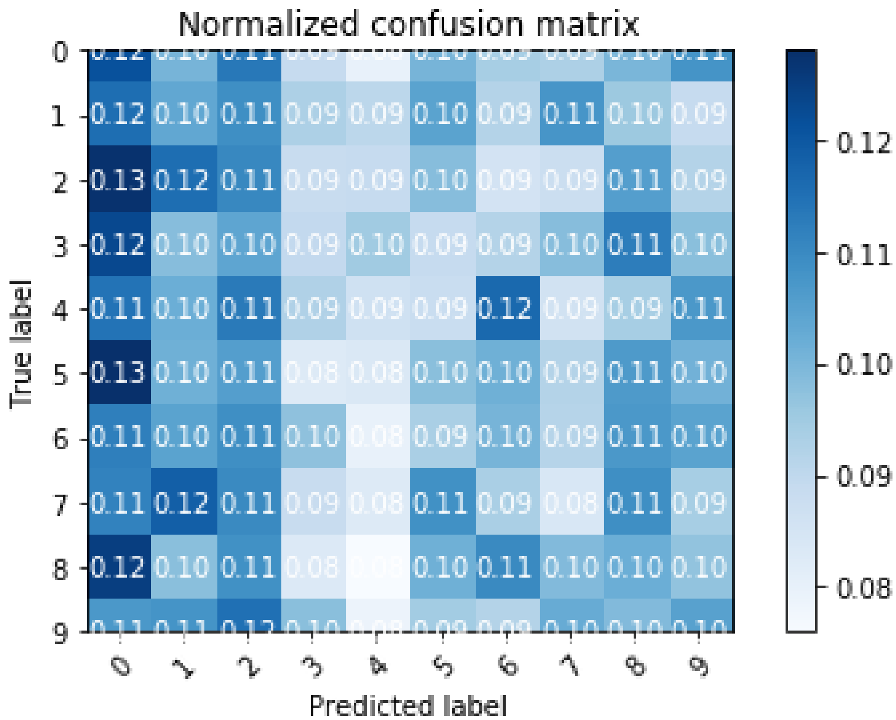
4.E.f RandomForest Evaluation

1. Geometric
2. Textural

4.E.f.i Geometrical Random Forest

In [ ]:
```
pred = randomforest_geo.predict(geometrical_features_test)
draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.1001
Confusion Matrix =
[[0.122 0.1   0.114 0.089 0.08  0.1   0.094 0.093 0.1   0.108]
 [0.116 0.104 0.109 0.093 0.09  0.104 0.092 0.108 0.096 0.089]
 [0.128 0.116 0.11  0.088 0.089 0.098 0.086 0.088 0.106 0.092]
 [0.123 0.098 0.104 0.09  0.095 0.089 0.092 0.098 0.112 0.098]
 [0.114 0.102 0.113 0.092 0.086 0.088 0.116 0.086 0.094 0.107]
 [0.128 0.102 0.106 0.082 0.084 0.098 0.102 0.092 0.106 0.101]
 [0.112 0.104 0.109 0.098 0.08  0.094 0.1   0.092 0.107 0.104]
 [0.112 0.118 0.11  0.088 0.082 0.108 0.094 0.084 0.109 0.094]
 [0.125 0.098 0.108 0.083 0.076 0.102 0.11  0.099 0.102 0.097]
 [0.107 0.108 0.115 0.098 0.079 0.094 0.092 0.102 0.099 0.105]]
```

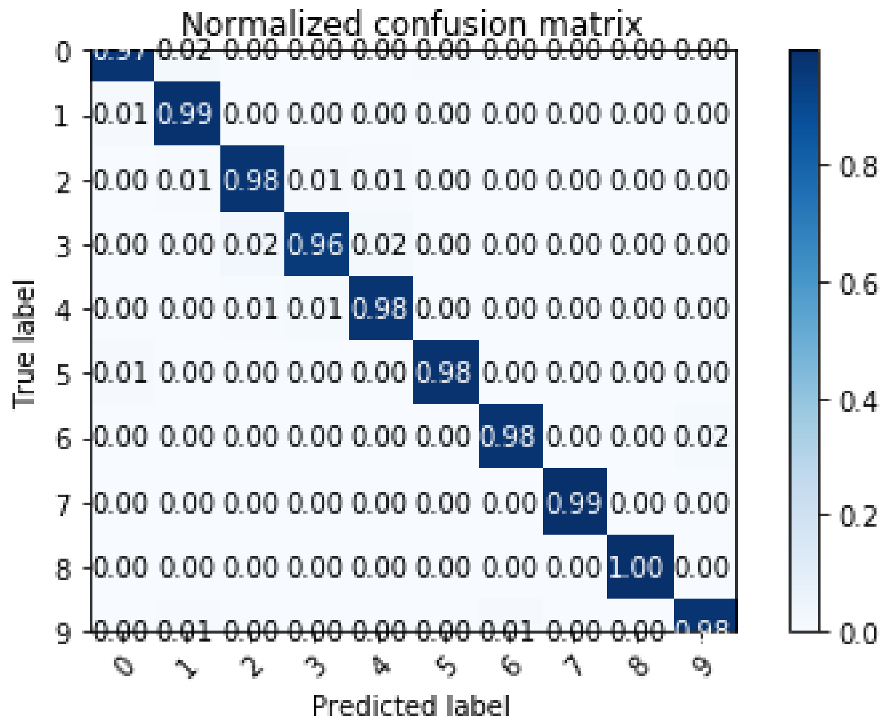



```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fd459c022e8>
```

4.E.f.ii HOG Textural Random Forest

```
In [44]: pred = randomforest_tex_hog.predict(textural_features_hog_test)
         draw_confusion_matrix(test_labels, pred)
```

```
Accuracy = 0.9796
Confusion Matrix =
[[0.974 0.02  0.    0.    0.    0.004 0.    0.001 0.    0.   ]
 [0.011 0.986 0.002 0.    0.    0.    0.    0.    0.    0.001]
 [0.    0.005 0.976 0.012 0.006 0.    0.    0.001 0.    0.002]
 [0.    0.    0.024 0.956 0.018 0.001 0.    0.    0.    0.   ]
 [0.    0.001 0.005 0.012 0.979 0.002 0.001 0.    0.    0.   ]
 [0.011 0.002 0.    0.    0.002 0.984 0.    0.    0.001 0.   ]
 [0.    0.002 0.    0.    0.    0.002 0.978 0.    0.    0.016]
 [0.    0.002 0.003 0.    0.    0.    0.002 0.992 0.    0.   ]
 [0.001 0.    0.    0.    0.    0.001 0.    0.    0.996 0.002]
 [0.002 0.006 0.    0.002 0.002 0.002 0.011 0.    0.    0.976]]
```



Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x7fef8c37ce48>