**Guided Imagery and Progressive Muscle Relaxation in Group Psychotherapy**

Hannah K. Greenbaum

Department of Psychology, The George Washington University

PSYC 3170: Clinical Psychology

Dr. Tia M. Benedetto

October 1, 2019

# Guided Imagery and Progressive Muscle Relaxation in Group Psychotherapy

A majority of Americans experience stress in their daily lives (American Psychological Association, 2017). Thus, an important goal of psychological research is to evaluate techniques that promote stress reduction and relaxation. Two techniques that have been associated with reduced stress and increased relaxation in psychotherapy contexts are guided imagery and progressive muscle relaxation (McGuigan & Lehrer, 2007). *Guided imagery* aids individuals in connecting their internal and external experiences, allowing them, for example, to feel calmer externally because they practice thinking about calming imagery. *Progressive muscle relaxation* involves diaphragmatic breathing and the tensing and releasing of 16 major muscle groups; together these behaviors lead individuals to a more relaxed state (Jacobson, 1938; Trakhtenberg, 2008). Guided imagery and progressive muscle relaxation are both cognitive behavioral techniques (Yalom & Leszcz, 2005) in which individuals focus on the relationship among thoughts, emotions, and behaviors (White, 2000).

Group psychotherapy effectively promotes positive treatment outcomes in patients in a cost-

effective way. Its efficacy is in part attributable to variables unique to the group experience of therapy as compared with individual psychotherapy (Bottomley, 1996; Yalom & Leszcz, 2005). That is, the group format helps participants feel accepted and better understand their common struggles; at the same time, interactions with group members provide social support and models of positive behavior (Yalom & Leszcz, 2005). Thus, it is useful to examine how stress reduction and relaxation can be enhanced in a group context.

The purpose of this literature review is to examine the research base on guided imagery and progressive muscle relaxation in group psychotherapy contexts. I provide overviews of both guided imagery and progressive muscle relaxation, including theoretical foundations and historical context. Then I examine guided imagery and progressive muscle relaxation as used on their own as well as in combination as part of group psychotherapy (see Baider et al., 1994, for more). Throughout the review, I highlight themes in the research. Finally, I end by pointing out limitations in the existing literature and exploring potential directions for future research.

**Guided Imagery**

# Features of Guided Imagery

Guided imagery involves a person visualizing a mental image and engaging each sense (e.g., sight, smell, touch) in the process. Guided imagery was first examined in a psychological context in the 1960s, when the behavior theorist Joseph Wolpe helped pioneer the use of relaxation techniques such as aversive imagery, exposure, and imaginal flooding in behavior therapy (Achterberg, 1985; Utay & Miller, 2006). Patients learn to relax their bodies in the presence of stimuli that previously distressed them, to the point where further exposure to the stimuli no longer provokes a negative response (Achterberg, 1985).

Contemporary research supports the efficacy of guided imagery interventions for treating medical, psychiatric, and psychological disorders (Utay & Miller, 2006). Guided imagery is typically used to pursue treatment goals such as improved relaxation, sports achievement, and pain reduction. Guided imagery techniques are often paired with breathing techniques and other forms of relaxation, such as mindfulness (see Freebird Meditations, 2012). The evidence is sufficient to call guided imagery an effective, evidence-based treatment for a variety of stress-related psychological concerns (Utay & Miller,

2006).

# Guided Imagery in Group Psychotherapy

Guided imagery exercises improve treatment outcomes and prognosis in group psychotherapy contexts (Skovholt & Thoen, 1987). Lange (1982) underscored two such benefits by showing (a) the role of the group psychotherapy leader in facilitating reflection on the guided imagery experience, including difficulties and stuck points, and (b) the benefits achieved by social comparison of guided imagery experiences between group members. Teaching techniques and reflecting on the group process are unique components of guided imagery received in a group context (Yalom & Leszcz, 2005).

Empirical research focused on guided imagery interventions supports the efficacy of the technique with a variety of populations within hospital settings, with positive outcomes for individuals diagnosed with depression, anxiety, and eating disorders (Utay & Miller, 2006). Guided imagery and relaxation techniques have even been found to “reduce distress and allow the immune system to function more effectively” (Trakhtenberg, 2008, p. 850). For example, Holden-Lund (1988) examined effects of a guided imagery intervention on surgical stress and wound healing in a group of 24 patients. Patients listened to guided imagery recordings and reported reduced state anxiety, lower cortisol levels following surgery, and less irritation in wound healing compared with a control group. Holden-Lund concluded that the guided imagery recordings contributed to improved surgical recovery. It would be interesting to see how the results might differ if guided imagery was practiced continually in a group context.

Guided imagery has also been shown to reduce stress, length of hospital stay, and symptoms related to medical and psychological conditions (Scherwitz et al., 2005). For example, Ball et al. (2003) conducted guided imagery in a group psychotherapy format with 11 children (ages 5–18) experiencing recurrent abdominal pain. Children in the treatment group (*n* = 5) participated in four weekly group psychotherapy sessions where guided imagery techniques were implemented. Data collected via pain diaries and parent and child psychological surveys showed that patients reported a 67% decrease in pain. Despite a small sample size, which contributed to low statistical power, the researchers concluded that guided imagery in a group psychotherapy format was effective in reducing pediatric recurrent abdominal pain.

However, in the majority of guided imagery studies, researchers have not evaluated the technique in the context of traditional group psychotherapy. Rather, in these studies participants usually met once in a group to learn guided imagery and then practiced guided imagery individually on their own (see Menzies et al., 2014, for more). Thus, it is unknown whether guided imagery would have different effects if implemented on an ongoing basis in group psychotherapy.

**Progressive Muscle Relaxation**

# Features of Progressive Muscle Relaxation

Progressive muscle relaxation involves diaphragmatic or deep breathing and the tensing and releasing of muscles in the body (Jacobson, 1938). Edmund Jacobson developed progressive muscle relaxation in 1929 (as cited in Peterson et al., 2011) and directed participants to practice progressive muscle relaxation several times a week for a year. After examining progressive muscle relaxation as an intervention for stress or anxiety, Joseph Wolpe (1960; as cited in Peterson et al., 2011) theorized that relaxation was a promising treatment. In 1973, Bernstein and Borkovec created a manual for helping professionals to teach their clients progressive muscle relaxation, thereby bringing progressive muscle relaxation into the fold of interventions used in cognitive behavior therapy. In its current state, progressive muscle relaxation is often paired with relaxation training and described within a relaxation framework (see Freebird Meditations, 2012, for more).

Research on the use of progressive muscle relaxation for stress reduction has demonstrated the efficacy of the method (McGuigan & Lehrer, 2007). As clients learn how to tense and release different muscle groups, the physical relaxation achieved then influences psychological processes (McCallie et al., 2006). For example, progressive muscle relaxation can help alleviate tension headaches, insomnia, pain, and irritable bowel syndrome. This research demonstrates that relaxing the body can also help relax the mind and lead to physical benefits.

# Progressive Muscle Relaxation in Group Psychotherapy

Limited, but compelling, research has examined progressive muscle relaxation within group psychotherapy. Progressive muscle relaxation has been used in outpatient and inpatient hospital settings to reduce stress and physical symptoms (Peterson et al., 2011). For example, the U.S.

Department of Veterans Affairs integrates progressive muscle relaxation into therapy skills groups (Hardy, 2017). The goal is for group members to practice progressive muscle relaxation throughout their inpatient stay and then continue the practice at home to promote ongoing relief of symptoms (Yalom & Leszcz, 2005).

Yu (2004) examined the effects of multimodal progressive muscle relaxation on psychological distress in 121 elderly patients with heart failure. Participants were randomized into experimental and control groups. The experimental group received biweekly group sessions on progressive muscle relaxation, as well as tape-directed self-practice and a revision workshop. The control group received follow-up phone calls as a placebo. Results indicated that the experimental group exhibited significant improvement in reports of psychological distress compared with the control group. Although this study incorporated a multimodal form of progressive muscle relaxation, the experimental group met biweekly in a group format; thus, the results may be applicable to group psychotherapy.

Progressive muscle relaxation has also been examined as a stress-reduction intervention with large groups, albeit not therapy groups. Rausch et al. (2006) exposed a group of 387 college students to 20 min of either meditation, progressive muscle relaxation, or waiting as a control condition. Students exposed to meditation and progressive muscle relaxation recovered more quickly from subsequent stressors than did students in the control condition. Rausch et al. (2006) concluded the following:

A mere 20 min of these group interventions was effective in reducing anxiety to normal levels . . . merely 10 min of the interventions allowed [the high-anxiety group] to recover from the stressor. Thus, brief interventions of meditation and progressive muscle relaxation may be effective for those with clinical levels of anxiety and for stress recovery when exposed to brief, transitory stressors. (p. 287)

Thus, even small amounts of progressive muscle relaxation can be beneficial for people experiencing anxiety.

**Guided Imagery and Progressive Muscle Relaxation in Group Psychotherapy** Combinations of relaxation training techniques, including guided imagery and progressive muscle relaxation, have been shown to improve psychiatric and medical symptoms when delivered in a group psychotherapy context (Bottomley, 1996; Cunningham & Tocco, 1989). The research supports the existence of immediate and long-term positive effects of guided imagery and progressive muscle relaxation delivered in group psychotherapy (Baider et al., 1994). For example, Cohen and Fried (2007) examined the effect of group psychotherapy on 114 women diagnosed with breast cancer. The researchers randomly assigned participants to three groups: (a) a control group, (b) a relaxation psychotherapy group that received guided imagery and progressive muscle relaxation interventions, or (c) a cognitive behavioral therapy group. Participants reported less psychological distress in both intervention groups compared with the control group, and participants in the relaxation psychotherapy group reported reduced symptoms related to sleep and fatigue. The researchers concluded that relaxation training using guided imagery and progressive muscle relaxation in group psychotherapy is effective for relieving distress in women diagnosed with breast cancer. These results further support the utility of guided imagery and progressive muscle relaxation within the group psychotherapy modality.

**Conclusion**

# Limitations of Existing Research

Research on the use of guided imagery and progressive muscle relaxation to achieve stress reduction and relaxation is compelling but has significant limitations. Psychotherapy groups that implement guided imagery and progressive muscle relaxation are typically homogeneous, time limited, and brief (Yalom & Leszcz, 2005). Relaxation training in group psychotherapy typically includes only one or two group meetings focused on these techniques (Yalom & Leszcz, 2005); thereafter, participants are usually expected to practice the techniques by themselves (see Menzies et al., 2014). Future research should address how these relaxation techniques can assist people in diverse groups and how the impact of relaxation techniques may be amplified if treatments are delivered in the group setting over time.

Future research should also examine differences in inpatient versus outpatient psychotherapy groups as well as structured versus unstructured groups. The majority of research on the use of guided imagery and progressive muscle relaxation with psychotherapy groups has used unstructured inpatient groups (e.g., groups in a hospital setting). However, inpatient and outpatient groups are distinct, as are structured versus unstructured groups, and each format offers potential advantages and limitations (Yalom & Leszcz, 2005). For example, an advantage of an unstructured group is that the group leader can reflect the group process and focus on the “here and now,” which may improve the efficacy of the relaxation techniques (Yalom & Leszcz, 2005). However, research also has supported the efficacy of structured psychotherapy groups for patients with a variety of medical, psychiatric, and psychological disorders (Hashim & Zainol, 2015; see also Baider et al., 1994; Cohen & Fried, 2007). Empirical research assessing these interventions is limited, and further research is recommended.

# Directions for Future Research

There are additional considerations when interpreting the results of previous studies and planning for future studies of these techniques. For example, a lack of control groups and small sample sizes have contributed to low statistical power and limited the generalizability of findings. Although the current data support the efficacy of psychotherapy groups that integrate guided imagery and progressive muscle relaxation, further research with control groups and larger samples would bolster confidence in the efficacy of these interventions. In order to recruit larger samples and to study participants over time, researchers will need to overcome challenges of participant selection and attrition. These factors are especially relevant within hospital settings because high patient turnover rates and changes in medical status may contribute to changes in treatment plans that affect group participation (L. Plum, personal communication, March 17, 2019). Despite these challenges, continued research examining guided imagery and progressive muscle relaxation interventions within group psychotherapy is warranted (Scherwitz et al., 2005). The results thus far are promising, and further investigation has the potential to make relaxation techniques that can improve people’s lives more effective and widely available.

# References

Achterberg, J. (1985). *Imagery in healing*. Shambhala Publications.

American Psychological Association. (2017). *Stress in America: The state of our nation*.

<https://www.apa.org/news/press/releases/stress/2017/state-nation.pdf>

Baider, L., Uziely, B., & Kaplan De-Nour, A. (1994). Progressive muscle relaxation and guided imagery in cancer patients. *General Hospital Psychiatry*, *16*(5), 340–347. [https://doi.org/10.1016/0163-](https://doi.org/10.1016/0163-8343(94)90021-3)

[8343(94)90021-3](https://doi.org/10.1016/0163-8343(94)90021-3)

Ball, T. M., Shapiro, D. E., Monheim, C. J., & Weydert, J. A. (2003). A pilot study of the use of guided imagery for the treatment of recurrent abdominal pain in children. *Clinical Pediatrics*, *42*(6),

527–532[. https://doi.org/10.1177/000992280304200607](https://doi.org/10.1177/000992280304200607)

Bernstein, D. A., & Borkovec, T. D. (1973). *Progressive relaxation training: A manual for the helping professions*. Research Press.

Bottomley, A. (1996). Group cognitive behavioural therapy interventions with cancer patients: A review of the literature. *European Journal of Cancer Cure*, *5*(3), 143–146.

<https://doi.org/10.1111/j.1365-2354.1996.tb00225.x>

Cohen, M., & Fried, G. (2007). Comparing relaxation training and cognitive-behavioral group therapy for women with breast cancer. *Research on Social Work Practice*, *17*(3), 313–323.

<https://doi.org/10.1177/1049731506293741>

Cunningham, A. J., & Tocco, E. K. (1989). A randomized trial of group psychoeducational therapy for cancer patients. *Patient Education and Counseling*, *14*(2), 101–114.

<https://doi.org/10.1016/0738-3991(89)90046-3>

Freebird Meditations. (2012, June 17). *Progressive muscle relaxation guided meditation* [Video].

YouTube. <https://www.youtube.com/watch?v=fDZI-4udE_o>

Hardy, K. (2017, October 8). Mindfulness is plentiful in “The post-traumatic insomnia workbook.”

*Veterans Training Support Center*[. http://bit.ly/2D6ux8U](http://bit.ly/2D6ux8U)

Hashim, H. A., & Zainol, N. A. (2015). Changes in emotional distress, short term memory, and sustained attention following 6 and 12 sessions of progressive muscle relaxation training in 10–11 years old primary school children. *Psychology, Health & Medicine*, *20*(5), 623–628.

<https://doi.org/10.1080/13548506.2014.1002851>

Holden-Lund, C. (1988). Effects of relaxation with guided imagery on surgical stress and wound healing.

*Research in Nursing & Health*, *11*(4), 235–244[. http://doi.org/dztcdf](http://doi.org/dztcdf)

Jacobson, E. (1938). *Progressive relaxation* (2nd ed.). University of Chicago Press.

Lange, S. (1982, August 23–27). *A realistic look at guided fantasy* [Paper presentation]. American

Psychological Association 90th Annual Convention, Washington, DC.

McCallie, M. S., Blum, C. M., & Hood, C. J. (2006). Progressive muscle relaxation. *Journal of Human*

*Behavior in the Social Environment*, *13*(3), 51–66[. http://doi.org/b54qm3](http://doi.org/b54qm3)

McGuigan, F. J., & Lehrer, P. M. (2007). Progressive relaxation: Origins, principles, and clinical

applications. In P. M. Lehrer, R. L. Woolfolk, & W. E. Sime (Eds.), *Principles and practice of stress management* (3rd ed., pp. 57–87). Guilford Press.

Menzies, V., Lyon, D. E., Elswick, R. K., Jr., McCain, N. L., & Gray, D. P. (2014). Effects of guided imagery on biobehavioral factors in women with fibromyalgia. *Journal of Behavioral Medicine*, *37*(1), 70–

80[. https://doi.org/10.1007/s10865-012-9464-7](https://doi.org/10.1007/s10865-012-9464-7)

Peterson, A. L., Hatch, J. P., Hryshko-Mullen, A. S., & Cigrang, J. A. (2011). Relaxation training with and without muscle contraction in subjects with psychophysiological disorders. *Journal of Applied*

*Biobehavioral Research*, *16*(3–4), 138–147. <https://doi.org/10.1111/j.1751-9861.2011.00070.x>

Rausch, S. M., Gramling, S. E., & Auerbach, S. M. (2006). Effects of a single session of large-group meditation and progressive muscle relaxation training on stress reduction, reactivity, and recovery. *International Journal of Stress Management*, *13*(3), 273–290.

<https://doi.org/10.1037/1072-5245.13.3.273>

Scherwitz, L. W., McHenry, P., & Herrero, R. (2005). Interactive guided imagery therapy with medical patients: Predictors of health outcomes. *The Journal of Alternative and Complementary*

*Medicine*, *11*(1), 69–83. <https://doi.org/10.1089/acm.2005.11.69>

Skovholt, T. M., & Thoen, G. A. (1987). Mental imagery and parenthood decision making. *Journal of*

*Counseling & Development*, *65*(6), 315–316. <http://doi.org/fzmtjd>

Trakhtenberg, E. C. (2008). The effects of guided imagery on the immune system: A critical review.

*International Journal of Neuroscience*, *118*(6), 839–855[. http://doi.org/fxfsbq](http://doi.org/fxfsbq)

Utay, J., & Miller, M. (2006). Guided imagery as an effective therapeutic technique: A brief review of its history and efficacy research. *Journal of Instructional Psychology*, *33*(1), 40–43.

White, J. R. (2000). Introduction. In J. R. White & A. S. Freeman (Eds.), *Cognitive-behavioral group therapy: For specific problems and populations* (pp. 3–25). American Psychological Association. <https://doi.org/10.1037/10352-001>

Yalom, I. D., & Leszcz, M. (2005). *The theory and practice of group psychotherapy* (5th ed.). Basic Books.

Yu, S. F. (2004). *Effects of progressive muscle relaxation training on psychological and health-related quality of life outcomes in elderly patients with heart failure* (Publication No. 3182156) [Doctoral dissertation, The Chinese University of Hong Kong]. ProQuest Dissertations and Theses Global.

Journal of Physics: Conference Series

**PAPER • OPEN ACCESS**

# Rock images classification by using deep convolution neural network

To cite this article: Guojian Cheng and Wenhui Guo 2017 *J. Phys.: Conf. Ser.* **887** 012089

View the [article online](https://doi.org/10.1088/1742-6596/887/1/012089) for updates and enhancements.

Related content

* [Fuzzy Logic Module of Convolutional](http://iopscience.iop.org/article/10.1088/1742-6596/738/1/012123)

[Neural Network for Handwritten Digits](http://iopscience.iop.org/article/10.1088/1742-6596/738/1/012123)

[Recognition](http://iopscience.iop.org/article/10.1088/1742-6596/738/1/012123)

E.A. Popko and I.A. Weinstein

* [Energy reconstruction in a highly granularity semi-digital hadronic calorimeter](http://iopscience.iop.org/article/10.1088/1742-6596/664/7/072033) Sameh Mannai, Kais Manai, Eduardo Cortina et al.
* [Temporal Classification Error Compensation of Convolutional Neural](http://iopscience.iop.org/article/10.1088/1742-6596/806/1/012007)

[Network for Traffic Sign Recognition](http://iopscience.iop.org/article/10.1088/1742-6596/806/1/012007)

Seungjong Yoon and Eungtae Kim

This content was downloaded from IP address 154.16.44.133 on 09/09/2017 at 21:45

**Rock images classification by using deep convolution neural network**

## Guojian Cheng and Wenhui Guo

School of Computer Science, Xi’an Shiyou University, Xi’an Shanxi, 710065, China. Email: gjcheng@xsyu.edu.cn, 846522705@qq.com

**Abstract.** Granularity analysis is one of the most essential issues in authenticate under microscope. To improve the efficiency and accuracy of traditional manual work, an convolutional neural network based method is proposed for granularity analysis from thin section image, which chooses and extracts features from image samples while build classifier to recognize granularity of input image samples. 4800 samples from Ordos basin are used for experiments under colour spaces of HSV, YCbCr and RGB respectively. On the test dataset, the correct rate in RGB colour space is 98.5%, and it is believable in HSV and YCbCr colour space. The results show that the convolution neural network can classify the rock images with high reliability.

### **1. Introduction**

For the effective development of reservoirs, it is necessary to provide a comprehensive reservoir description and characterization to determine the underground gas content. Granularity analysis is an important work of it[1]. The traditional method for rock classification is a manual work with many problems such as time-consuming and low accuracy. With the development of science and technology, Artificial intelligence is successfully applied in all walks of life. Many domestic and foreign scholars have done researches in the automatic classification of rock images, such as, Cheng Guojian and Liu Ye[2-3] used shallow neural network and SVM to classify rock images. Mariusz Młynarczuk et al.[4] performed the Classification of thin rock images respectively in RGB, CIELab, YIQ and HSV colour spaces using the nearest neighbour algorithm, K-nearest neighbour, the nearest pattern algorithm, and the optimized spherical neighbourhood; Hossein Izadi et al.[5] established a neural network to identify the rock mineral, whose accuracy was 93.81%. The above methods show that the application of machine learning in rock classification can improve its efficiency and accuracy.

However, using machine learning to classify rock images still has the following shortcomings. Firstly, to classify rock images by machine learning is based on the premise of artificial extraction of image features. Secondly, if the images are large, training a shallow neural network is almost impossible.

Convolution neural network (CNN) is an important deep learning architecture. It can extract the image features automatically and has a high classify accuracy. CNN has achieved a wide range of applications such as plant classification, face recognition, handwritten Chinese character recognition and so on[6-8]. In this paper, we construct a new convolution neural network for rock classification, rock images respectively in RGB, HSV, YCbCr colour spaces are used to train it, then contrasted the results and choose the best one.

### **2. The Rock Images**

It is usually determined by professional geological researchers for types and structural parameters of rocks after identifying rock thin section under polarized light microscopy. The rock images used in

Content from this work may be used under the terms of the[CreativeCommonsAttribution 3.0 licence.](http://creativecommons.org/licenses/by/3.0) Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

Published under licence by IOP Publishing Ltd

this paper are all feldspar sandstones collected from an oil field in Ordos, they are divided into three types: (1) Coarse feldspar sandstones, as is shown in figure 1(a). (2) Medium granular feldspar sandstone, as is shown in figure 1(b). (3) Fine feldspar sandstone, as is shown in figure 1(c).

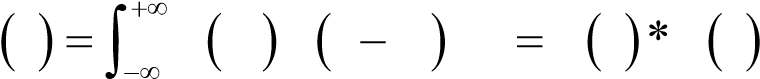
  

### (a) Course feldspar sandstone (b) Medium granular feldspar sandstone (c) Fine feldspar sandstone **Figure 1.** Example of three types of rock images

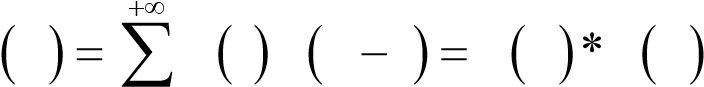
#### 3. Convolution Neural Network

CNN was proposed by LeCun et al. [9] inspired by natural mechanisms in the 1990s.CNN are composed of several convolutional layers alternately connected with a number of pooling layers and can effectively characterize the essential features of the original image. It needs very little pre-process with original image. Convolution operations include continuous convolutions and discrete convolutions. The formulas are shown as Formula (1) and Formula (2):

Continuous convolution:

 *y t x p h t p dp x t h t* (1)

Discrete convolution:

*y n* *x i h n i x n h n* (2)

*i*=−∞

There are some challenges in using CNN such as how many convolutional layers, how large the size of convolutional kernel and the learning rate of the network should be set are all worth to study carefully.

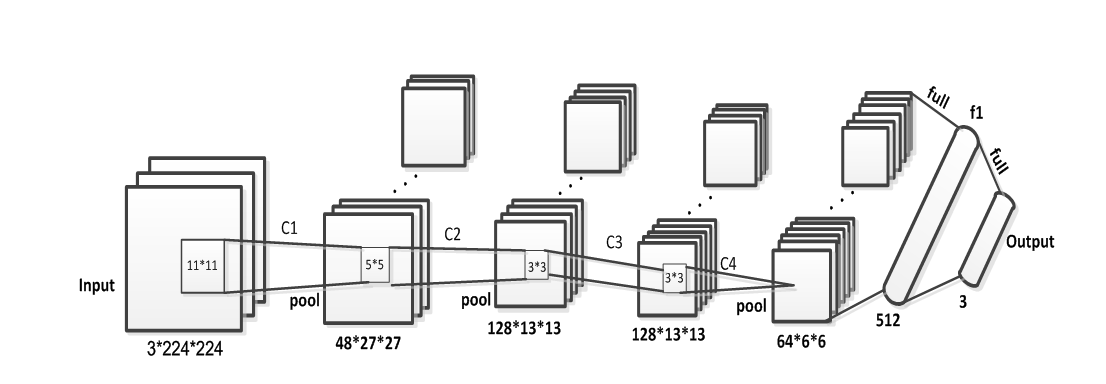
#### 4. Experiment

##### 4.1. Data Sources

In this paper, 4800 rock images in RGB colour space are selected as experimental samples, normalize the size of them to 224\*224. There are 1600 coarse-grained rock images, 1600 medium-grained rock images and 1600 fine-grained rock images. And 1200 rock images of each type are used as the training set, the remaining 400 are used as the test set. Then converting the 4800 rock images to YCbCr colour space and HSV colour space respectively, whose training set and test set distribution remains unchanged.

##### 4.2. The Architecture

The convolution neural network structure designed in this paper is shown in figure 2, which is a 6-layer structure, 4 layers are convoluted and 2 layers are fully connected. The convolution layers use ReLU [10] as the activation function and the fully connected layers do classification by the Softmax classifier.



### **Figure 2.** CNN structure

The original image is in RGB colour space, convert it to an RGB three-channel grayscale image as input. As is shown in figure 2 (The marks of the pooling layers S1, S2 and S3 are omitted in the figure), the size of the input image is 224\*224. The first convolution layer C1 uses 48 convolution kernels of 11\*11 (convolution step is 4 pixels) to obtain 48 feature maps of 56\*56 by convolution operation, and then let the 48 feature maps go through a pooling layer with a window whose size is 3\*3 (moving step is 2 pixels) obtaining 48 feature maps of 27\*27(S1). The second convolution layer C2 takes S1 as input and convolves them with 64 convolution kernels of 5\*5 (convolution step is 1 pixel) to obtain 64 slices of 27\*27 feature map, then let the 64 feature maps go through a pooling layer with a window whose size is 3\*3 (moving step size of 2 pixels) to get 64 feature maps S2 whose size are 13\*13(S2).The third convolution layer C3 takes S2 as input and convolves them with 128 convolution kernels of 3\*3 (convolution step size of 1 pixel) to obtain 128 slices of 13\*13 feature map. The fourth convolution layer C4 takes the 128 slices feature map as input and convolves them with 64 convolution cores of 3\*3 (convolution step size of 1 pixel) to obtain 64 feature maps whose size are 13\*13. Then let these 64 feature maps go through a pooling layer with a window size of 3\*3 (moving in steps of 2 pixels) to obtain 64 feature maps whose size are 6\*6(S3). Finally, transforming the result into a one-dimensional vector and use it as the input of the fully connected layer, which is connected with the fully connected layer f1 which has 512 neurons and classifies the rock images according to its granularity size by the Softmax classifier.

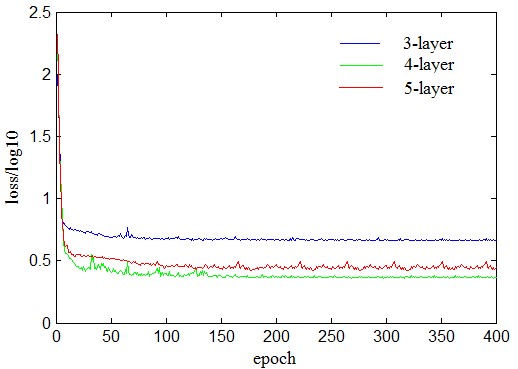
#### 4.3. Architecture Adjustment

The experimental data is loaded into memory by batch whose size is 100. An iteration is performed while a batch of data is loaded, where the dropout is set to 0.5.

*4.3.1. Number of layers.* Setting an appropriate number of convolution layers is one of the key steps in constructing a CNN. If the convolution layers are too less, the network will be not able to learn the essential features of the original image, if there are too many convolution layers, it may lead the network over-fitting. In this paper, the number of convolution layers of 5, 4 and 3 are studied respectively. Compared the convergence and error rate while each network has been subjected to 400 iterations, the results are shown in table 1 and figure 3.

### **Table 1.** Error rate of different convolution layers

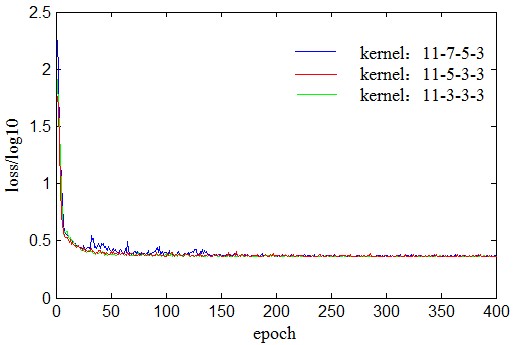
|  |  |  |  |
| --- | --- | --- | --- |
| Number of convolution layers | 5 | 4 | 3 |
| Network structure | 11-7-5-3-3 | 11-7-5-3 | 11-7-5 |
| Error rate | 16.4% | 3.1% | 5.1% |



### **Figure 3.** Network loss function for different convolution layers

It can be seen from figure.3 and table 1 that whenever the number of convolution layers is 3, 4 or 5, the network can converge quickly. However, when the 4-layer convolution structure is used, the loss function and the error rate are the lowest.

*4.3.2. Convolution kernel.* Convolution kernel size is another important factor affecting the efficiency of CNN. When using a 4-layer CNN, the convolution kernel size of it is set to 11-7-5-3, 11-5-3-3 and 11-3-3-3 respectively for experiment in this paper. After 400 iterations, the error rate is shown in Table 2 and the loss function curve is shown in Figure.4.



**Figure 4.** Loss function of different convolution kernel network

### **Table 2.** Error rate of different convolution kernel network

|  |  |  |  |
| --- | --- | --- | --- |
| Network structure | 11-7-5-3 | 11-5-3-3 | 11-3-3-3 |
| Error rate | 3.1% | 1.5% | 2.4% |

From table 2 and figure.4, we can see that setting the convolution kernel size to 11-7-5-3, 11-5-3-3, 11-3-3-3 respectively, the network all can get convergence fast. However, when it is 11-7-5-3, the network convergence fluctuates greatly than the other two. But, the network with convolution kernel of 11-5-3-3 has the lowest error rate. Therefore, a 4-layer CNN whose convolution kernel is 11-5-3-3 is used in this paper.

*4.3.3. Learning rate.* Learning rate is a key factor influencing the convergence rate and classification accuracy. When a 4-layer CNN whose convolution kernel size is 11-5-3-3 by setting the initial learning rate as 0.01, 0.001, 0.0005, 0.0001 respectively, the error rate and iterations times are shown in Table 3.

### **Table 3.** Relationship between convergence and learning rate

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Learning rate | 0.01 | 0.001 | 0.0005 | 0.0001 |
| Convergence iterations | Doesn’t converge | 26 | 21 | 39 |
| Error rate of test set | 56.8% | 3.6% | 1.5% | 7.5% |

It can be seen from table 3 that when the initial learning rate is 0.01 the network does not converge because of the gradient step is too large and deviates from the optimal point. When the initial learning rate is 0.001, the gradient step is larger and the convergence speed of the network is slower and the error classification rate is lower. When the initial learning rate is 0.0005, the network convergences fast and the error classification rate is the lowest. When the initial learning rate is 0.0001, the network can convergence and finds the best point, but needs to iterate more times and the classification accuracy is lower. In summary, setting the initial learning rate as 0.0005 is the most appropriate. **5. Validation**

In order to prevent the network from over-fitting, this paper use cross-validation. Each type of rock image data set is randomly divided into ten subsets, which is 160 per subset for cross-validation. The production of data set and experimental process in YCbCr colour space and HSV colour space are consistent with that in RGB colour space. Table 4 shows the cross-validation results for RGB, YCbCr and HSV colour spaces.

### **Table 4.** Cross-validation error rates

Time Average

1

2

3

4

5

6

7

8

9

10

0

0.21

0.21

0

0.21

0

0

0

0.21

HSV 0.21 0.117

YCbCr 0.41 0.21 0 0.21 0.41 0.21 0 0.41 0 0.21 0.253

RGB 2.1 1.04 1.2 2.3 1.0 0.83 1.04 0.83 2.3 2.5 1.66

It can be seen from table 4 that the error rates of cross-validation in HSV, YCbCr and HSV colour spaces are all small. So the network does not appear the over-fitting phenomenon in the three colour spaces.

Granularity analysis can provide authenticate researchers essential basis for determining types and structural parameters of rocks, but it is a manual work with low reliability in traditional. However, the experiment results above shows that do the rock granularity analysis using CNN is with high accuracy which could improve the reliability and efficiency.

#### 6. Conclusion

In this paper, CNN is used to identify the rock granularity. The experiments show that it has high reliability whether in HSV, YCbCr or RGB colour space. In RGB colour space, the classification accuracy achieves 98.5% with high efficiency. However, the experimental results still have deviation may be caused by the use of single polarized images. The next step of study can be committed to multi-polarized light in the rock image. In view of the high reliability of the application of CNN in rock image classification based on rock granularity, it can be considered to apply to the classification of rock components.

#### 7. Acknowledgments

The main project is supported by the National Science and Technology (No.2011ZX05044) and Shaanxi Province industrial science and technology (No.2015GY104).

#### 8. References

1. Wang Pujun, Jiao Yangyang, Uang Kaikai, Zengbao, Bian Weihua, Classification ofVolcanogenic Successions and Its Application to Volcanic Reservoir Exploration in the Junggar Basin, NW China, Journal of Jilin University(Earth Science Edition), Volume 46,No.4,July 2016, Pages1056-1070
2. Cheng Guojian,Ma Wei,Wei Xinshan, Rong Chunlong,Nan Junxiang, Research of rock texture identification based on image processing and neural network, Journal of Xi'an Shiyou

University( Natural Science Edition), Volume 28, September 2013, Pages 105-109

1. Guo Chao, Liu Ye, Recognition of Rock Images Based on Multiple Colour Spaces, Science Technology and Engineering, Volume 14, June 2014, Pages 247-251+255
2. Mariusz Młynarczuk, Andrzej Górszczyk, Bartłomiej Ślipek, The application of pattern recognition in the automatic classification of microscopic rock images, Computers &

Geosciences, Volume 60, October 2013, Pages 126-133

1. Hossein Izadi, Javad Sadri, Mahdokht Bayati, An intelligent system for mineral identification in thin sections based on a cascade approach, Computers & Geosciences, Volume 99, February 2017, Pages 37-49, ISSN 0098-3004
2. Yuma Mikia, Chisako Muramatsua, Tatsuro Hayashib, Xiangrong Zhoua, Takeshi Haraa,Akitoshi Katsumatac, Hiroshi Fujitaa, Classification of teeth in cone-beam CT using deep convolutional neural network[J], Computers in Biology and Medicine 80 (2017) 24–29
3. Mads Dyrmann, Henrik Karstoft, Henrik Skov Midtiby, Plant species classification using deep convolutional neural network[J], biosystemsengineering151(2016)72-80
4. André Teixeira Lopes a, Edilson de Aguiar b, Alberto F. De Souza a, Thiago Oliveira-Santos, Facial expression recognition with Convolutional Neural Networks:Coping with few data

and the training sample order[J], Pattern Recognition 61 (2017) 610–628

1. Hinton G E, Salakhutdinov R. Reducing the dimensionality of data with neural networks [J].Science, 2006, 313(5786):504-507.
2. Krizhevsky A, Sutskever I, Hinton G E. Imagenet classification with deep convolutional neural networks[C] Advances in neural information processing systems (NIPS 2012), 2012: 1097-1105.