DETECTING MILD TRAUMATIC BRAIN INJURY USING DYNAMIC LOW LEVEL CONTEXT

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ABSTRACT

Mild traumatic brain injury is difficult to detect in standard magnetic resonance (MR) images due to the low contrast appearance of lesions. In this paper a discriminative approach is presented, using a classifier to directly estimates the posterior probability of lesion at every voxel using low-level context learned from previous classifiers. Both visual features including multiple texture measures, and context features, which include novel features such as proximity, directional distance, and posterior marginal edge distance, are used. The context is also taken from previous time points, so the system automatically captures the dynamics of the injury progression. The approach is tested on an mTBI rat model using MR imaging at multiple time points. Our results show an improved performance in both the dice score and convergence rate compared to other approaches.

Index Terms— Context, Magnetic Resonance Imaging, Traumatic Brain injury, Low Contrast, Dynamic

1. INTRODUCTION

Awareness of mild traumatic brain injury (mTBI) has increased dramatically in recent years. Causes of mTBI include sports injuries, automobile accidents, blast injuries in the military, and falls in the workplace [1]. The long term effects of mTBI are just being recognized, leading to the need for quantitative techniques to characterize and measure the injured tissue.

Clinical evaluation of mTBI has been qualitative relying on the Glasgow Coma Scale, to assess loss of consciousness, loss of memory, alteration in mental status, and focal neurological deficits. When imaging is used to assist in diagnosis, MR imaging or computed tomography (CT), a quantitative measurement of the size nor location of injury is typically obtained. The primary focus of imaging is only to assess for hematoma [1]. Some computational approaches have been proposed for quantifying lesions in moderate to severe TBI [2], which have high contrast, but these have been unsuccessful when attempting to evaluate the subtle MR signature of mTBI.

Lesions caused by mTBI appear as small low contrast regions (Figure 1) in both T2 weighted images and T2maps. The T2 values within these lesions often fall within the range of normal tissue values. Therefore the T2 value of a voxel cannot be used by itself. In [3] it was shown that there are significant texture changes in brain tissues as a result of mTBI, that provides a measure of the underlying structure of the tissue. Therefore, our proposed approach uses multiple texture measures to improve the discriminative ability of mTBI detection from MR images.

Multiple sclerosis (MS) shows similar low contrast lesions. The approaches for detecting these lesions [4,5] take advantage of the knowledge that MS occurs in a specific tissue type, which is consistently located in the same location. This is a type of context that is being exploited, more specifically *anatomical context*. Context is exploited when traditional methods for detection fail. Context can be defined as information that aids in detection, but does not directly come from an image itself. In past work [6] we have used a high level contextual model that simulates the progression of the lesion to estimate the location of mTBI lesions. In this paper we propose a low level (voxel level) contextual modeling to aid in detection of mTBI. Recently [7] proposed autocontext, which is a way to model context at the pixel level. The main premise is to estimate an object

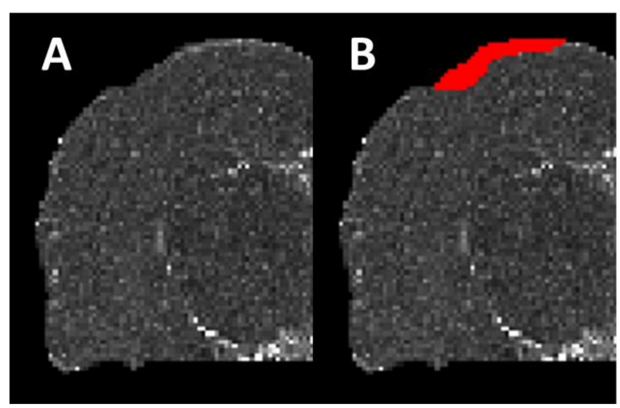

Figure 1: T2 weighted MR image from the rat model dataset. A) Original T2 weighted image. B) Manual detection of the mTBI lesion (highlighted in color). This shows the low contrast appearance of the lesions as a result of mTBI.

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with a discriminative classifier and use a sampling of the estimated posterior probability as additional features to a subsequent classifier. It is able to take information from far away compared to other methods like conditional random fields (CRF) [8] which are local. The context features in this case are a sparse sampling of a distant neighborhood around every pixel. This can lead to overfitting due to the very specific locations this can be seen in one of the examples in [7]. We adopted the idea of cascading classifiers, but developed features that are more generalizable and integrate temporal information.

The contributions of our paper are: 1) development of three new contextual features to be used with a cascade of classifiers. These features include a proximity feature, a directional feature, and a maximum a posteriori edge distance feature. 2) Use of a temporal sequence of MR images to provide context from a previous time point, capturing the dynamics of the injury progression automatically. 3) Analysis of multiple contextual feature configurations on a rat controlled cortical impact (CCI) mTBI model dataset.

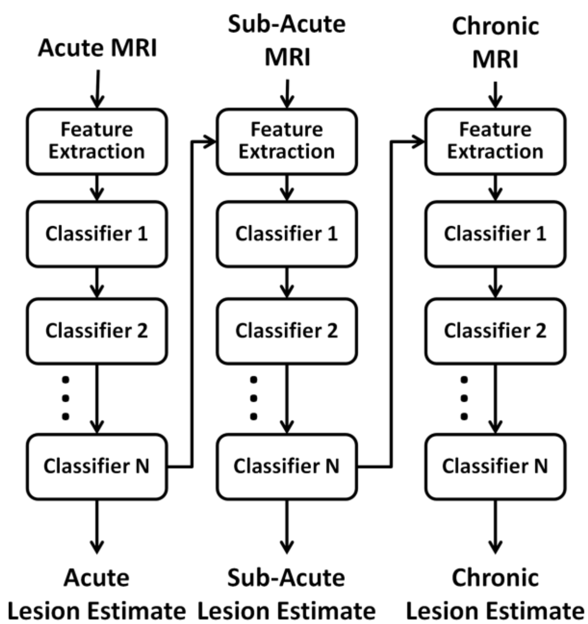

Figure 2: Overview of the proposed system. Context information is sent from one classifier to the next.

2. TECHNICAL RATIONALE

A discriminative approach is taken where classifiers are used to directly estimate the posterior probability of lesion and non-lesion voxels. The ground-truth for training the classifiers is obtained from manual segmentation. A cascade of classifiers is used for estimating the detected lesion at each time point. The first classifier in the cascade estimates the lesion using only the visual features. Then context features are made from the posterior probability map estimated by the classifier. These features are recalculated for each iteration in the process, for a given number of classifiers as shown in Figure 2. The first classifiers of the second time point, uses contextual features generated by the final classifier in the previous time point.

2.1 Visual Features

Due to the low contrast nature of the unimodal MR images and the mild nature of the TBI, texture features are used to increase discrimination. Four types of texture features are used: uniform local binary pattern (LBP) [9] in the coronal plane (59 features), statistical features (mean, variance, skewness, kurtosis) of a Gabor filter bank with 8 orientations and 4 scales in the coronal plane (128 features), basic histogram of oriented gradients in the coronal plane [10] (9 features), and basic neighborhood statistical features (mean, variance, skewness, kurtosis, range, entropy, gradient magnitude xyz) (9 features). This gives a total of 205 visual features. This wide variety of features provides many different characteristics without being too specific (i.e., they will generalize well). The classifier we have chosen, adaboost [11], inherently does feature selection.

2.2 Contextual Features

The contextual features come from the posterior probability estimated by an already learned classifier. Previous approaches [7] have directly sampled a dense neighborhood around an observed voxel, making each location a potential feature. This method can lead to large feature sizes and can cause overfitting due to the specific locations that are learned. In this paper, two new features are proposed to overcome this problem. One incorporates a sense of the surrounding without a known direction, while the other gives a general sense of direction.

The first feature, shown in Figure 3A, gives the average posterior probability at various distances around the observed voxel. This can be thought of as what is a close, medium and far away in distance. The distance function used here is the Manhattan distance allowing for a cuboidal region. These features are directionally invariant and can

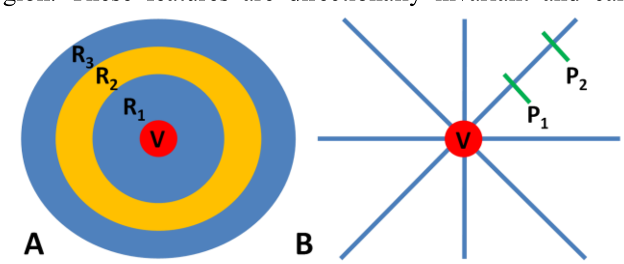

Figure 3: A) Illustration of the proximity feature. V is the observed voxel and the feature is the average probability of the regions (R_1, R_2, R_3). B) Illustration of the distance features. V is the observed voxel and an example feature is the average probability between P_1 and P_2 along the 45° ray.

lead to better generalization since they describe a general area. By having a nesting of boxes the integral image can be utilized for quick computation of the features. In 3D only 8 point are needed to find the average of a cuboidal region, using integral images [12]. Equation 1 provides these features, where f_{xyz} is the proximity feature and B_{1xyz}, B_{2xyz} are square neighborhoods around the voxel at xyz.

$$f_{xyz} = \left(\sum B_{1xyz} - \sum B_{2xyz}\right)\left(\frac{1}{size(B_{1xyz}) - size(B_{2xyz})}\right) \quad (1)$$

Directional information is important for classification since the objects are rigidly registered. The second contextual feature describes the posterior probability in various directions from the observed voxel. Rays are sampled at various distance ranges and angles from the observed voxel (see Figure 3B). From the distance ranges along the rays the mean is calculated. This gives a refined sense of the surrounding. An example would be what is close and above the observed voxel. The integral image can also be used to calculate these features. Both features can be used at coarse or fine distance bins without a significant increase in computational time.

The posterior marginal edge distance (PMED) feature is the distance a voxel is from the perimeter of objects of a class found by the maximum posterior marginal (MPM) estimate. To create this feature first the MPM at a voxel is obtained from a classifier. This gives a binary image for each class. The distance transform is applied to the image and the inverse image and the feature is given by equation 2.

$$\text{PMED} = \text{d}(\text{MPM}) - \text{d}(\sim\text{MPM}) \quad (2)$$

$$MPM = \underset{c}{\text{argmax}}\, p(\omega = c|f) \quad (3)$$

Here d() is the distance transform. This gives an image that is increasing as the voxels become farther away from the edge and smaller (more negative) as the voxels get further into the object. Where ω is the estimated class, c is a specific class (lesion or normal brain in our case), and f is the features at a given voxel (see Figure 4).

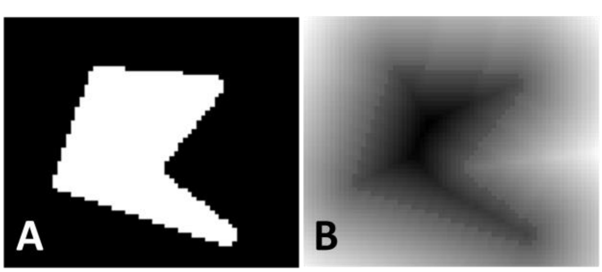

Figure 4: A) Example MAP estimate. B) Corresponding MAPED feature. Note that the values become more negative towards the center of the object and more positive farther away from the object.

2.3 Classifier

The classifier being used is adaboost [11] with small decision trees as base classifiers. Using small trees as a weak classifier ($h()$) allows for inherent feature selection, mean erroneous features are disregarded. In each iteration (t), the best classifier is selected and weighted with α. During the training process a cost matrix is used, such that the priors are offset to be even. This is done to account for the large disparity between the classes. It has been shown that the posterior marginal can be estimated using logistic regression [7] (equation 4). An example of the training process is shown in Figure 5.

$$p(\omega_{xyz} = c|f_{xyz}) = \frac{e^{H_c(f_{xyz})}}{\sum_{c=1}^{C} e^{H_c(f_{xyz})}} \quad (4)$$

$$H_c(f_{xyz}) = \sum_{t=1}^{T} \alpha_t h_t(f_{xyz}) \quad (5)$$

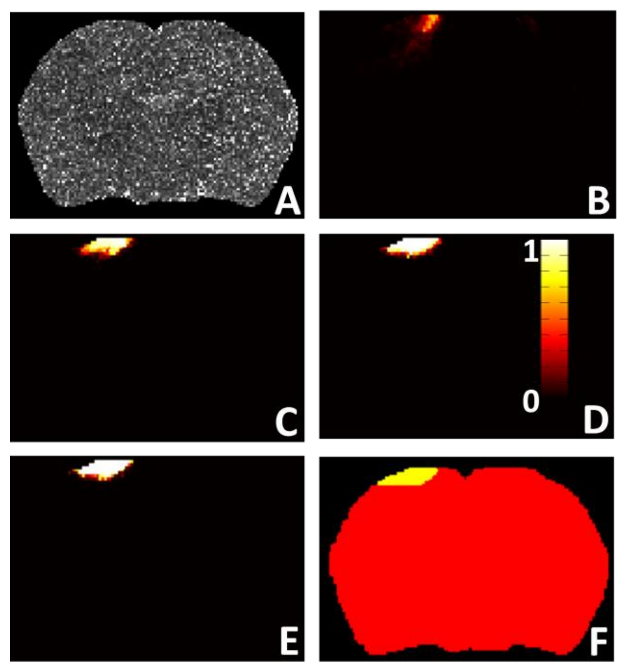

Figure 5: Example probability maps after each classifier. A) T2 MRI. B-E) Classifier output probability map for the training of classifier 1-4 respectively. (F) Manual Segmentation where yellow denotes the lesion. This shows the convergence of the algorithm to the manually segmented injury.

3. EXPERIMENTAL RESULTS

3.1 Dataset

Sprague Dawley rats were used as an animal model of mTBI using single impact controlled cortical impact (CCI). The animals were imaged at 3 time points post injury: acute

Figure 7: Qualitative of the proposed approach. Each coronal slice is from a separate volume. Color code: yellow = true positive, black = true negative, orange = false negative, brown = false positive.

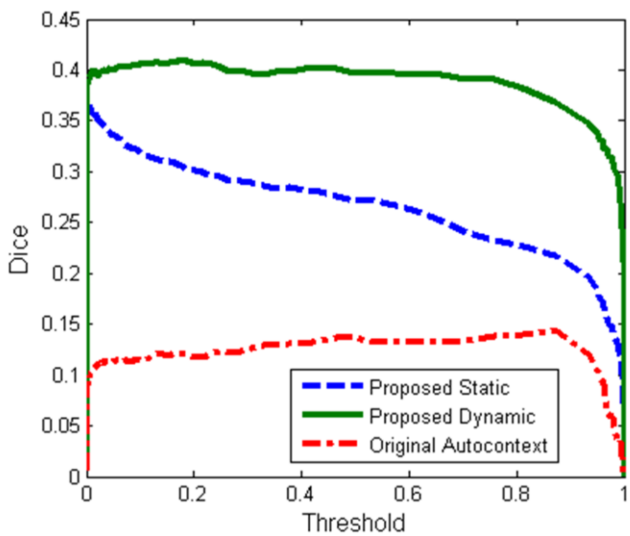

Figure 6: Dice value after thresholding the posterior probability map.

(1[st]day), sub-acute (8[th] day), and chronic (14[th] day). There are a total of 6 sequences (each with 3 time points). MRI data were acquired using a Bruker Advance 4.7T for T2 weighted images (T2WI; TR/TE/FA=3453 ms/20 ms/20°, 25x1 mm slices) with a 256x256 matrix and 3cm field of view. The images were converted to T2 maps. ROIs were manually segmented using Cheshire image processing software (Hayden Image/Processing Group, Waltham, MA) and included the right and left hemispheres and injured tissue volumes that were defined as abnormal (hyper/hypo-intense) signal intensities within the cortex with the remaining tissues designated as normal appearing brain matter.

3.2 Comparison of Features

Here the effect of the proposed features and effect of the dynamic information is examined. For the training/testing split leave-one-out validation is used where a whole sequence is left out (resulting in 6 folds). The parameters used were: 300 weak learners, learning rate 1, and 4 cascaded classifiers. Three approaches were tested: the original autocontext features [7], the proposed approach with only the new features (Proposed Static), and the proposed approach with the new features and the dynamic information (Proposed Dynamic).

From Figure 6 it is clear that the proposed dynamic approach outperforms the other methods. This shows it is important to use the dynamic information. The original autocontext tends to over fit due the specific locations the features represent. During the training phase it obtains a dice score above 0.9, but it does not generalize to the testing data. The proposed approach has a very flat dice curve, so it is not sensitive to a chosen threshold. This makes the selection of a threshold less critical. From the qualitative results (Figure 7) it is clear that the results of proposed dynamic approach work on small to medium size lesions and false positive are only close to the majority of the lesion.

4. CONCLUSIONS

A fully automated method of detecting lesions from a mTBI that integrates low-level dynamic context is proposed. Three new features are proposed that describe the posterior probability of classifier outputs in a cascade. These feature were shown the have good qualitative and quantitative results. The proposed approach outperformed the original autocontext [7], by being able to generalize. This approach performed well on a small training set, with a larger training set this method performance should increase further.

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5. REFERENCES

[1] T. Morris, "Traumatic Brain Injury," in Handbook of Medical

Neuropsychology, C.L. Armstrong and L. Morrow, eds., Springer New York, 2010, pp. 17-32.

[2] A. Irimia, et al., “Comparison of acute and chronic traumatic brain injury using semi-automatic multimodal segmentation of MR volumes”. Journal of Neurotrauma. 28(11):2287:2306, 2011.

[3] K. Holli, et al., “Texture analysis of MR images of patients with Mild Traumatic Brain Injury.” BMC Medical Imaging, 10(1), 2010.

[4] P. Anbeek, et al., “Automatic segmentation of different-sized white matter lesions by voxel probability estimation,” Medical Image Analysis, 8(3):205-215, 2004.

[5] F. Kruggel, et al., “Texture-based segmentation of diffuse lesions of the brain’s white matter,” NeuroImage, 39(3):987-996, 2008.

[6] A. Bianchi, et al., “Contextual and visual modeling for detection of mild traumatic brain injury in MRI,” ICIP, Orlando, FL, 2012.

[7] Z. Tu and X. Bai, “Auto-Context and Its Application to High-Level Vision Tasks and 3D Brain Image Segmentation,” IEEE TPAMI, 32(10):1744-1757, Oct. 2010.

[8] J. Lafferty, et al., “Conditional Random Fields: Probabilistic Models for Segmenting and Labeling Sequence Data,” Proc. 10th Int’l Conf. Machine Learning, pp. 282-289, 2001.

[9] T. Ojala, et al., “Multiresolution gray-scale and rotation invariant texture classification with Local Binary Patterns,” IEEE TPAMI, 24(7):971-987, 2002.

[10] N. Dalal and B. Triggs, “Histograms of oriented gradients for human detection,” CVPR, pp.886-893, June 2005.

[11] Freund, Y. and R. E. Schapire, “A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting.” J. of Computer and System Sciences, 55:119–139, 1997.

[12] P. Viola and M. J. Jones, "Rapid Object Detection using a Boosted Cascade of Simple Features", CVPR, pp.511–518, 2001.