BRAIN TUMOUR DIAGNOSIS USING MACHINE LEARNING

Thatchana, Visiting PhD Researcher from the Department of Experimental Molecular Imaging, University Hospital Aachen, Germany shares his expertise on the matter.

A brain tumour is a group of abnormal cells that grows in or around the brain. Tumours can directly destroy healthy brain cells. They can also indirectly damage healthy cells by crowding other parts of the brain and causing inflammation, brain swelling and pressure within the skull. Brain tumours are either malignant or benign. A malignant tumour, also called brain cancer, grows rapidly and often invades or crowds healthy areas of the brain. Benign brain tumours do not contain cancer cells. They look normal under a microscope and are usually slow growing. Brain tumours fall into two different categories: Primary or metastatic. Primary brain tumours begin within the brain. A metastatic tumour is formed when cancer cells located elsewhere in the body break away and travel to the brain. For this reason, metastatic brain tumours are almost always malignant, while primary brain tumours may be benign or malignant. Brain tumours are classified based on where the tumour is located, the type of tissue involved, whether the tumour is benign or malignant, and other factors. If a tumour is determined malignant, the tumour cells are examined under a microscope to determine how malignant they are. In the Malaysia, over 1,000 people are diagnosed with a brain tumour every year (2013 estimates). There are about 200 other types of tumours diagnosed in Malaysia each year.

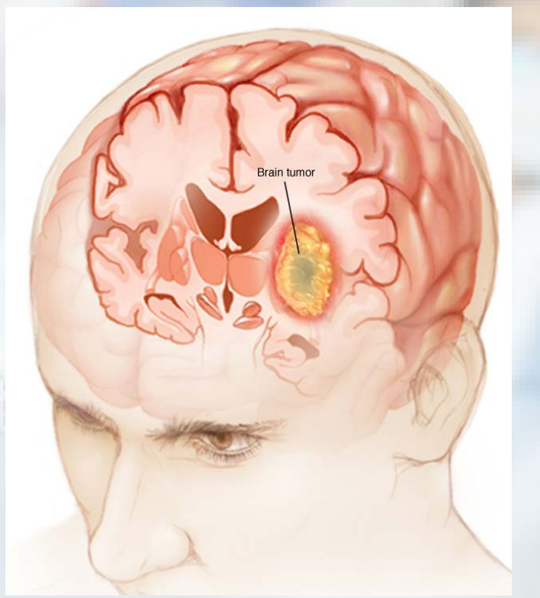
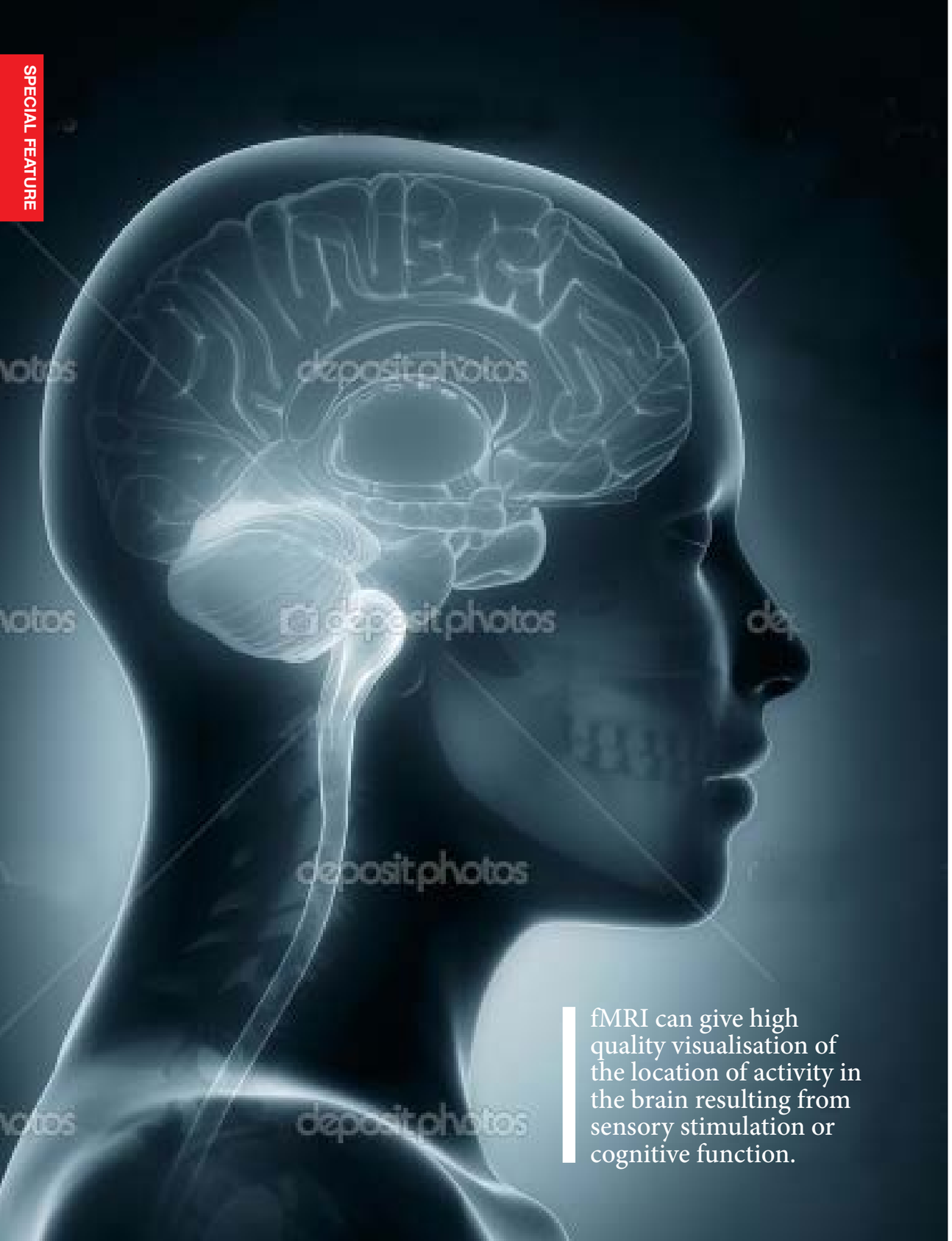


FIGURE 1 BRAIN TUMOUR

DIAGNOSIS

fMRI (functional magnetic resonance imaging) is a powerful non-invasive tool in the study of the function of the brain, used, for example, by psychologists, psychiatrists and neurologists. fMRI can give high quality visualisation of the location of activity in the brain resulting from sensory stimulation or cognitive function. It therefore allows the study of how the healthy brain functions, how it is affected by different diseases, how it attempts to recover after damage and how drugs can modulate activity or post-damage recovery. The goal of fMRI analysis is to detect, in a robust, sensitive and valid way, those parts of the brain that show increased intensity at the points in time that stimulation was applied. fMRI monitors the growth and function of brain tumours. Resection of brain tumours involving eloquent cortical areas has remained a challenging task. Intra-operative electric direct cortical stimulation (DCS) and mapping can accurately identify and define eloquent cortical areas, can examine their spatial relationships with the tumour, and can facilitate aggressive tumour resection. However, DCS mapping requires either an awake craniotomy and a cooperative patient, at least for language area mapping, or a second operative procedure for extraoperative cortical stimulation and mapping via previously implanted subdural electrodes. In addition, DCS can identify cortical language-associated areas but cannot easily outline subcortical or intrasulcal speech areas.

The change in signal detected by fMRI as neuronal activation is presumed to result from changes in regional, temporary concentrations of oxyhemoglobin caused by increased regional blood flow. It has been extensively described that fMRI is based on a complex physiological phenomenon called Blood-Oxygenation-Level-Dependent (BOLD) effect. The employment of fMRI in the presurgical planning of patients with brain tumours adjacent or in eloquent cortical areas has been increasing, in order to minimise the possibility of postoperative neurological deficit while may maximise the extent of tumour resection. An exponentially increasing number of clinical investigators have been applying various fMRI paradigms and protocols in patients with primary or metastatic tumours for identifying preoperatively their relationship with eloquent cortical areas. However, there is a significant variation in the reported fMRI accuracy rates, and frequently conflicting conclusions regarding the value of fMRI in the preoperative evaluation of patients with intracranial tumours.



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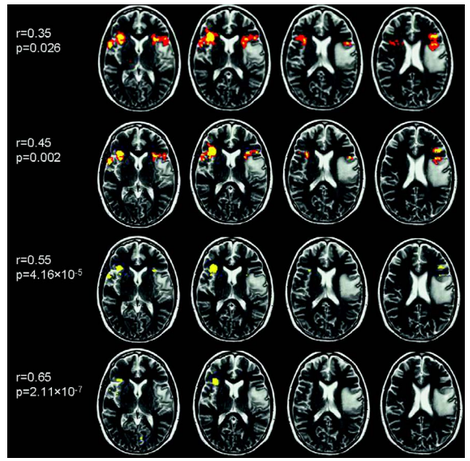

FIGURE 2 FMRI OF METASTATIC BRAIN TUMOUR

Patients can undergo functional MRIs (fMRI) to help delineate a roadmap of important structures (such as areas that control the arms, legs, or speech) prior to surgery. The example shown above demonstrates a tumour near the area for extremity movement.

MACHINE LEARNING

Machine learning is the subfield of computer science that studies programs that generalise from past experience. The medical research looks at classification, where a machine learning algorithm tries to predict the tumour for a sample. The research use machine learning algorithm called Support Vector Machine (SVM) classification applied to growth of Brain tumour using functional magnetic resonance imaging (fMRI) images. As the SVM has many unique properties, examine the interpretation of support vector models with respect to neuroimaging data. The most appropriate role for fMRI in the treatment of brain tumour is in the detection of tumour and direction of its resection and/or irradiation. fMRI is used to monitor ongoing treatment and to survey for recurrence. To improve the generalisation ability and efficiency of the classification, from the extracted regional features, a hybrid feature selection method is utilised to select the most discriminative features, which are used to train a SVM classifier for decoding brain states from fMRI images. The performance of this method will be validated in a deception fMRI study. Typically, most of the algorithms perform at least as well as the physicians and often the classification accuracy of machine classifiers is better than that of physicians when using the same description of the patients. Therefore, if there is a possibility to measure the accuracy of physicians, their performance can be used as a lower bound on the required accuracy of the machine learning system in the given problem. The eventual goal of machine learning in brain tumour diagnosis is to have a trained machine learning algorithm that, given the gene expression levels or other data from a cancer patient, can accurately predict what type and severity of cancer they have, aiding the doctor in treating it.

PRE-PROCESSING DIAGNOSIS PHASE

This first phase ensures the pre-processing step. It is composed six steps:

Acquisition This step ensured via fMRI and represents a primordial step since the remainder of the process will depend on the quality of acquired images. In this step it is very likely that noise could be introduced, thus the quality of the image could be decreased

Reconstruction This step maps the 2D sequential slices of each patient to an entirely volume. This step needs our system in order to register images using the Matlab software that handles 3D images.

Co-registration This step spatially aligns volumes of each patient having different modalities. The common tool to ensure this task is Matlab software.

Template registration Having as input co-registered volumes, this step consists on aligning the modalities with a template image in the standard coordinate system in order to average signals from brain images of different subjects.

Extraction of slices of interest In this step we will choose the 'interesting' slices from the registered volumes. i.e the slices where we can see the tumour regions.

Noise reduction This step improves the quality of data through the application of methods of denoising.

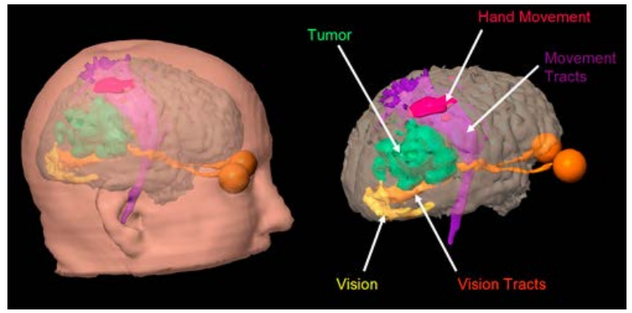

FIGURE 3 3D RECONSTRUCTIONS FROM FMRI AND DTI IMAGES SHOWS THE VISION AND HAND MOVEMENT AREAS THAT LIE CLOSE TO THE BRAIN TUMOUR (GREEN AREA).

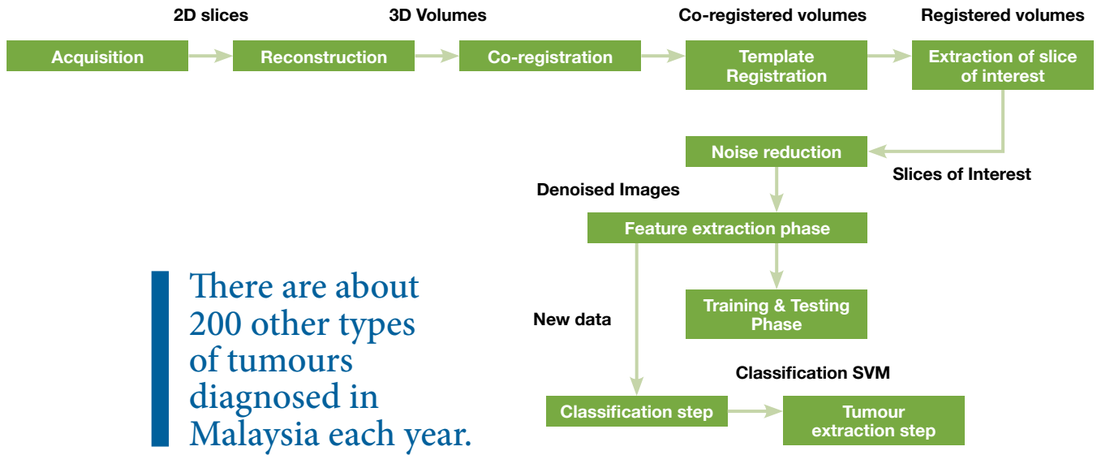

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FIGURE 4 SEGMENTATION PHASE

TUMOUR ACTIVATION

In the first approach, the interaction between tumour locations and fMRI activation areas is explored. The tumour distance parameter can be adjusted, thus increasing the volume of the offset surface surrounding it. Activation areas that are intersected by this volume are updated in real-time. This allows the surgeon to experiment with the safety zone surrounding the tumour, and to explore the degrees of freedom that should be available during the resection procedure. The combined visualisation of the activation areas and the tumour assists the highest level of pre-surgical planning. The information presented allows the surgeon to pinpoint the location of the motor areas in the brain, and use this to estimate a surgical path to the tumour that avoids these areas.

RESULTS

The relation of the tumour border to the primary motor area (PMA), primary sensory area, speech areas and visual areas could be established with fMRI using different tasks. This relation was classified according to the distance between the eloquent brain area and the tumour border into:

(a) Brain area is more than 2cm away from the tumour.
(b) Brain area is 1 to 2cm away from the tumour.
(c) Brain area less than 1cm away from the tumour.
(d) Brain area lies within the tumour and/or infiltrated by it.

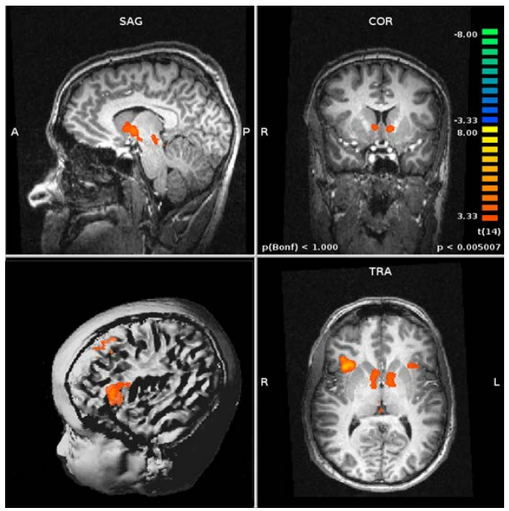
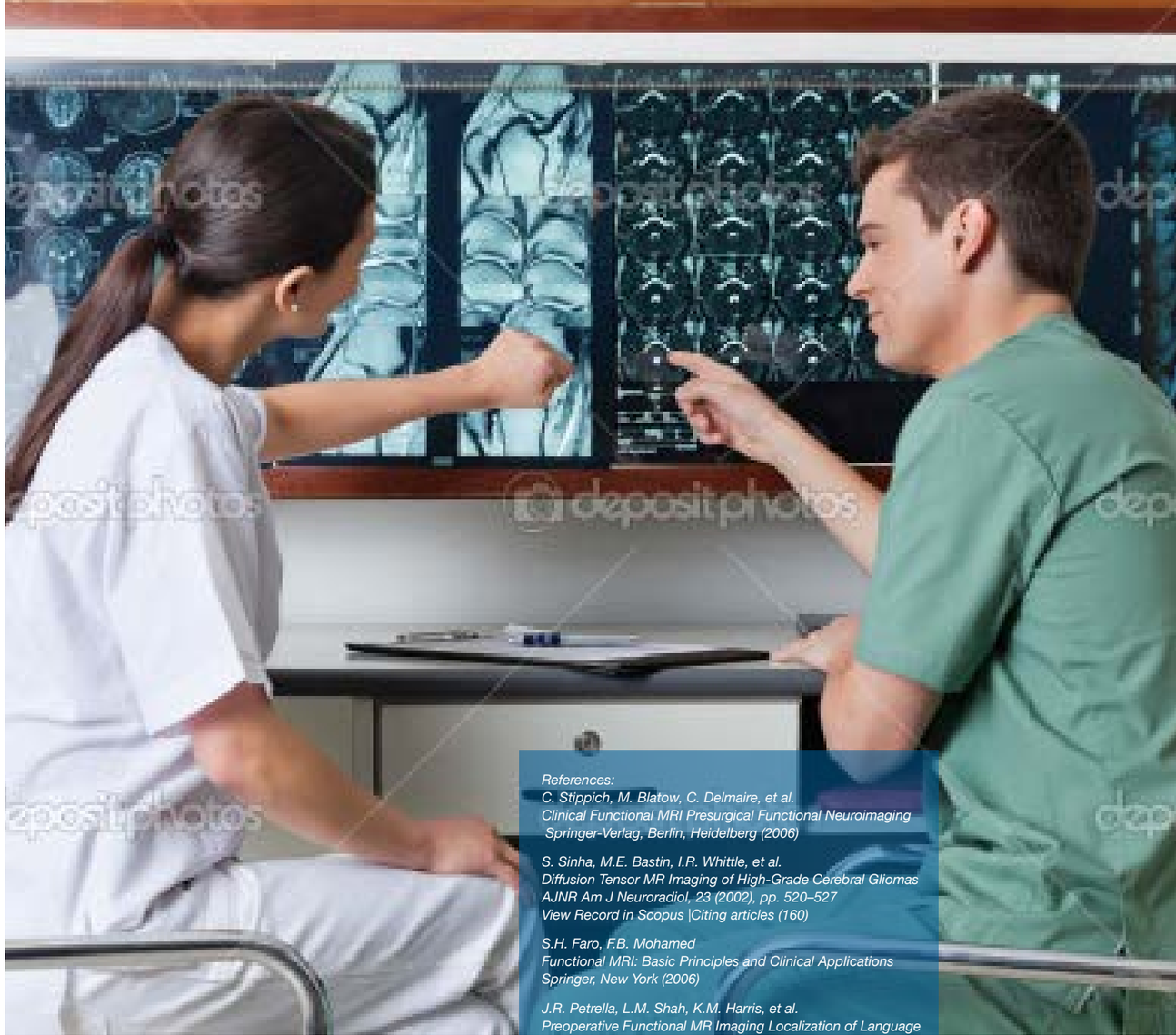


FIGURE 5

Different relations between the eloquent brain areas and the brain tumours as shown by fMRI. (A) PMA for the hand (white arrow) is more than 2 cm from the tumour (grey arrow) (B) PMA for the right foot (white arrow) is 1 to 2cm from the tumour (grey arrow). (C) PMA for the right hand (white arrow) is less than 1cm from the tumour (grey arrow). (D) 'X' area is totally infiltrated by the tumour (grey arrow).



CONCLUSION

Brain tumour tools have already proved their efficiency in research application and are now used for machine learning for classification. They will be valuable in areas such as computer integrated surgery, where the visualisation of the functional is fundamental.

This article proposes a machine learning processing system which is a user interactive tool for image segmentation. More precisely, we focus on brain tumour images issued from fMRI device.

SVM constructs a classification model allowing the discrimination between normal and brain tumour pixels. Finally the model is used to classify new pixels in order to extract tumour regions. ■

References:

C. Stippich, M. Blatow, C. Delmaire, et al.
Clinical Functional MRI Presurgical Functional Neuroimaging
Springer-Verlag, Berlin, Heidelberg (2006)

S. Sinha, M.E. Bastin, I.R. Whittle, et al.
Diffusion Tensor MR Imaging of High-Grade Cerebral Gliomas
AJNR Am J Neuroradiol, 23 (2002), pp. 520–527
View Record in Scopus |Citing articles (160)

S.H. Faro, F.B. Mohamed
Functional MRI: Basic Principles and Clinical Applications
Springer, New York (2006)

J.R. Petrella, L.M. Shah, K.M. Harris, et al.
Preoperative Functional MR Imaging Localization of Language and Motor Areas: Effect on Therapeutic Decision Making in Patients with Potentially Resectable Brain Tumours
Radiology, 240 (2006), pp. 793–802
View Record in Scopus | Full Text via CrossRef | Citing articles (63)

[I.D. Wilkinson, C.A. Romanowski, D.A. Jellinek, et al.
Motor Functional MRI for Pre-operative and Intraoperative Neurosurgical Guidance
Br J Radiol, 76 (902) (2003), pp. 98–103

[Burges C., "A Tutorial on Support Vector Machines for Pattern Recognition", In "Data Mining and Knowledge Discovery". Kluwer Academic Publishers, Boston, 1998, (Volume 2).

V. Vapnik, S. Golowich, and A. Smola. Support Vector Method for Function Approximation, Regression Estimation, and Signal Processing. In M. Mozer, M. Jordan, and T. Petsche, editors, Advances in Neural Information Processing Systems 9, pages 281– 287, Cambridge, MA, 1997. MIT Press.

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