



Medical image fusion: A survey of the state of the art

Alex Pappachen James^{a,*}, Belur V. Dasarathy^b

^a School of Engineering, Nazarbayev University, Astana, Kazakhstan

^b Information Fusion Consultant, USA



ARTICLE INFO

Article history:

Received 20 October 2013

Accepted 26 December 2013

Available online 8 January 2014

Keywords:

Image fusion

Medical imaging

Medical image analysis

Diagnostics

ABSTRACT

Medical image fusion is the process of registering and combining multiple images from single or multiple imaging modalities to improve the imaging quality and reduce randomness and redundancy in order to increase the clinical applicability of medical images for diagnosis and assessment of medical problems. Multi-modal medical image fusion algorithms and devices have shown notable achievements in improving clinical accuracy of decisions based on medical images. This review article provides a factual listing of methods and summarizes the broad scientific challenges faced in the field of medical image fusion. We characterize the medical image fusion research based on (1) the widely used image fusion methods, (2) imaging modalities, and (3) imaging of organs that are under study. This review concludes that even though there exists several open ended technological and scientific challenges, the fusion of medical images has proved to be useful for advancing the clinical reliability of using medical imaging for medical diagnostics and analysis, and is a scientific discipline that has the potential to significantly grow in the coming years.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

Medical image fusion encompasses a broad range of techniques from image fusion and general information fusion to address medical issues reflected through images of human body, organs, and cells. There is a growing interest and application of the imaging technologies in the areas of medical diagnostics, analysis and historical documentation. Since computer aided imaging techniques enable a quantitative assessment of the images under evaluation, it helps to improve the efficacy of the medical practitioners in arriving at an unbiased and objective decision in a short span of time. In addition, the use of multi-sensor [1] and multi-source image fusion methods offer a greater diversity of the features used for the medical analysis applications; this often leads to robust information processing that can reveal information that is otherwise invisible to human eye. The additional information obtained from the fused images can be well utilized for more precise localization of abnormalities.

The growing appeal of this research area can be observed from the large number of scientific papers published in the journals and magazines since year 2000 [2]. Fig. 1 shows the increased frequency of publications in the field of medical image fusion from year 1995 to 2013. This can be largely attributed to the increased use of medical diagnostic devices by the medical community

supported by rapid growth in low cost computing and imaging techniques. In addition to the rapid development of the imaging and computing technologies, there has been increased trust placed in diagnostics technologies in the medical field, as the new generation of medical practitioner finds the technologies user friendly. As opposed to the technologies that prevailed before the year 2000, the newer technologies pay a high level of attention on the usability and simplification of technical knowhow for the operator, making it friendly for the medical personnel. In addition, the services offered by the manufacturing companies have grown across in terms of geographic reach, speed and quality. These diverse set of factors has resulted in the medical imaging market annual growth rate of 7% and is expected to reach \$49 billion by 2020. The applicability of imaging has shifted from just being a research tool to more towards a necessary diagnostic tool even in regular (non-research) hospitals across the world.

There exist several medical imaging modalities that can be used as primary inputs to the medical image fusion studies. The selection of the imaging modality for a targeted clinical study requires medical insights specific to organs under study. It is practically impossible to capture all the details from one imaging modality that would ensure clinical accuracy and robustness of the analysis and resulting diagnosis and. The obvious approach is to look at images from multiple modalities to make a more reliable and accurate assessment. This often requires expert readers and is often targeted at assessing details that complement the individual modalities. Some of the major modalities in clinical practice includes the following: (a) angiography such as Quantitative

* Corresponding author.

E-mail addresses: apj@ieee.org (A.P. James), fusion-consultant@ieee.org (B.V. Dasarathy).

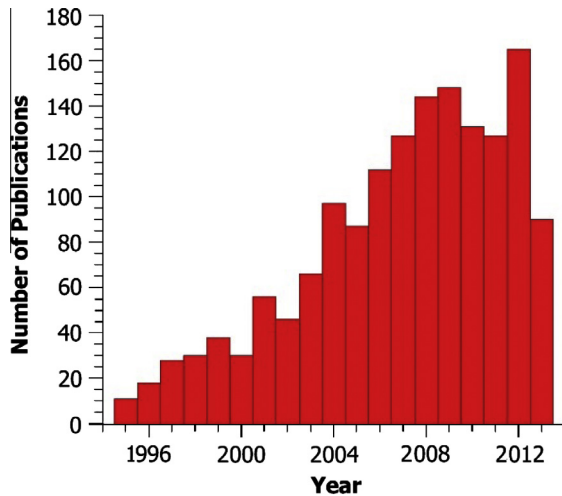


Fig. 1. The frequency of publications in medical image fusion as obtained from the ISI knowledge of web indexing service.

Coronary Angiography (QCA) and Quantitative Vascular Angiography (QVA), (b) Computer Tomography such as angiography (CTA), Quantitative Computed Tomography (QCT), (c) Dual-energy X-ray absorptiometry (DXA) such as for Bone Mineral Density (BMD) and Hip Structural Analysis (HSA), (d) Magnetic resonance imaging such as for Angiography (MRA), Body and Neuro, Cardiac, Dynamic Contrast-Enhanced Magnetic Resonance Imaging (DCE-MRI), (e) Nuclear Medicine such as using Multi-Gated Acquisition Scan (MUGA) and Single Photon Emission Computed Tomography (SPECT), (f) PET, (g) Ultrasound such as for Abdominal/small parts Ultrasound, Echocardiography, Intima-Media Thickness (IMT), Intravascular Ultrasound (IVUS), FMD (flow mediated dilation), Duplex, Duplex Doppler, CEUS (Contrast Enhanced Ultrasound), B-Mode and M-Mode, and (h) X-ray imaging such as for mammography. These imaging modalities find a range of application in diagnosis and assessments of medical conditions effecting brain, breast, lungs, liver, bone marrow, stomach, mouth, teeth, intestines, soft tissues and bones.

The aim of this review is to provide a collective view of the applicability and progress of information fusion techniques in medical imaging useful for clinical studies [3–14]. Fig. 2 shows the three major focused areas of studies in medical image fusion: (a) identification, improvement and development of imaging modalities useful for medical image fusion, (b) development of different techniques for medical image fusion, and (c) application of medical image fusion for studying human organs of interest in assessments of medical conditions. There exist several image

fusion studies that can be directly applied for fusing medical images. On a first look, this may seem a field that does not involve specific technical challenges and the reuse of image fusion algorithms for medical image rather a trivial task. However, the task of image fusion with medical images involve several technical challenges ranging from the limitations imposed by specific imaging modality, the nature of the clinical problem, the technology costs for the user, and the trust placed by the medical practitioners in the imaging technique. In the subsequent sections, we review these aspects of the medical image fusion, not just limiting to the grouping of medical image fusion algorithms, but also to categorizing the fusion techniques and applications based on the imaging modalities and organs of study.

2. Medical image fusion methods

Fig. 3 shows the summary of the two stages involved in medical image fusion methods. The two stages of any classical image fusion method are (a) image registration and (b) fusion of relevant features from the registered images. The registration of the images requires a method to correct the spatial misalignment between the different image data sets that often involve compensation of variability resulting from scale changes, rotations, and translations. The problem of registration becomes complicated in the presence of inter-image noise, missing features and outliers in the images. On the other hand, the fusion of the features involve the identification and selection of the features with a focus on relevance of the features for a given clinical assessment purpose. Table 1 shows the summary of the major medical image fusion methods, the modalities that these methods are applied and the applications in medical imaging studies.

2.1. Morphological methods

The morphology operators has been explored by image processing community for long, and the concept is used by the medical imaging community to detect spatially relevant information from the medical images. The morphological filtering methods for medical image fusion have been applied, for example, in brain diagnosis [47,15,49]. An example of modalities used in morphology based fusion can be seen in the fusion of CT and MR images [15–17]. In such applications, the morphology operators depend heavily on the structuring operator that defines the opening and closing operations. A calculated sequencing of the operations results in the detection of scale specific features. These features from different modalities can be used in for image fusion. The inaccuracies of detecting the features are high when the images are prone to noise and sensing errors. The operators such as averaging, morphology towers, K-L transforms and morphology pyramids are used for

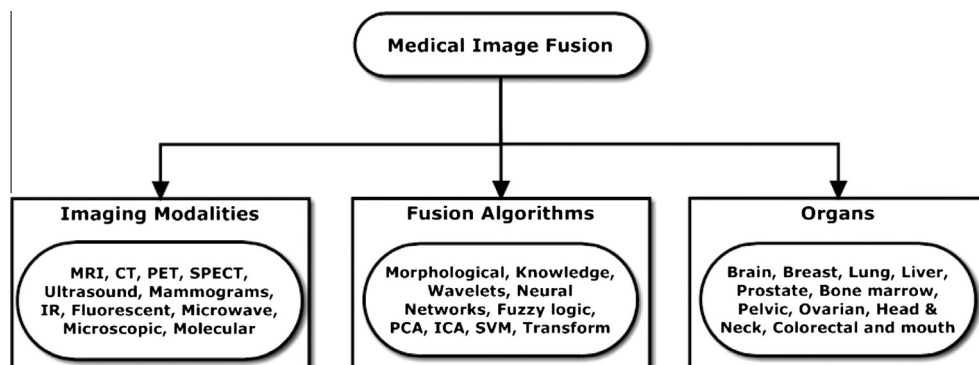


Fig. 2. A chart showing the nature of modalities, methods and organs of interest as applied in medical image fusion studies.

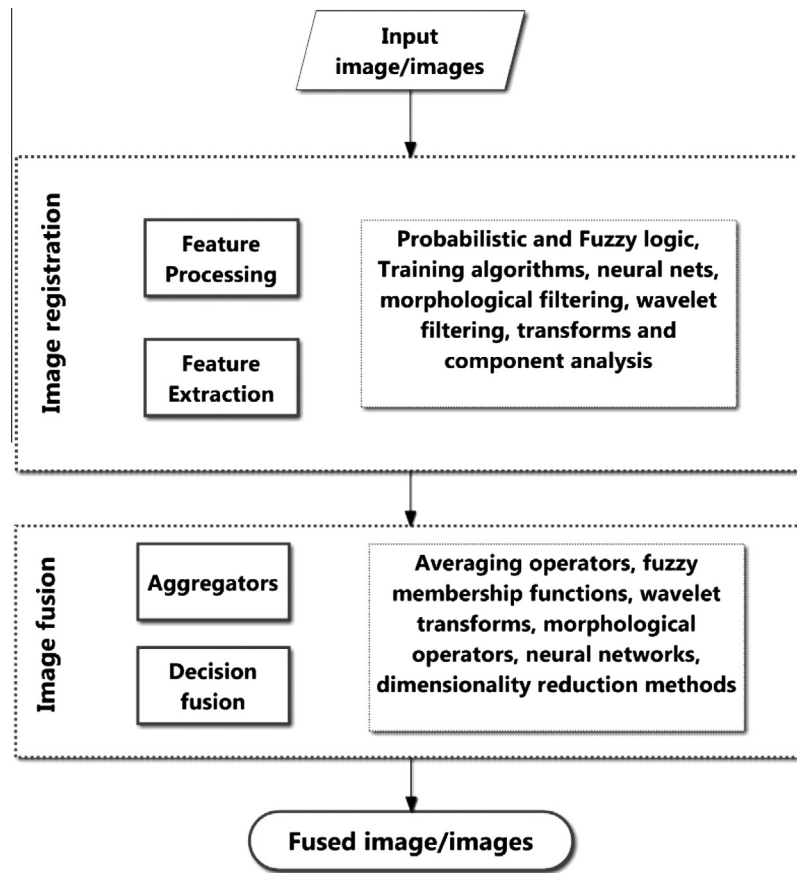


Fig. 3. The summary of the stages in the image fusion of medical images. The two stage process consists of image registration followed by image fusion.

Table 1
Major medical image fusion methods and its applications.

Method	Modalities	Applications	Fusion strategies
Morphology Knowledge	MRI, CT MRI, CT, PET, Ultrasound, Mammogram	Brain diagnosis [15–17] Segmentation [18], micro-calcification diagnosis [19], tissue classification [20], brain diagnosis [20], classifier fusion [21], breast cancer tumor detection [21,22], delineation & recognition of anatomical brain object [18] and medical image retrieval [23–25]	Morphology filters and pyramids Knowledge learning systems, expert systems
Wavelets	CT, PET, MRI, Mammograms, MRA, fMRI, SPECT, ultrasound	Pseudo coloring, super resolution [26], medical diagnosis [27–30], feature level image fusion [31], lifting scheme [31], segmentation [32], 3D conformal radiotherapy treatment planning [33] and color visualization [34]	Wavelet transform, multi resolution analysis [35], Discrete wavelet transform, Stationary wavelet transform, dual tree discrete wavelet transform, Lifting wavelet transform, Multi-wavelet transform Coupled
Artificial neural networks	CT, PET, MRI, Mammograms, MRA, fMRI, SPECT, ultrasound	Feature generation [36], classification [36], fusion [36,19,27,37,38,27,39–43], micro-calcification diagnosis [19], breast cancer detection [38,44,45], medical diagnosis [27,28,42], cancer diagnosis [46]	Neural networks, clustering neural network, fuzzy neural networks, wavelet neural networks
Fuzzy logic	CT, PET, MRI, Mammograms, MRA, fMRI, SPECT, ultrasound	Brain diagnosis [47–50], cancer treatment [51], image segmentation and integration [51,52], maximization mutual information [53], deep brain stimulation [54], brain tumor segmentation [55], image retrieval [56,57], spatial weighted entropy [56], feature fusion [56], multimodal image fusion [41,58,59], ovarian cancer diagnosis [60]	Image fuzzification, modification of membership values, Image defuzzification, fuzzy combination operators, neuro-fuzzy networks

achieving the data fusion. These methods are highly sensitive to the inter-image variability resulting from outliers, noise, size and shape of the features.

2.2. Knowledge based methods

In medical imaging, there are several instances where the medical practitioner's knowledge can be used in designing

segmentation, labeling and registration of the images. Generally, the domain-dependent knowledge is needed to set constraints on region-based segmentation and to make explicit the expectation of the appearance of the anatomy under the imaging modality at the stage of grouping the detected regions of interest. There are a range of applications where the domain-dependent knowledge is useful for image fusion such as for segmentation [18], micro-calcification diagnosis [19], tissue classification [20], brain diagnosis

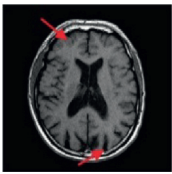
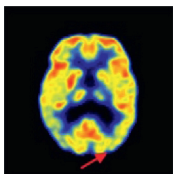
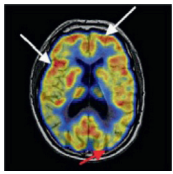

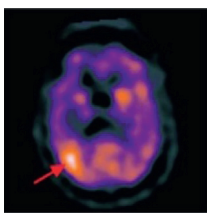
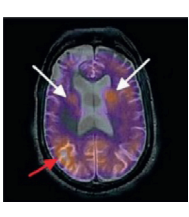
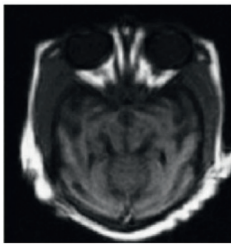

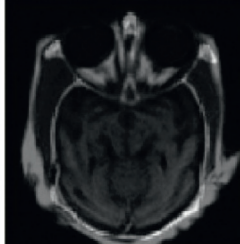
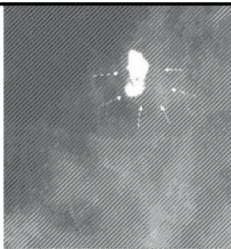
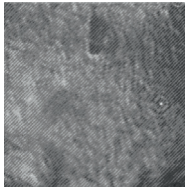

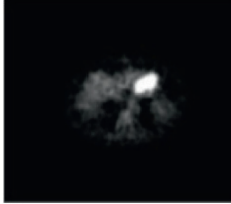
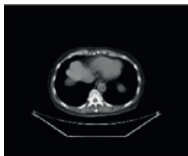
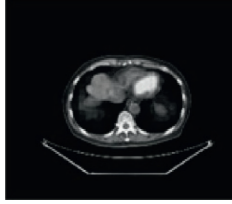
Combination	Modality 1	Modality 2	Fused Image
MRI-PET			
MRI-SPECT			
MRI-CT			
Xray-VA			
PET-CT			

Fig. 4. Examples of multi-modal medical image fusion. The combination of modality 1 with modality 2 using specific image fusion techniques results in improved feature visibility for medical diagnostics and assessments as shown in the fused image column.

[20], classifier fusion [21], breast cancer tumor detection [21] and delineation & recognition of anatomical brain object [18]. The knowledge based systems can be used in combination with other methods such as pixel intensity [19]. These methods place a significant amount of trust in the medical expert in labeling and identifying the domain knowledge relevant to the fusion task. The advantage is the ability to benchmark the images with the known human vision standards, while the drawback is the limitations imposed by human judgment in images that are prone to large pixel intensity variability. The use of preprocessing techniques in images can improve the imaging quality and increase the accuracy of ground truths.

2.3. Wavelet based methods

The primary concept used by the wavelet based image fusion [61,26,27,32,62–66,40,29,30,67,68,33,69–72,32,73–75,59,

76–80,34,81–84] is to extract the detail information from one image and inject it into another. The detail information in images is usually in the high frequency and wavelets would have the ability to select the frequencies in both space and time. The resulting fused image would have the “good” characteristics in terms of the features from both images that improve the quality of the imaging. There are several models for injection, the simplest being substitution. There exist several mathematical models for injection, such as simple addition operation and aggregator functions to more complex mathematical models. Irrespective of the models used, for practical reasons, the image resolution remains same before and after the fusion. In addition, the image resolution of the reference image enforces the required number of multiple levels of decomposition, such that a high resolution image would require more number of decomposition levels than a low resolution image. There are several applications of the wavelets in image fusion such as medical image pseudo coloring [85], super resolution

[26], medical diagnosis [27–30], feature level image fusion [31], lifting scheme [31], segmentation [32], 3D conformal radiotherapy treatment planning [33] and color visualization [34].

The feature level improvements on the images by combining wavelets with other techniques have proved to be useful for wavelet based image fusion. The most prominent approach of wavelet image fusion is with neural network [27,28,40], where the neural network often takes the roles of feature processing and wavelets take the role of a fusion operator. Similar to neural network, the kernel based operators such as support vector machines (SVM) can be used along with wavelets to achieve image fusion at feature levels [66]. Considering wavelets as a fusion operator, several feature processing methods can be combined such as wavelet–SVM [66], wavelet–texture measure [29], wavelet–MRA [30,67], wavelet–self adaptive operator [69], wavelet–resolution–entropy [70,72], nonlinear wavelet–shift invariant imaging [71], ICA–wavelet [86], wavelet–edge feature [75], wavelet–genetic [59], wavelet–contourlet transform [81], neuro-fuzzy–wavelet [82] and wavelet–entropy [84].

2.4. Neural network based methods

Artificial Neural Networks (ANN) are inspired from the idea of biological neural network having the ability to learn from inputs for processing features and for making global decisions. The artificial neural network models require an input training set to identify the set of parameters of the network referred to as weights. The ability of the neural network models to predict, analyze and infer information from a given data without going through a rigorous mathematical solution is often seen as an advantage. This makes the neural network attractive to image fusion as the nature of variability between the images is subjected to change every time a new modality is used. The ability to train the neural network to adopt to these changes enable several applications for medical image fusion such as solving the problems of feature generation [36], classification [36], data fusion [36,19,27], image fusion [37,38,27,39–43], micro-calcification diagnosis [19], breast cancer detection [38,44,45], medical diagnosis [27,28,42], cancer diagnosis [46], natural computing methods [87] and classifier fusion [45].

Although ANN offers generality in terms of having the ability to apply the concept of training, the robustness of ANN methods is limited by the quality of the training data and the accuracy of convergence of the training algorithm. In order to improve the quality of the features and thereby to improve the robustness of the ANN, hybrids of neural networks and sequential processing with other fusion techniques can be employed. Some of examples of these are wavelet–neural network [27,28,40], neural-fuzzy [41,43], fuzzy–genetic–neural network–rough set [87] and SVM–ANN–GMM [45]. It is practically very difficult to prove the effectiveness of these combinations across all the different imaging modalities as these approaches are skewed towards the quality of the images selected for training that can vary significantly from one imaging condition to another.

2.5. Methods based on fuzzy logic

The conjunctive, disjunctive and compromise properties of the fuzzy logic have been widely explored in image processing and have proved to be useful in image fusion. The fuzzy logic is applied both as a feature transform operator or a decision operator for image fusion [47,51,48,52,53,49,54,55,50,56,41,57,58,60,88,59,87,89–91,43,82,92]. There are several applications of fuzzy logic base image fusion such as brain diagnosis [47–50], cancer treatment [51], image segmentation and integration [51,52], maximization mutual information [53], deep brain stimulation [54], brain tumor

segmentation [55], image retrieval [56,57], spatial weighted entropy [56], feature fusion [56], multimodal image fusion [41,58,59], ovarian cancer diagnosis [60], sensor fusion [88], natural computing methods [87] and gene expression [89,90].

The selection of membership functions and fuzzy sets that result in the optimal image fusion is an open problem. The improvements of feature processing and analysis can be improved to fit the fuzzy space better when combined with probabilistic approaches such as fuzzy–neural network [41,43], fuzzy–genetic–neural network–rough set [87], fuzzy–probability [89] and neuro-fuzzy–wavelet [82].

2.6. Other methods

There are several methods that are based on dimensionality reduction techniques such as independent component analysis (ICA) [86,93] and principal component analysis (PCA) [94–97]. These dimensionality reduction techniques often find their use as feature processing methods and are used in combination with techniques such as ones based on wavelets [86]. A first order fusion of volumetric medical imagery is presented in [98]. A multimodal image fusion based on PCA using the Intensity–Hue–Saturation (IHS) transform has been shown to preserve spatial features and required functional information without color distortion [97]. There are different mathematical transforms on features that can enhance the performance of the image fusion. For example, combination of complex contourlet transform with wavelet has been shown to result in robust image fusion [95,96]. Transforms based methods are also applied for liver diagnosis [99], risk factor fusion [100], prediction of multifactorial diseases [100], parametric classification [100], local image analysis [101], and multi-modality image fusion [102,103,95,104,96,81]. Possibilistic clustering methods show improvement over the fuzzy c-means clustering and have a wide range of application in registration stages of image fusion. Some of the applications of possibilistic clustering include tissue classification [105], brain diagnosis [48,106] and automatic segmentation [52]. SVM based techniques are kernel based techniques that are data and parameter driven having a strong control over the feature space. The ability of the SVM to reject the outliers in the data makes it a useful tool in image fusion, and leads to their being used in applications of cancer diagnosis [46,107], classifier fusion [107,108,45], breast cancer tumor [108,45], image fusion [66,109], content-based image retrieval [110,111], tumor segmentation [109], gene classification [112] and feature fusion [111]. Since SVMs can be used in registration as well as fusion stages, they can be combined with other methods to improve the speed of processing and accuracy when processing large image feature space under the influence of noise. Some examples of combined use of SVM with other methods include SVM–wavelet [66], SVM–adaptive similarity [110], SVM–data fusion [109] and SVM–ANN–GMM [45]. A prediction fusion is explained in [113]. Use of quaternionic signals representation for analysis and fusion of multi-components 2D medical images is presented in [114]. The use of ICA for the fusion of brain imaging data is presented in [115]. A Text fusion watermarking in medical image with semi-reversible for secure transfer and authentication is explained in [116]. Fusion of multiple expert annotations for medical image diagnosis is reported [117]. Fast fusion of medical images based on Bayesian risk minimization and pixon map is presented [118].

3. Imaging modalities used in image fusion

Fig. 4 shows a few examples of image fusion with different medical imaging modalities. In this example, the image fusion is achieved in MRI–PET fusion [119] using a contourlet method,

MRI–SPECT [119] uses a wavelet based approach, MRI–CT [82] uses a Integer Wavelet Transform and Neuro-Fuzzy method, PET–CT [76] uses a wavelet coefficients fusion method, and Vibroacoustography images with X-ray mammography [120] uses a linear combination approach.

3.1. Magnetic resonance imaging

Magnetic Resonance Imaging (MRI) plays an important role in non-invasive diagnosis of brain tumors and is one of the most widely used imaging modalities in medical studies in trusted clinical settings. Previous work [121,16,61,122,123,26,124,53,125,126,64,127–130,91,131–133] reports the successful fusion of MR images with different types of modalities. The image fusion methods are widely applied for brain diagnosis and treatment [47,15,134,48,20,135,136,49,137,138,50,139–143], wherein the fusion techniques have been demonstrated to show improved imaging and diagnostic performances.

Image segmentation is widely used to identify objects and regions of interest in the images. In MR medical imaging, the most common use of segmentation is for extraction of the different types of tissues and to identify abnormal regions such as reflective of tumors. Several tumor segmentation methods are reported [18,52,122,125,32,50,144,109,51,143,145,146] that aid to improve the accuracy of tumor identification and automatic detection of tumors from the MR images. The segmentation along with medical image fusion techniques have been widely used in prostate localization [147–163,145,130,164–168,132].

There are several clinical visualization applications such as 3D conformal radiation therapy [147,169] that employ fusion techniques. Following along similar lines, medical image visualization method [126], and its extension to adaptive medical image visualization system, is developed using the hierarchical neural network and intelligent decision fusion [36]. The fusion techniques are even extended to 3D voxel fusion in a view to achieve multi-modality image fusion [170].

The MRI based image fusion also finds application in prostate studies. Image fusion techniques [171,149,150,172,153,155,162,173] are extensively used in prostate seed implant quality assessment. The fusion techniques are even applied to develop stereotactic prostate biopsy system [174]. There are methodological advancements in the fusion of MR images such as structure similarity match measure (SSIM) [175] that can improve the accuracy of these applications. Other potential applications that incorporate MRI based fusion include image regeneration [176,177,142], potential field visualization [178], lung/liver diagnosis [179], tissue classification [105,20], breast cancer assessment [180–182], surgical planning and training [183], multi-dimensional visualization [123], extraction of shape, color and structure of specimen [184], visualization and pattern recognition [185], image registration [124,151,53,126,186,131], MRI guided treatment [151,152], gynecological cancer diagnosis [187] and 3D tumor simulation [188].

The advantage of MRI is that it is very safe for pregnant women and babies as it does not involve any exposure to radiation. In addition, the soft issue structures in organs such as brain, heart and eyes are imaged with high accuracy. The major disadvantage of the MRI images is its relative sensitivity to movement, making it a difficult technique for assessing organs that involve movement such as with mouth tumors. The use of image fusion can overcome this limitation in a multi-modal imaging environment, enabling reconstruction and prediction of the missing information from MRI. The MR images along with other modalities when used together with modern image fusion techniques have shown to improve the imaging accuracy, and practical clinical applicability. There exists several studies that attempt to combine the MRI with other modalities using image fusion methods, some examples of this are the

following: MRI–CT–PET–SPECT–DSA–MEG [47,134], MRI–CT [15–17,147,171,176,177,189,190,61,149,184,191,150,170,53,172,153,169,154–156,186,64,192,193,158,194,175,161,195,141,162,128,91,164,165,196,132,173], MRI–CT–PET [51,188,197–199], EEG–MRI [178], CT–FOCAL [179], MRI–Mammogram [180,182], MR–SPECT [48,123,185,151,200,136,140], MRI–SPECT–PET [48], nuclear medicine–MRI [201], endoscopy–MRI [183], MRI–CT–SPECT [26,202], MRI–Molecular [135], MRA–DSA [124], MRI/CT–PET–SPECT [187], MRI–iMRI–SPECT [152], MRI–PET [203–205,139,181,206,129,130], MRI–DTI [207,144,142], ultrasound–MRI [208,148,159,167,174], and MRI–TRUS [209,163,145,166,168], MRI–MRSI [160]. The most prominent combination is the MRI–CT studies largely because of the maturity in the technology and practical usability in clinical settings.

3.2. Computerized tomography

Computerized Tomography (CT) is a medical imaging technique that has made a prominent impact on medical diagnosis and assessments. This is a popular modality used in multi-modal medical image fusion [16,61,210,26,211,212,64,213,29,214,68,215,128,76,91,132]. Similar to MR images, the CT images are used in a vast range of medical applications under practical clinical conditions. Computerized assessment using CT images has been one of the early attempts towards modern medical imaging; an example system is one that uses knowledge-based image interpretation system for the segmentation and labeling of a series of 2-D brain X-ray CT-scans [18]. Another application of the image fusion using CT images has been for assistance in surgical planning, training and guidance using images obtained from a tracked endoscope to surfaces derived from CT data [183].

The CT images have gain importance as a 3D imaging technique, and image fusion has been applied in applications such as those that use 3D tumor simulations [188]. Similar to MRI, the application of CT images in brain diagnosis and treatment [47,15,134,141] has also been reported. There are several application areas where CT images are considered the prime modality. some of these major applications are the following: (1) head and neck cancer diagnosis [216,189,217–219,196], (2) cancer treatment [51,220], (3) image segmentation and integration [51,213], (4) lung cancer treatment [221,222,179,223–229], (5) prostate cancer treatment [147,230,231,149,232,150,153,233,234,154,155,235,156,236,157,213,127,237,161,238,162,164,165,239,132], (6) 3D conformal radiation therapy [147,224,169,229], (7) liver diagnosis [99,179], (8) prostate seed implant quality assessment [171,149,150,172,153,155,240,173], (9) image regeneration [176,177], (10) tumor detection [241,242,217,243], (11) extraction of shape, color and structure of specimen [184], (12) gynecological cancer diagnosis [187], (13) 3D Voxel fusion [170], (14) gross tumor volume detection [197,244], (15) pelvic irradiation treatment [233,235,245], (16) diagnosis of local recurrence of rectal cancer [211], (17) colorectal cancer treatment and chemotherapy [246], (18) pediatric solid extracranial tumors [247], (19) deep brain stimulation [192], (20) bone tumor surgery [193], (21) telemedicine [198], (22) localization [237], (23) breast cancer assessment [214,248,249], (25) vulvar cancer treatment [202], (26) oral cancer treatment [250], (27) bone cancer diagnosis [251], (28) lung cancer diagnosis [252], (29) radiation therapy and planning [227,161], (30) biopsy [253], (31) cervical cancer treatment [199], (32) orbital tumor surgery [128], (33) liver tumor diagnosis [254], classification fusion [255], (34) esophageal cancer diagnosis [256], and (35) pancreatic tumors characterization [257].

The main advantages of the CT scan are the relative short scan times and high imaging resolutions. However, the exact radiation levels are not well understood topics, and CT has several other limitations such as limited tissue characterization because of the

nature of X-ray probe, restriction of CT scan to transverse slices and practical limitation on number of X-rays that can be produced in the short scan times. Fusion combinations in which CT is one of the main modalities include MRI-CT-PET-SPECT-DSA-MEG [47,134,161], MRI-CT [15–17,147,171,176,177,258,61,149,184,150,259,170,153,172,169,154–156,186,64,192,157,193,127,158,175,195,141,162,128,91,164,165,196,239,132,173], SPECT-CT [216,221,99,241,233,246,235,213,214,253,215,243,251], MRI-CT-PET [51,188,197–199], CT-FOCAL [179], ultrasound-CT [260,231,234,238], FDG-CT [223,224], nuclear medicine-CT [201], endoscopy-MRI [183], MRI-CT-SPECT [26,202], MRI/CT-PET-SPECT [187], CT/SPET-SRS [242], FDG-PET-CT [261,226,247,249], PET-CT [244,262,211,217,236,29,220,218,68,250,252,248,219,76,255,263,257], TRUS-CT [264], ultrasound-CT [265,240,254], PET-CT-ultrasound [256].

3.3. Positron emission tomography

Positron emission tomography, widely known as PET imaging or a PET scan, is a useful type of nuclear medicine imaging. Here, we discuss some application areas where PET is a prime modality considered in the data fusion. Similar to CT and MRI, a major application of PET is in radiology studies for brain diagnosis and treatment [47,134,48,205,139,142]. There are a wide range of the application of image fusion using PET, some of which are for cancer treatments [51,220,217,159,219,206,222,226,130], image segmentation and integration [51,255], 3D tumor simulation [188], gynecological cancer diagnosis [187], inertial electrostatic confinement fusion [266], gross tumor volume detection [197,267], diagnosis of local recurrence of rectal cancer [211], tumor detection and treatment [217], pediatric solid extracranial tumors [247], telemedicine [198], breast cancer detection [181,248,249], oral cancer treatment [250], lung cancer diagnosis [252,268], cervical cancer treatment [199], esophageal cancer diagnosis [256], and pancreatic tumors characterization [204,257].

The resolution limits of PET image are one of the main challenges. There is often an integrated approach to reduce the limitations by modeling finite resolution effects in image reconstruction, and improved detector design. The high sensitivity provided by the molecular imaging is often seen as an advantage of PET images. There is increased interest in using fusion techniques to improve the imaging quality. The use of PET data in combination with some of the existing modalities using the image fusion techniques include MRI-CT-PET-SPECT-DSA-MEG [47,134], MRI-CT-PET [51,188,197–199], MRI-SPECT-PET [48], MRI/CT-PET-SPECT [187], MRI-PET [204,205,139,181,206,142,129,130], FDG-PET-CT [226,247,249], PET-CT [269,244,211,217,218,236,29,220,68,250,252,248,219,76,270,257], FDG-PET [268], and PET-CT-ultrasound [256].

3.4. Single-photon emission computed tomography

Single Photon Emission Computed Tomography (SPECT) scan is useful nuclear imaging method that is widely used to study the blood flow to tissues and organs. The application areas include brain diagnosis and treatment [47,134,48,136,140], head and neck cancer diagnosis [216,200], lung cancer treatment [221], liver diagnosis [99], tumor detection [241], fusion of multi-modality images [123,26,53,236,213,215], multi-dimensional visualization [123], visualization and pattern recognition [185], fMRI guided treatment [151,152], prostate cancer treatment [152,233,235,236,213], gynecological cancer diagnosis [187], image registration [53], pelvis irradiation treatment [233,235], colorectal cancer treatment and chemotherapy [246], breast cancer assessment [214], vulvar cancer treatment [202], bone cancer diagnosis [251], and biopsy [253].

Improving the sensitivity of the SPECT without reducing the image resolution is one of the main challenges in SPECT imaging. The developments in pin-hole SPECT is used to enhance the resolution capabilities to sub millimeter range. The imaging quality is however still affected by the signal noise, and improving the image quality and resolution requires post-processing techniques. The image fusion with PET attempts to improve the imaging quality and includes PET-CT [271], PET-MRI-CT [272,273], MRI-CT-PET-SPECT-DSA-MEG [47,134], SPECT-CT [216,221,99,241,233,246,235,236,213,214,253,251], MR-SPECT [48,123,185,124,53,200,136,140,215], MRI-CT-SPECT [26,202], MRI/CT-PET-SPECT [187] and MRI-iMRI-SPECT [152].

3.5. Ultrasound

Ultrasound imaging is sonar based imaging technique that has been used widely due to its low cost and no known side effects to the patients. There is a wide range of applications where the ultrasound images are used to infer medical data. Some of these are for prostate cancer treatment [267,148,274,231,275,234,159,161,238,167], conformal radiation therapy [267], brachytherapy prostate implant [260,274,231,234,161], image fusion [275,61,159], breast cancer detection [276], liver tumor diagnosis [254], prostate biopsy [174], and esophageal cancer diagnosis [256].

There are some major limitations of the ultrasound imaging that are tightly linked to the operator skills, such as the need to ensure no air gaps between the probe and body, and the need to avoid bone structures in the path of organ imaged. These major deficiencies necessitate the need to use other modalities to ensure the accuracy of imaging and localization of the regions under test for diagnostic measurements. Examples of fusion techniques that incorporate ultrasound in it are ultrasound-X-rays [267], ultrasound-CT [260,231,234,161,238,254], ultrasound-uoroscopic [274], nuclear medicine-ultrasound [201], microscopy-ultrasound [37], ultrasound-CAD-mammograms-infrared [276], ultrasound-MRI [148,159,167,174] and PET-CT-ultrasound [256].

3.6. Other modalities

Along with the modalities mentioned in the previous subsections, there are several other imaging methods such as infrared, fluorescent, microwave and microscopic imaging that find application through medical image fusion. Infrared as an imaging modality is used in the application of breast cancer detection [38,276]. A fusion combination that includes infrared can be seen in [276] where the combination consists of ultrasound, CAD, mammograms and infrared images. Fluorescent imaging has been used as an application to oral cancer detection [277] and prostate brachytherapy and treatment [274,278,279]. The image fusion of fluorescent images with other modalities can be found between ultrasound-fluoroscopic [274] and TRUS-fluoroscopic images [278]. Microwave imaging is used in breast cancer detection [280,281] and tumor identification [280]. Another modality to point out is the microscopic imaging used in image fusion [37,282]. Microscopic imaging is used in fusion methods as an application to image mosaicing [282], multi-feature fusion, feature extraction, and global/local recognition [283]. A feedback retina model for improving medical images fusion is presented in [284]. In [285], an attempt to use information fusion in medical decision support systems is presented. There have been successful attempts to apply image fusion techniques with microscopy and ultrasound images [37]. Trans-Rectal Ultrasound (TRUS) is a variant of ultrasound imaging that is used in prostate brachytherapy dosimetry [278,150,163,145,166,168], image guided prostate intervention [286], biopsy planning [209,166,168], segmentation [145], and

prostate seed implant quality assessment [240]. Fusion combinations with TRUS with other imaging modalities can be found in TRUS–uroscopic [278], TRUS–MRI [286,209,163,145,166,168] and TRUS–CT [240]. Mammography is an X-ray based imaging modality that has been widely used for breast cancer assessment [180,276,182], micro-calcification diagnosis [19] and image registration [287]. The image fusion of mammogram with other modalities can significantly improve the detection accuracies of problems such as abnormal tissue identification in case of calcification. There exist several combinations of modalities with mammograms such as MRI–mammogram [180], ultrasound–CAD–mammograms–infrared [276] and MR Mammogram–X-ray mammogram [135]. A tool for medical image fusion and visualization is presented in [288]. Another modality which is gaining popularity is molecular imaging and image fusion in application to brain diagnosis and treatment [135] has shown to improve the imaging interpretations. An example of the image fusion with molecular imaging is in combination with MRI [135].

4. Major application domains

4.1. Brain

Brain is one of the important organs that have been subjected to a wide range of medical image analysis and research. The imaging studies reveal several important pieces of information about the brain which are otherwise not visible to human sensory mechanisms. The most commonly used image modalities to study the brain include CT [47,15–18,134,183,289,290,141,255], MRI [47,15–17,85,178,105,134,48,52,183,123,20,135,136,125,49,205,291,54,138,55,207,93,290,140,141,143,292], DSA [47], PET [47,134,48,205,255], SPECT [47,134,48,123,136,140], MEG [47], EEG [178], Endoscopy [183], Molecular [135] and DTI [207].

Medical image fusion in brain studies has been employed for segmentation of brain tissues [18,105,52,125,291,138,55,50,207,143,255,292], pseudo coloring for MRI based brain segmentation [85], visualizing cortical potential fields [178], stereotactic brachytherapy of brain tumors [134], brain tissue map and volume identification [105], image guided neuro-surgery [183,293], development of stereoscopic panoramas of brain images [183], 2D–3D registration of brain images [183,135,205], volumetric fusion with brain images [123], classification of abnormal brain tissues [20], semiautomatic 3D fusion with brain images [135], image fusion with multimodal brain images [294,135,289,205,192,207,140], verification of implanted catheters [289], surface projection maximum mutual information fusion of brain images [136], parametric classification of differential brain activity [295], locating anatomical targets with MRI brain images [291], microelectrode recording and test stimulation [192], multi-classifier fusion based brain image segmentation [138], classification of differential brain activity [296], sensor fusion for surgical navigation [297], emulation of perceptual system of brain [298], ensemble based data fusion for diagnosis of Alzheimer's disease [299], filter bank selection for brain computer interaction [300], feature based fusion of brain images [93], optic chiasm contouring for monitoring of brain tumors [290], brain tumor biopsy [301], multimodal fusion of muscles and brain signals [302], and decoding visual brain states [303,304].

4.2. Breast

The breast has been subject of several studies due to the high rates of breast cancer in women. The most commonly used modality for breast studies is mammogram (both analog and digital), followed by MRI and/or CT. The combinations of PET (functional

imaging) and X-ray computed tomography (CT, anatomical localization) has shown significant improvements in diagnostic accuracy, allowing better differentiation between normal (e.g. bowel) and pathological uptake. The modalities that has been used to study breast include MRI [180–182], Mammogram [180,276,182], Infrared [38,276], Ultrasound [276], Microwave [280,281], PET [181,248], SPECT [214,253] and CT [248,253]. The image fusion applications targeted on breast include prediction breast cancer tumors [21,108,44], breast surgery [305], ultrawideband breast cancer detection [281], and breast cancer detection in premenopausal women [306].

4.3. Prostate

Prostate is another organ that has been studied using multimodal medical images. There exists a range of techniques and studies on prostate based image fusion, that often face the challenge deformation of prostate in multi-modal imaging setups [267,147,148,171,260,274,231,275,278,149–151,307,308,153,233,234,212,156,236,157,309,159,160,238,162,165,166,168]. The medical image analysis techniques on prostate include localization of the prostate for 3D conformal radiation therapy [147], prostate localization in the post-planning setting [310] evaluation of prostate gland motion and volume changes [311], evaluation of prostate seed brachytherapy [231], thermal ablation of the prostate cancer [151,152], histology study of prostate tissue [275], post implant dosimetric analysis of prostate brachytherapy [154,158], prostate brachytherapy [234,154,158], and biomechanical modeling of prostate motion [312]. The imaging modalities that deal with prostate include ultrasound [267,148,260,274,231,275,234,159,238,312], X-rays [267], CT [147,171,260,231,149,153,236,150,233,234,154,157,309,158,238,162,165], MRI [147,148,171,149,152,153,150,154,157–160,162,165,166,168], uroscopic [274,278], fMRI [151,152], SPECT [151,152,233,309], PET [236,157], and TRUS [278,166,168].

4.4. Lungs

Lung is a vital organ that undergoes direct contact with environment through the air intake and is the main part of respiratory system. Lungs are prone to damage from pollutants and viruses. The imaging of the lungs can often reveal several details that reflect the condition of the internal tissues. The ability to distinguish a damaged tissue, cancerous tissue and a healthy tissue is not an easy task in early diagnosis. Image fusion techniques have been shown to improve the diagnostic performance and screening, and especially improve the clinical monitoring outcomes [221,222,179,223,224,226,252,227,228,268,229,313]. Example of medical image analysis on lungs includes localization study on potentially operable non-small cell lung cancer [222] and dosimetric planning for non-small-cell lung cancer [313]. There exists several modalities that is applied in lungs studies such as SPECT [221], PET–CT [271], FDG–PET [314], CT [221,222,179,223,224,226,252,227–229], PET [222,223,226,252,268] and FDG [223,224,226,268].

4.5. Other organs

Liver is another vital organ that is being increasingly studied using images, and the complexity of the liver tissue makes the medical imaging studies challenging. The registration and fusion of liver images for medical diagnosis is a task of primary importance [99]. The major modalities that deal with liver studies include SPECT [221], CT [221,179,315,254], PET [315] and ultrasound [254]. In bone marrow imaging, the medical diagnosis that performs image fusion includes tumor cell identification in bone

marrow [316], extraction of bone shape, color and structure of bone specimen [184] and bone tumor surgery [193,317]. MRI [184,193] and CT [184,193,317] are the modalities that are used for bone marrow imaging. On pelvis, image fusion methods are used for gynecological cancer diagnosis [187,318] and analysis of conformal pelvic irradiation [233]. Ovarian cancer diagnosis uses fuzzy rule base classifier fusion [60]. The use of secondary data to estimate instantaneous model parameters of diabetic heart disease is explained in [319]. A semantic based fusion technique in application to Alzheimer's disease is presented in [320]. A fusion imaging using a hybrid SPECT–CT camera is used in colorectal [246] cancer patients. The imaging of gross tumor volume delineation in head and neck cancer also investigated in the past [217]. Detection of oral cancer using fluorescent image by color image fusion is also explored [277].

5. Discussions and conclusions

The field of medical diagnostics and monitoring using medical images faces several technological, scientific and societal challenges. The technological advancements in imaging technologies have resulted in improved imaging accuracies. However, every modality of imaging has its own practical limitations, which is further imposed by the underlying nature of the organ and tissue structures. This enforces the need to explore the possibility to newer imaging technologies and to explore the possibility of using multiple imaging modalities. The ability of image fusion techniques to quantitatively and qualitatively improve the quality of imaging features makes multi-modal approaches efficient and accurate relative to unimodal approaches. The availability of a large number of techniques in feature processing, feature extraction and decision fusion makes the field of image fusion appealing to be used by medical imaging community. The methodological innovations specific to medical image fusion algorithms is rather limited at this stage, as majority of medical image fusion algorithms are derived from existing image fusion studies. The main challenge in applying image fusion algorithms is to ensure the medical relevance and aid for a better clinical outcome. The right combination of the imaging modalities, feature processing, feature extraction and decision fusion algorithms that targets a specific clinical problem in itself is a challenging and nontrivial task. Even the same images under consideration often require very different types of processing for different types of diagnostics over a region of interest. The major issues concerning feature processing and extraction algorithms resulting from the presence of pixel intensity outliers, missing features, sensors errors, spatial inaccuracies, and inter-image variability remain an open problem in medical image fusion. The inaccurate registration of the objects between the images is tightly linked to the poor performance of feature or decision level fusion on medical image fusion algorithms, and requires medical domain knowledge and algorithmic insights to reduce the fusion inaccuracies.

Another, point of interest is that when addressing the medical image fusion problems, the emphasis has been in the direction of developing algorithms that try to improve the imaging quality and regions of interest within images. The need for improving the image quality arises from the signal noise and the physical limitations of the imaging modality. The estimation of signal noise and compensation is considered as an important problem in medical imaging, and the advancements in enhancements to image quality can have a positive impact on the image fusion process. Another area of interest is to improve the speed of processing especially in the cases of volumetric image fusion. An algorithmic approach is to develop algorithms that are optimized for high speed processing. However, they would be limited by the hardware and

operating system capabilities. An alternate approach is to develop real-time processing systems in field programmable gate arrays and dedicate parallel computing graphical processing units. The speed is of primary importance in real-time image fusion during surgery or that involve continuous real-time monitoring. These are emerging areas of thoughts, and would require substantial progress in image fusion systems research.

The progress of this field largely depends on the trust that the medical practitioner and medical institutions place on the clinical improvements resulting from medical image fusion approaches. This is not an easy task, and would require a substantial convincing effort through technology improvements, access to the technological advancements and improving the usability of multi-modal systems in clinical setup. There are several technological advancements that can propel this growth. The primary growth comes from low-power high performance computing hardware developments for imaging that can process large volumes of high resolution images. In many medical imaging applications, although image resolutions are very high, the existing limitation in computing hardware makes the processing of such images in a time-limited clinical setup impossible. The advancements in parallel computing hardware such as low cost graphical processing units can overcome much of the problems facing conventional algorithmic approaches. The development of low cost computing also depends on the advancements in the semiconductor technologies and how quickly the technologies can be transferred to the market. The development in cognitive computing algorithms and hardware is another major technological advancement that could have a significant impact in the way in which the images are processed and presented. The incorporation of natural learning techniques in imaging hardware and software would be the natural progression that would aim to compete with human judgment – which by far would be the most challenging aspect to adopt in the medical service industry, but an obvious technological advancement for progressing medical image fusion research.

In conclusion, image fusion techniques in terms of medical image modalities and organs of study have been discussed in this survey. The extensive developments in medical image fusion research summarized in this literature review indicate the importance of this research in improving the medical services such as diagnosis, monitoring and analysis. The availability and growth of a wide range of imaging modality has enabled progress in medical image fusion to be useful for clinical deployment. Although, there has been significant progress in the medical image fusion research, the application of the general fusion algorithms is limited by the practical clinical implications as imposed by the medical experts based on the requirements of specific medical studies. In addition to medical reasons, there exists technical challenges in image registration and fusion resulting from image noise, resolution difference between images, inter-image variability between the images, lack of sufficient number of images per modality, high cost of imaging and increased computational complexity with increasing image space and time resolution. Nonetheless, even under these challenging situations, the fused images provide the human observers improved viewing and interpretation of medical images. The algorithms used for medical image fusion studies have resulted in the improved imaging quality and have proved to be useful for clinical applications. The prominent approaches include wavelets transforms, neural networks, fuzzy logic, morphology methods, and classifiers such as support vector machines. Combining one or more image fusion methods is also observed to be successful in medical image analysis. The algorithmic approaches to image fusion are also limited by the imaging hardware. The development of equipment that can perform multi-modal scanning is a challenging topic as it involves the risk of exposing the patients to additional radiation, longer examination time, and increased cost

of the device. This also involves having to look at compatibility issue of technologies as the space–time resolution and scanning speeds vary substantially from one imaging modality to another. The problem is much more significant in developing image fusion algorithms and devices for real-time medical applications such as robotic guided surgery. Since several of these challenges remain open and the image fusion in medical imaging has proved to be useful and the trust in these techniques is on the rise, it is expected that the innovation and practical advancements would continue to grow in the upcoming years.

References

- [1] B.V. Dasarathy, A special issue on natural computing methods in bioinformatics, *Inform. Fus.* 10 (3) (2009) 209.
- [2] B.V. Dasarathy, Editorial: information fusion in the realm of medical applications – a bibliographic glimpse at its growing appeal, *Inform. Fus.* 13 (1) (2012) 1–9.
- [3] B.V. Dasarathy, A special issue on biologically inspired information fusion, *Inform. Fus.* 11 (1) (2010) 1.
- [4] M.C. Casey, R.I. Damper, Editorial: special issue on biologically-inspired information fusion, *Inform. Fus.* 11 (1) (2010) 2–3.
- [5] J. Navarra, A. Alsius, S.S. Faraco, C. Spence, Assessing the role of attention in the audiovisual integration of speech, *Inform. Fus.* 11 (1) (2010) 4–11.
- [6] C.E. Hugenschmidt, S. Hayasaka, A.M. Peier, P.J. Laurienti, Applying capacity analyses to psychophysical evaluation of multisensory interactions, *Inform. Fus.* 11 (1) (2010) 12–20.
- [7] J. Greensmith, U. Aickelin, G. Tedesco, Information fusion for anomaly detection with the dendritic cell algorithm, *Inform. Fus.* 11 (1) (2010) 21–34.
- [8] J. Twycross, U. Aickelin, Information fusion in the immune system, *Inform. Fus.* 11 (1) (2010) 35–44.
- [9] S. Wuerger, G. Meyer, M. Hofbauer, C. Zetsche, K. Schill, Motion extrapolation of auditory–visual targets, *Inform. Fus.* 11 (1) (2010) 45–50.
- [10] T.D. Dixon, S.G. Nikolov, J.J. Lewis, J. Li, E.F. Canga, J.M. Noyes, T. Troscianko, D.R. Bull, C.N. Canagarajah, Task-based scanpath assessment of multi-sensor video fusion in complex scenarios, *Inform. Fus.* 11 (1) (2010) 51–65.
- [11] J.-B. Lei, J.-B. Yin, H.-B. Shen, Feature fusion and selection for recognizing cancer-related mutations from common polymorphisms, in: 2010 Chinese Conference on Pattern Recognition (CCPR), IEEE, 2010, pp. 1–5.
- [12] S. Tsevas, D. Iakovidis, Dynamic time warping fusion for the retrieval of similar patient cases represented by multimodal time-series medical data, in: 10th IEEE International Conference on Information Technology and Applications in Biomedicine (ITAB), 2010, IEEE, 2010, pp. 1–4.
- [13] H. Müller, J.K. Cramer, The image CLEF medical retrieval task at ICPR 2010—information fusion to combine visual and textual information, in: *Recog. Patt. Sig., Speech, Images Videos*, Springer, 2010, pp. 99–108.
- [14] Z.R. Mnatsakanyan, H.S. Burkom, M.R. Hashemian, M.A. Coletta, Distributed information fusion models for regional public health surveillance, *Inform. Fus.* 13 (2) (2012) 129–136.
- [15] S. Marshall, G. Matsopoulos, Morphological data fusion in medical imaging, in: IEEE Winter Workshop on Nonlinear Digital Signal Processing, 1993, IEEE, 1993, pp. 6–1.
- [16] K. Mikoajczyk, J. Owczarczyk, W. Recko, A test-bed for computer-assisted fusion of multi-modality medical images, in: *Comput. Anal. Images Patt.*, Springer, 1993, pp. 664–668.
- [17] G. Matsopoulos, S. Marshall, J. Brunt, Multiresolution morphological fusion of MR and CT images of the human brain, *IEE Proc. Vis., Image Signal Process.*, vol. 141, IET, 1994, pp. 137–142.
- [18] H. Li, R. Deklerck, B. De Cuyper, A. Hermanus, E. Nyssen, J. Cornelis, Object recognition in brain CT-scans: knowledge-based fusion of data from multiple feature extractors, *IEEE Trans. Med. Imag.* 14 (2) (1995) 212–229.
- [19] G.L. Rogova, P.C. Stomper, Information fusion approach to microcalcification characterization, *Inform. Fus.* 3 (2) (2002) 91–102.
- [20] W. Dou, S. Ruan, Q. Liao, D. Bloyet, J.-M. Constans, Knowledge based fuzzy information fusion applied to classification of abnormal brain tissues from MRI, in: *Proceedings of the Seventh International Symposium on Signal Processing and its Applications*, 2003, vol. 1, IEEE, 2003, pp. 681–684.
- [21] M. Raza, I. Gondal, D. Green, R.L. Coppel, Classifier fusion to predict breast cancer tumors based on microarray gene expression data, in: *Knowledge-Based Intelligent Information and Engineering Systems*, Springer, 2005, pp. 866–874.
- [22] Y. Wu, J. Zhang, C. Wang, S. C. Ng, Linear decision fusions in multilayer perceptrons for breast cancer diagnosis, in: 17th IEEE International Conference on Tools with Artificial Intelligence, 2005, ICTAI 05, IEEE, 2005, p. 2.
- [23] S. Radhouani, J.K. -Cramer, S. Bedrick, B. Bakke, W. Hersh, Using media fusion and domain dimensions to improve precision in medical image retrieval, in: *Multilingual Information Access Evaluation II – Multimedia Experiments*, Springer, 2010, pp. 223–230.
- [24] J.R. Jensen, W.R. Hersh, Manual query modification and data fusion for medical image retrieval, in: *Accessing Multilingual Information Repositories*, Springer, 2006, pp. 673–679.
- [25] D. Racoceanu, C. Lacoste, R. Teodorescu, N. Vuilleminot, A semantic fusion approach between medical images and reports using UMLS, in: *Information Retrieval Technology*, Springer, 2006, pp. 460–475.
- [26] R. Kapoor, A. Dutta, D. Bagai, T. S. Kamal, Fusion for registration of medical images—a study, in: *Proceedings of the 32nd Applied Imagery Pattern Recognition Workshop*, 2003, IEEE, 2003, pp. 180–185.
- [27] Q. Zhang, W. Tang, L. Lai, W. Sun, K. Wong, Medical diagnostic image data fusion based on wavelet transformation and self-organising features mapping neural networks, in: *Proceedings of 2004 International Conference on Machine Learning and Cybernetics*, 2004, vol. 5, IEEE, 2004, pp. 2708–2712.
- [28] Q. Zhang, M. Liang, W. Sun, Medical diagnostic image fusion based on feature mapping wavelet neural networks, in: *Proceedings of the Third International Conference on Image and Graphics*, 2004, IEEE, 2004, pp. 51–54.
- [29] K. Yuanyuan, L. Bin, T. Lianfang, M. Zongyuan, Multi-modal medical image fusion based on wavelet transform and texture measure, in: *Chinese Control Conference*, 2007, CCC 2007, IEEE, 2007, pp. 697–700.
- [30] B. Alfano, M. Ciampi, G.D. Pietro, A wavelet-based algorithm for multimodal medical image fusion, in: *Semantic Multimedia*, Springer, 2007, pp. 117–120.
- [31] S. Kor, U. Tiwary, Feature level fusion of multimodal medical images in lifting wavelet transform domain, in: 26th Annual International Conference of the IEEE on Engineering in Medicine and Biology Society, 2004, IEMBS'04, vol. 1, IEEE, 2004, pp. 1479–1482.
- [32] S. Garg, K. U. Kiran, R. Mohan, U. Tiwary, Multilevel medical image fusion using segmented image by level set evolution with region competition, in: 27th Annual International Conference of the Engineering in Medicine and Biology Society, 2005, IEEE-EMBS 2005, IEEE, 2006, pp. 7680–7683.
- [33] L. Bin, T. Lianfang, K. Yuanyuan, Y. Xia, Parallel multimodal medical image fusion in 3D conformal radiotherapy treatment planning, in: *The 2nd International Conference on Bioinformatics and Biomedical Engineering*, 2008, ICBBE 2008, IEEE, 2008, pp. 2600–2604.
- [34] M. Ciampi, Medical image fusion for color visualization via 3D RDWT, in: 10th IEEE International Conference on Information Technology and Applications in Biomedicine (ITAB), 2010, IEEE, 2010, pp. 1–6.
- [35] J. Montagner, V. Barra, J. Boire, Synthesis of a functional information with anatomical landmarks by multiresolution fusion of brain images, in: 27th Annual International Conference of the Engineering in Medicine and Biology Society, IEEE, 2006, pp. 6547–6550.
- [36] S.-H. Lai, M. Fang, Adaptive medical image visualization based on hierarchical neural networks and intelligent decision fusion, in: *Proceedings of the 1998 IEEE Signal Processing Society Workshop on Neural Networks for Signal Processing VIII*, 1998, IEEE, 1998, pp. 438–447.
- [37] S. Constantinos, M. S. Pattichis, E. M. Tzanakou, Medical imaging fusion applications: an overview, in: *Conference Record of the Thirty-Fifth Asilomar Conference on Signals, Systems and Computers*, 2001, vol. 2, IEEE, 2001, pp. 1263–1267.
- [38] H. Szu, I. Kopriva, P. Hoekstra, N. Diakides, M. Diakides, J. Buss, J. Lupo, Early tumor detection by multiple infrared unsupervised neural nets fusion, in: *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2003, vol. 2, IEEE, 2003, pp. 1133–1136.
- [39] W. Li, X.-f. Zhu, A new algorithm of multi-modality medical image fusion based on pulse-coupled neural networks, in: *Advances in Natural Computation*, Springer, 2005, pp. 995–1001.
- [40] L. Xiaoqi, Z. Baohua, G. Yong, Medical image fusion algorithm based on clustering neural network, in: *The 1st International Conference on Bioinformatics and Biomedical Engineering*, 2007, ICBBE 2007, IEEE, 2007, pp. 637–640.
- [41] Y.-P. Wang, J.-W. Dang, Q. Li, S. Li, Multimodal medical image fusion using fuzzy radial basis function neural networks, in: *International Conference on Wavelet Analysis and Pattern Recognition*, 2007, ICWAPR'07, vol. 2, IEEE, 2007, pp. 778–782.
- [42] Z. Wang, Y. Ma, Medical image fusion using *m*-PCNN, *Inform. Fus.* 9 (2) (2008) 176–185.
- [43] J. Teng, S. Wang, J. Zhang, X. Wang, Neuro-fuzzy logic based fusion algorithm of medical images, in: 3rd International Congress on Image and Signal Processing (CISP), 2010, vol. 4, IEEE, 2010, pp. 1552–1556.
- [44] Y. Wu, C. Wang, S.C. Ng, A. Madabhushi, Y. Zhong, Breast cancer diagnosis using neural-based linear fusion strategies, in: *Neural Information Processing*, Springer, 2006, pp. 165–175.
- [45] D. Lederman, B. Zheng, X. Wang, X.H. Wang, D. Gur, Improving breast cancer risk stratification using resonance-frequency electrical impedance spectroscopy through fusion of multiple classifiers, *Ann. Biomed. Eng.* 39 (3) (2011) 931–945.
- [46] M. S. B. Sehgal, I. Gondal, L. Dooley, Support vector machine and generalized regression neural network based classification fusion models for cancer diagnosis, in: *Fourth International Conference on Hybrid Intelligent Systems*, 2004, HIS'04, IEEE, 2004, pp. 49–54.
- [47] C. Barillot, D. Lemoine, L.L. Briquer, F. Lachmann, B. Gibaud, Data fusion in medical imaging: merging multimodal and multipatient images, identification of structures and 3D display aspects, *Euro. J. Radiol.* 17 (1) (1993) 22–27.
- [48] V. Barra, J.-Y. Boire, A general framework for the fusion of anatomical and functional medical images, *NeuroImage* 13 (3) (2001) 410–424.

- [49] I. Bloch, O. Colliot, O. Camara, T. Geraud, Fusion of spatial relationships for guiding recognition, example of brain structure recognition in 3D MRI, *Patt. Recog. Lett.* 26 (4) (2005) 449–457.
- [50] W. Dou, S. Ruan, Y. Chen, D. Bloyet, J.-M. Constans, A framework of fuzzy information fusion for the segmentation of brain tumor tissues on MR images, *Image Vision Comput.* 25 (2) (2007) 164–171.
- [51] R. Wasserman, R. Acharya, C. Sibata, K. Shin, A data fusion approach to tumor delineation, in: *Proceedings of the International Conference on Image Processing*, 1995, vol. 2, IEEE, 1995, pp. 476–479.
- [52] V. Barra, J.-Y. Boire, Automatic segmentation of subcortical brain structures in MR images using information fusion, *IEEE Trans. Med. Imag.* 20 (7) (2001) 549–558.
- [53] C.-H. Huang, J.-D. Lee, Improving MMI with enhanced-FCM for the fusion of brain MR and SPECT images, in: *Proceedings of the 17th International Conference on Pattern Recognition*, 2004, ICPR 2004, vol. 3, IEEE, 2004, pp. 562–565.
- [54] A. Villegier, L. Ouchchane, J.-J. Lemaire, J.-Y. Boire, Data fusion and fuzzy spatial relationships for locating deep brain stimulation targets in magnetic resonance images, in: *Advanced Concepts for Intelligent Vision Systems*, Springer, 2006, pp. 909–919.
- [55] W. Dou, S. Ruan, Q. Liao, D. Bloyet, J.-M. Constans, Y. Chen, Fuzzy information fusion scheme used to segment brain tumor from MR images, in: *Fuzzy Logic and Applications*, Springer, 2006, pp. 208–215.
- [56] X. Tai, W. Song, An improved approach based on FCM using feature fusion for medical image retrieval, in: *Fourth International Conference on Fuzzy Systems and Knowledge Discovery*, 2007, FSKD 2007, vol. 2, IEEE, 2007, pp. 336–342.
- [57] W. Song, T. Hua, Analytic implementation for medical image retrieval based on FCM using feature fusion with relevance feedback, in: *The 2nd International Conference on Bioinformatics and Biomedical Engineering*, 2008, ICBBE 2008, IEEE, 2008, pp. 2590–2595.
- [58] Y. Na, H. Lu, Y. Zhang, Content analysis based medical images fusion with fuzzy inference, in: *Fifth International Conference on Fuzzy Systems and Knowledge Discovery*, 2008, FSKD'08, vol. 3, IEEE, 2008, pp. 37–41.
- [59] A. Das, M. Bhattacharya, Evolutionary algorithm based automated medical image fusion technique: comparative study with fuzzy fusion approach, in: *World Congress on Nature & Biologically Inspired Computing*, 2009, NaBIC 2009, IEEE, 2009, pp. 269–274.
- [60] A. Assareh, L. G. Volkert, Fuzzy rule base classifier fusion for protein mass spectra based ovarian cancer diagnosis, in: *IEEE Symposium on Computational Intelligence in Bioinformatics and Computational Biology*, 2009, CIBCB'09, IEEE, 2009, pp. 193–199.
- [61] Q. Guihong, Z. Dali, Y. Pingfan, Medical image fusion by wavelet transform modulus maxima, *Optics Exp.* 9 (4) (2001) 184–190.
- [62] L. X. Mei, L. Jin, W. S. Hui, New medical image fusion algorithm based on second generation wavelet transform, in: *IMACS Multiconference on Computational Engineering in Systems Applications*, IEEE, 2006, pp. 1460–1464.
- [63] W. Li, X. Zhu, S. Wu, A novel approach to fast medical image fusion based on lifting wavelet transform, in: *The Sixth World Congress on Intelligent Control and Automation*, 2006, WCICA 2006, vol. 2, IEEE, 2006, pp. 9881–9884.
- [64] A. Wang, H. Sun, Y. Guan, The application of wavelet transform to multimodality medical image fusion, in: *Proceedings of the 2006 IEEE International Conference on Networking, Sensing and Control*, 2006, ICNSC'06, IEEE, 2006, pp. 270–274.
- [65] H. Zhang, L. Liu, N. Lin, A novel wavelet medical image fusion method, in: *International Conference on Multimedia and Ubiquitous Engineering*, 2007, MUE'07, IEEE, 2007, pp. 548–553.
- [66] W. Anna, L. Dan, C. Yu, et al., Research on medical image fusion based on orthogonal wavelet packets transformation combined with 2v-SVM, in: *IEEE/ICME International Conference on Complex Medical Engineering*, 2007, CME 2007, IEEE, 2007, pp. 670–675.
- [67] X. Li, X. Tian, Y. Sun, Z. Tang, Medical image fusion by multi-resolution analysis of wavelets transform, in: *Wavelet Analysis and Applications*, Springer, 2007, pp. 389–396.
- [68] C. Shangli, L. Junmin, L. Zhongwei, Medical image of PET/CT weighted fusion based on wavelet transform, in: *The 2nd International Conference on Bioinformatics and Biomedical Engineering*, 2008, ICBBE 2008, IEEE, 2008, pp. 2523–2525.
- [69] Y. Licai, L. Xin, Y. Yucui, Medical image fusion based on wavelet packet transform and self-adaptive operator, in: *The 2nd International Conference on Bioinformatics and Biomedical Engineering*, 2008, ICBBE 2008, IEEE, 2008, pp. 2647–2650.
- [70] Z. Wencang, C. Lin, Medical image fusion method based on wavelet multi-resolution and entropy, in: *IEEE International Conference on Automation and Logistics*, 2008, ICAL 2008, IEEE, 2008, pp. 2329–2333.
- [71] B. Yang, Z. Jing, Medical image fusion with a shift-invariant morphological wavelet, in: *IEEE Conference on Cybernetics and Intelligent Systems*, 2008, IEEE, 2008, pp. 175–178.
- [72] R. Singh, M. Vatsa, A. Noore, Multimodal medical image fusion using redundant discrete wavelet transform, in: *Seventh International Conference on Advances in Pattern Recognition*, 2009, ICAPR'09, IEEE, 2009, pp. 232–235.
- [73] Z. Xiao, C. Zheng, Medical image fusion based on an improved wavelet coefficient contrast, in: *3rd International Conference on Bioinformatics and Biomedical Engineering*, IEEE, 2009, pp. 1–4.
- [74] L. Chiorean, M.-F. Vaida, Medical image fusion based on discrete wavelet transform using java technology, in: *Proceedings of the ITI 2009 31st International Conference on Information Technology Interfaces*, 2009, ITI'09, IEEE, 2009, pp. 55–60.
- [75] X. Zhang, Y. Zheng, Y. Peng, W. Liu, C. Yang, Research on multi-mode medical image fusion algorithm based on wavelet transform and the edge characteristics of images, in: *2nd International Congress on Image and Signal Processing*, 2009, CISP'09, IEEE, 2009, pp. 1–4.
- [76] Y. Liu, J. Yang, J. Sun, PET/CT medical image fusion algorithm based on multiwavelet transform, in: *2nd International Conference on Advanced Computer Control (ICACC)*, 2010, vol. 2, IEEE, 2010, pp. 264–268.
- [77] Y. Yang, Multimodal medical image fusion through a new DWT based technique, in: *4th International Conference on Bioinformatics and Biomedical Engineering (ICBBE)*, 2010, IEEE, 2010, pp. 1–4.
- [78] B. Li, L. Tian, S. Ou, Rapid multimodal medical image registration and fusion in 3D conformal radiotherapy treatment planning, in: *4th International Conference on Bioinformatics and Biomedical Engineering*, 2010, IEEE, 2010, pp. 1–5.
- [79] M. Agrawal, P. Tsakalides, A. Achim, Medical image fusion using the convolution of meridian distributions, in: *Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2010, IEEE, 2010, pp. 3727–3730.
- [80] W. Xue-jun, M. Ying, A medical image fusion algorithm based on lifting wavelet transform, in: *2010 International Conference on Artificial Intelligence and Computational Intelligence (AICI)*, vol. 3, IEEE, 2010, pp. 474–476.
- [81] S. Rajkumar, S. Kavitha, Redundancy discrete wavelet transform and contourlet transform for multimodality medical image fusion with quantitative analysis, in: *3rd International Conference on Emerging Trends in Engineering and Technology (ICETET)*, 2010, IEEE, 2010, pp. 134–139.
- [82] C. Kavitha, C. Chellamuthu, Multimodal medical image fusion based on integer wavelet transform and neuro-fuzzy, in: *2010 International Conference on Signal and Image Processing (ICSIP)*, IEEE, 2010, pp. 296–300.
- [83] S. Vekkot, Wavelet based medical image fusion using filter masks, in: *Trends in Intelligent Robotics*, Springer, 2010, pp. 298–305.
- [84] J. Teng, X. Wang, J. Zhang, S. Wang, P. Huo, A multimodality medical image fusion algorithm based on wavelet transform, in: *Advances in Swarm Intelligence*, Springer, 2010, pp. 627–633.
- [85] C. Kok, Y. Hui, T. Nguyen, Medical image pseudo coloring by wavelet fusion, in: *Proceedings of the 18th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 1996, Bridging Disciplines for Biomedicine, vol. 2, IEEE, 1996, pp. 648–649.
- [86] Z. Cui, G. Zhang, J. Wu, Medical image fusion based on wavelet transform and independent component analysis, in: *International Joint Conference on Artificial Intelligence*, 2009, IJCAI'09, IEEE, 2009, pp. 480–483.
- [87] F. Masulli, S. Mitra, Natural computing methods in bioinformatics: a survey, *Inform. Fus.* 10 (3) (2009) 211–216.
- [88] J. K. Avor, T. Sarkodie-Gyan, An approach to sensor fusion in medical robots, in: *IEEE International Conference on Rehabilitation Robotics*, 2009, ICORR 2009, IEEE, 2009, pp. 818–822.
- [89] G.N. Brock, W.D. Beavis, L.S. Kubatko, Fuzzy logic and related methods as a screening tool for detecting gene regulatory networks, *Inform. Fus.* 10 (3) (2009) 250–259.
- [90] R.K. De, A. Ghosh, Linguistic recognition system for identification of some possible genes mediating the development of lung adenocarcinoma, *Inform. Fus.* 10 (3) (2009) 260–269.
- [91] J. Teng, S. Wang, J. Zhang, X. Wang, Fusion algorithm of medical images based on fuzzy logic, in: *Seventh International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)*, 2010, vol. 2, IEEE, 2010, pp. 546–550.
- [92] M. Bhattacharya, A. Das, Multimodality medical image registration and fusion techniques using mutual information and genetic algorithm-based approaches, in: *Software Tools and Algorithms for Biological Systems*, Springer, 2011, pp. 441–449.
- [93] V.D. Calhoun, T. Adali, Feature-based fusion of medical imaging data, *IEEE Trans. Inform. Technol. Biomed.* 13 (5) (2009) 711–720.
- [94] W. Hao-quan, X. Hao, Multi-mode medical image fusion algorithm based on principal component analysis, in: *International Symposium on Computer Network and Multimedia Technology*, 2009, CNMT 2009, IEEE, 2009, pp. 1–4.
- [95] N. Al-Azzawi, H. A. M. Sakim, A. W. Abdullah, H. Ibrahim, Medical image fusion scheme using complex contourlet transform based on PCA, in: *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2009, EMBC 2009, IEEE, 2009, pp. 5813–5816.
- [96] N.A. Al-Azzawi, H. Mat Sakim, A.W. Abdullah, An efficient medical image fusion method using contourlet transform based on PCM, in: *IEEE Symposium on Industrial Electronics & Applications*, 2009, ISIEA 2009, vol. 1, IEEE, 2009, pp. 11–14.
- [97] C. He, Q. Liu, H. Li, H. Wang, Multimodal medical image fusion based on IHS and PCA, *Proc. Eng.* 7 (2010) 280–285.
- [98] C. Wang, Z. Ye, First-order fusion of volumetric medical imagery, *IEE Proc. – Vis., Image Sig. Process.* 153 (2) (2006) 191–198.
- [99] T. Chung, X. Liu, C. Chen, X. Sun, N. Chiu, J. Lee, Intermodality registration and fusion of liver images for medical diagnosis, in: *Proceedings of the Intelligent Information Systems*, 1997, IIS'97, IEEE, 1997, pp. 42–46.
- [100] J. Phegley, K. Perkins, L. Gupta, J.K. Dorsey, Risk-factor fusion for predicting multifactorial diseases, *IEEE Trans. Biomed. Eng.* 49 (1) (2002) 72–76.

- [101] B.E. -Ramirez, The hermite transform as an efficient model for local image analysis: an application to medical image fusion, *Comput. Elect. Eng.* 34 (2) (2008) 99–110.
- [102] Z. Zhang, J. Yao, S. Bajwa, T. Gudas, Automatic multimodal medical image fusion, in: *Proceedings of the 16th IEEE Conference on Computer-Based Medical Systems*, IEEE Computer Society, 2003, pp. 42–49.
- [103] L. Yang, B. Guo, W. Ni, Multimodality medical image fusion based on multiscale geometric analysis of contourlet transform, *Neurocomputing* 72 (1) (2008) 203–211.
- [104] Y. Wei, Y. Zhu, F. Zhao, Y. Shi, T. Mo, X. Ding, J. Zhong, Implementing contourlet transform for medical image fusion on a heterogenous platform, in: *International Conference on Scalable Computing and Communications; Eighth International Conference on Embedded Computing*, 2009, SCALCOM-EMBEDDEDCOM'09, IEEE, 2009, pp. 115–120.
- [105] V. Barra, J.-Y. Boire, Quantification of brain tissue volumes using MR/MR fusion, in: *Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2000, vol. 2, IEEE, 2000, pp. 1451–1454.
- [106] L. Gupta, B. Chung, D. L. Molfese, Multichannel fusion models for the parametric classification of multicategory differential brain activity, in: *26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2004, IEMBS'04, vol. 1, IEEE, 2004, pp. 940–943.
- [107] I. Dimou, G. Manikis, M. Zervakis, Classifier fusion approaches for diagnostic cancer models, in: *28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2006, EMBS'06, IEEE, 2006, pp. 5334–5337.
- [108] M. Raza, I. Gondal, D. Green, R. L. Coppel, Classifier fusion using dempster-shafer theory of evidence to predict breast cancer tumors, in: *2006 IEEE Region 10 Conference TENCN 2006*, IEEE, 2006, pp. 1–4.
- [109] N. Zhang, Q. Liao, S. Ruan, S. Lebonvallet, Y. Zhu, Multi-kernel SVM based classification for tumor segmentation by fusion of MRI images, in: *IEEE International Workshop on Imaging Systems and Techniques*, 2009, IST'09, IEEE, 2009, pp. 71–75.
- [110] M.M. Rahman, B.C. Desai, P. Bhattacharya, Medical image retrieval with probabilistic multi-class support vector machine classifiers and adaptive similarity fusion, *Computer. Med. Imag. Graph.* 32 (2) (2008) 95–108.
- [111] Y. Huang, J. Zhang, Y. Zhao, D. Ma, Medical image retrieval with query-dependent feature fusion based on one-class SVM, in: *IEEE 13th International Conference on Computational Science and Engineering (CSE)*, 2010, IEEE, 2010, pp. 176–183.
- [112] G. Pavesi, G. Valentini, Classification of co-expressed genes from DNA regulatory regions, *Inform. Fus.* 10 (3) (2009) 233–241.
- [113] L. Palopoli, S.E. Rombo, G. Terracina, G. Tradigo, P. Veltri, Improving protein secondary structure predictions by prediction fusion, *Inform. Fus.* 10 (3) (2009) 217–232.
- [114] J.Y. Njiwa, R. Goutte, Use of quaternionic signals representation for analysis and fusion of multi-components 2D medical images, in: *9th International Conference on Signal Processing*, 2008, ICSP 2008, IEEE, 2008, pp. 733–736.
- [115] V.D. Calhoun, T. Adali, ICA for fusion of brain imaging data, in: *Signal Processing Techniques for Knowledge Extraction and Information Fusion*, Springer, 2008, pp. 221–240.
- [116] P. Viswanathan, P.V. Krishna, Text fusion watermarking in medical image with semi-reversible for secure transfer and authentication, in: *International Conference on Advances in Recent Technologies in Communication and Computing*, 2009, ARTCom'09, IEEE, 2009, pp. 585–589.
- [117] T. Kauppi, J.-K. Kamarainen, L. Lensu, V. Kalesnykiene, I. Sorri, H. Kalviainen, H. Uusitalo, J. Pietila, Fusion of multiple expert annotations and overall score selection for medical image diagnosis, in: *Image Analysis*, Springer, 2009, pp. 760–769.
- [118] H. Zhou, Q. Cheng, M. Zargham, Fast fusion of medical images based on Bayesian risk minimization and pixon map, in: *International Conference on Computational Science and Engineering*, 2009, CSE'09, vol. 2, IEEE, 2009, pp. 1086–1091.
- [119] G. Bhatnagar, Q. Wu, Z. Liu, Directive contrast based multimodal medical image fusion in NSCT domain, *IEEE Trans. Multimedia* 15 (5) (2013) 1014–1024.
- [120] H. G. Hosseini, A. Alizad, M. Fatemi, Fusion of vibro-acoustography images and X-ray mammography, in: *28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2006, EMBS'06, IEEE, 2006, pp. 2803–2806.
- [121] L. Kronberger Jr., R. Nicoletti, G. Ranner, E. Graif, R. Stollberger, R. Einspieler, M. Wiltgen, G. Fueger, F. Ebner, P. Steindorfer, Computed fusion of MRI and anti-cea immunoscintigraphy in the follow up of operated rectal cancer, *Euro. J. Can.* 29 (1993) S97.
- [122] A.T. -Ahmed, L. Gautier, On information fusion to improve segmentation of MRI sequences, *Inform. Fus.* 3 (2) (2002) 103–117.
- [123] M. Aguilar, J. R. New, Fusion of multi-modality volumetric medical imagery, in: *Proceedings of the Fifth International Conference on Information Fusion*, 2002, vol. 2, IEEE, 2002, pp. 1206–1212.
- [124] M. Vermandel, N. Betrouni, G. Palos, J.-Y. Gauvrit, C. Vasseur, J. Rousseau, Registration, matching and data fusion in 2D/3D medical imaging: Application to DSA and MRA, in: *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2003*, Springer, 2003, pp. 778–785.
- [125] A.-S. Capelle, O. Colot, C.F. -Maloigne, Evidential segmentation scheme of multi-echo MR images for the detection of brain tumors using neighborhood information, *Inform. Fus.* 5 (3) (2004) 203–216.
- [126] Y.-M. Zhu, S.M. Cocho, An object-oriented framework for medical image registration, fusion, and visualization, *Comput. Meth. Prog. Biomed.* 82 (3) (2006) 258–267.
- [127] O. Tanaka, S. Hayashi, M. Matsuo, M. Nakano, H. Uno, K. Ohtakara, S. Okada, H. Hoshi, T. Deguchi, 4043 Poster effect of edema on postimplant dosimetry in prostate brachytherapy using CT/MRI fusion, *Euro. J. Can. Suppl.* 5 (4) (2007) 292.
- [128] S.F. Nemec, P. Peloschek, M.T. Schmook, C.R. Krestan, W. Hau, C. Matula, C. Czerny, CT-MR image data fusion for computer-assisted navigated surgery of orbital tumors, *Euro. J. Radiol.* 73 (2) (2010) 224–229.
- [129] S. Daneshvar, H. Ghassemani, MRI and PET image fusion by combining IHS and retina-inspired models, *Inform. Fus.* 11 (2) (2010) 114–123.
- [130] H. Park, C.R. Meyer, D. Wood, A. Khan, R. Shah, H. Hussain, J. Siddiqui, J. Seo, T. Chenevert, M. Pierr, Validation of automatic target volume definition as demonstrated for ¹¹C-choline PET/CT of human prostate cancer using multi-modality fusion techniques, *Acad. Radiol.* 17 (5) (2010) 614–623.
- [131] E. Faliagka, G. Matsopoulos, A. Tsakalidis, J. Tsaknakis, G. Tzimas, Registration and fusion techniques for medical images: Demonstration and evaluation, in: *Biomedical Engineering Systems and Technologies*, Springer, 2011, pp. 15–28.
- [132] B. Hentschel, W. Oehler, D. Straus, A. Ulrich, A. Malich, Definition of the CTV prostate in CT and MRI by using CT-MRI image fusion in IMRT planning for prostate cancer, *Strahlentherapie und Onkologie* 187 (3) (2011) 183–190.
- [133] C. Tsien, W. Parker, D. Parmar, D. Hristov, L. Souhami, C. Freeman, 81 the role of MRI fusion in radiotherapy planning of pediatric CNS tumors, *Int. J. Rad. Oncol. Biol. Phys.* 45 (3) (1999) 188–189.
- [134] J. Julow, T. Major, M. Emri, I. Valalik, S. Sagi, L. Mangel, G. Nemeth, L. Tron, G. Varallyay, D. Solymsi, et al., The application of image fusion in stereotactic brachytherapy of brain tumours, *Acta Neurochirurgica* 142 (11) (2000) 1253–1258.
- [135] R. Gorniak, E. Kramer, G.Q. Maguire Jr, M.E. Noz, C. Schettino, M.P. Zeleznik, Evaluation of a semiautomatic 3D fusion technique applied to molecular imaging and MRI brain/frame volume data sets, *J. Med. Syst.* 27 (2) (2003) 141–156.
- [136] J.-D. Lee, B.-R. Huang, C.-H. Huang, A surface-projection MMI for the fusion of brain MR and SPECT images, in: *IEEE Region 10 Conference*, 2004, TENCN 2004, IEEE, 2004, pp. 179–182.
- [137] S. David, M. Back, R. Mukherjee, K. Lim, J. Liade, Interclinician variability in delineation of tumour volumes for glioblastomas with the assistance of MRI fusion, *Euro. J. Can.* 3 (2) (2005) 400–401.
- [138] R.A. Heckemann, J.V. Hajnal, P. Aljabar, D. Rueckert, A. Hammers, Multiclassifier fusion in human brain MR segmentation: modeling convergence, in: *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2006*, Springer, 2006, pp. 815–822.
- [139] J. A. Marquez, A. Gastellum, M. A. Padilla, Image-fusion operators for 3D anatomical and functional analysis of the brain, in: *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2007, EMBS 2007, IEEE, 2007, pp. 833–835.
- [140] M.C. Dastjerdi, A. Karimian, H. Afarideh, A. Mohammadzadeh, FMDIB: a software tool for fusion of MRI and DHC-SPECT images of brain, in: *World Congress on Medical Physics and Biomedical Engineering*, September 7–12, 2009, Munich, Germany, Springer, 2009, pp. 741–744.
- [141] S.A. Kuhn, B. Romeike, J. Walter, R. Kal, R. Reichart, Multiplanar MRI-CT fusion neuronavigation-guided serial stereotactic biopsy of human brain tumors: proof of a strong correlation between tumor imaging and histopathology by a new technical approach, *J. Can. Res. Clin. Oncol.* 135 (9) (2009) 1293–1302.
- [142] H. Lee, J. Lee, G. Kim, Y.G. Shin, Efficient hybrid registration method using a shell volume for PET and high resolution MR brain image fusion, in: *World Congress on Medical Physics and Biomedical Engineering*, September 7–12, 2009, Munich, Germany, Springer, 2010, pp. 2326–2329.
- [143] F. Forbes, S. Doyle, D. G.-Lorenzo, C. Barillot, M. Dojat, Adaptive weighted fusion of multiple MR sequences for brain lesion segmentation, in: *IEEE International Symposium on Biomedical Imaging: From Nano to Macro*, 2010, IEEE, 2010, pp. 69–72.
- [144] S. P. Awate, H. Zhang, T. J. Simon, J. C. Gee, Multivariate segmentation of brain tissues by fusion of MRI and DTI data, in: *5th IEEE International Symposium on Biomedical Imaging: From Nano to Macro*, 2008, ISBI 2008, IEEE, 2008, pp. 213–216.
- [145] S. Martin, M. Baumann, V. Daanen, J. Troccaz, MR prior based automatic segmentation of the prostate in TRUS images for MR/TRUS data fusion, in: *IEEE International Symposium on Biomedical Imaging: From Nano to Macro*, 2010, IEEE, 2010, pp. 640–643.
- [146] S. Ahmed, K.M. Iftikharuddin, A. Vossough, Efficacy of texture, shape, and intensity feature fusion for posterior-fossa tumor segmentation in MRI, *IEEE Trans. Inform. Technol. Biomed.* 15 (2) (2011) 206–213.
- [147] K. Kagawa, W.R. Lee, T.E. Schultheiss, M.A. Hunt, A.H. Shaer, G.E. Hanks, Initial clinical assessment of CT-MRI image fusion software in localization of the prostate for 3D conformal radiation therapy, *Int. J. Rad. Oncol. Biol. Phys.* 38 (2) (1997) 319–325.
- [148] I. Kaplan, E. Holupka, M. Morrissey, MRI-ultrasound image fusion for 125I prostate implant treatment planning, *Int. J. Rad. Oncol. Biol. Phys.* 42 (1) (1998) 294.
- [149] V. Serois, L. Chauveinc, C. El Khoury, A. Lantoin, L. Ollivier, T. Flam, J. Rosenwald, J. Cosset, S. Neuenschwander, Comparaison de deux méthodes de recalage d'images de scanographie et d'IRM en curiethérapie prostatique, *Cancer/Radiothérapie* 7 (1) (2003) 9–16.

- [150] J. Crook, M. McLean, I. Yeung, T. Williams, G. Lockwood, MRI-CT fusion to assess postbrachytherapy prostate volume and the effects of prolonged edema on dosimetry following transperineal interstitial permanent prostate brachytherapy, *Brachytherapy* 3 (2) (2004) 55–60.
- [151] B. Fei, Z. Lee, D.T. Boll, J.L. Duerk, J.S. Lewin, D.L. Wilson, Image registration and fusion for interventional MRI guided thermal ablation of the prostate cancer, in: *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2003*, Springer, 2003, pp. 364–372.
- [152] B. Fei, Z. Lee, D.T. Boll, J.L. Duerk, D.B. Sodee, J.S. Lewin, D.L. Wilson, Registration and fusion of SPECT, high-resolution MRI, and interventional MRI for thermal ablation of prostate cancer, *IEEE Trans. Nucl. Sci.* 51 (1) (2004) 177–183.
- [153] D. Taussky, L. Austen, A. Toi, I. Yeung, T. Williams, S. Pearson, M. McLean, G. Pond, J. Crook, Sequential evaluation of prostate edema after permanent seed prostate brachytherapy using CT-MRI fusion, *Int. J. Rad. Oncol. Biol. Phys.* 62 (4) (2005) 974–980.
- [154] O. Tanaka, S. Hayashi, M. Matsuo, K. Sakurai, M. Nakano, S. Maeda, K. Kajita, T. Deguchi, H. Hoshi, Comparison of MRI-based and CT/MRI fusion-based postimplant dosimetric analysis of prostate brachytherapy, *Int. J. Rad. Oncol. Biol. Phys.* 66 (2) (2006) 597–602.
- [155] I. Yeung, S. Chen, Y. Cho, D. Taussky, A.B. Ardakani, J. Crook, 2786: Finite element modeling of prostate edema and seed dynamic post LDR prostate brachytherapy using CT-MRI fusion, *Int. J. Rad. Oncol. Biol. Phys.* 66 (3) (2006) S649–S650.
- [156] O. Tanaka, S. Hayashi, K. Sakurai, M. Matsuo, M. Nakano, S. Maeda, H. Hoshi, T. Deguchi, Importance of the CT/MRI fusion method as a learning tool for CT-based postimplant dosimetry in prostate brachytherapy, *Radioth. Oncol.* 81 (3) (2006) 303–308.
- [157] S. Wachter, S. Tomek, A. Kurtaran, N.W. Gerstner, B. Djavan, A. Becherer, M. Mitterhauser, G. Dobrozemsky, S. Li, R. Ptter, R. Dudczak, K. Kletter, ¹¹C-acetate positron emission tomography imaging and image fusion with computed tomography and magnetic resonance imaging in patients with recurrent prostate cancer, *J. Clin. Oncol.* 24 (16) (2006) 2513–2519.
- [158] O. Tanaka, S. Hayashi, M. Matsuo, M. Nakano, H. Uno, K. Ohtakara, T. Miyoshi, T. Deguchi, H. Hoshi, Effect of edema on postimplant dosimetry in prostate brachytherapy using CT/MRI fusion, *Int. J. Rad. Oncol. Biol. Phys.* 69 (2) (2007) 614–618.
- [159] A. Venkatesan, J. Kruecker, S. Xu, J. Locklin, P. Pinto, A. Singh, N. Glossop, B. Wood, Abstract no. 155: early clinical experience with real time ultrasound-MRI fusion-guided prostate biopsies, *J. Vasc. Interv. Radiol.* 19 (2) (2008) S59–S60.
- [160] J. Pouliot, A.J. Cunha, G.D. Reed, S.M. Noworolski, J. Kurhanewicz, I. Hsu, J. Chow, Multi-image fusions and their role in inverse planned high-dose-rate prostate brachytherapy for dose escalation of dominant intraprostatic lesions defined by combined MRI/MRSI, *Brachytherapy* 8 (2) (2009) 113–114.
- [161] N. Patanjali, M. Keyes, W.J. Morris, M. Liu, R. Harrison, I. Spadinger, V. Moravan, A comparison of post-implant US/CT image fusion and MRI/CT image fusion for ¹²⁵I prostate brachytherapy post implant dosimetry, *Brachytherapy* 8 (2) (2009) 124.
- [162] M. Aoki, A. Yoroizu, T. Dokiya, Evaluation of interobserver differences in postimplant dosimetry following prostate brachytherapy and the efficacy of CT/MRI fusion imaging, *Japan. J. Radiol.* 27 (9) (2009) 342–347.
- [163] J. Kruecker, S. Xu, B. Turkbey, P. Choyke, A. Rastinehad, J. Locklin, S. Gates, P. Pinto, B. Wood, Trus/MRI fusion-targeted prostate biopsy results correlate with MRI suspicion level, *J. Vasc. Interv. Radiol.* 21 (2) (2010) S25–S26.
- [164] P. Acher, S. Puttagunta, K. Rhode, S. Morris, J. Kinsella, A. Gaya, P. Dasgupta, C. Deehan, R. Beaney, R. Popert, et al., An analysis of intraoperative versus post-operative dosimetry with CT, CT-MRI fusion and xmr for the evaluation of permanent prostate brachytherapy implants, *Radioth. Oncol.* 96 (2) (2010) 166–171.
- [165] A. Mesa, L. Chittenden, J. Lizarde, J. Lee, M. Nelson, J. Lane, A. Spitz, K. Tokita, A gold fiducial based CT/MRI fusion method for prostate treatment planning, *Int. J. Rad. Oncol. Biol. Phys.* 78 (3) (2010) S375.
- [166] S. Kadoury, P. Yan, S. Xu, N. Glossop, P. Choyke, B. Turkbey, P. Pinto, B.J. Wood, J. Kruecker, Realtime TRUS/MRI fusion targeted-biopsy for prostate cancer: a clinical demonstration of increased positive biopsy rates, in: *Prostate Cancer Imaging, Computer-Aided Diagnosis, Prognosis, and Intervention*, Springer, 2010, pp. 52–62.
- [167] A. Rastinehad, J. Kruecker, C. Benjamin, P. Chung, B. Turkbey, S. Xu, J. Locklin, S. Gates, C. Buckner, M. Linehan, et al., 846 MRI/US fusion prostate biopsies: cancer detection rates, *J. Urol.* 185 (4) (2011) e340.
- [168] O. Ukimura, M. Desai, M. Aron, A. Hung, A. Berger, S. Valencerina, S. Palmer, I. Gill, 2131 Elastic registration of 3D prostate biopsy trajectory by real-time 3D TRUS with MR/TRUS fusion: pilot phantom study, *J. Urol.* 185 (4) (2011) e853.
- [169] D. Weber, G. Dipasquale, M. Rouzaud, R. Miralbell, A comparison of gross tumor volumes segmented on diagnostic MRI and planning CT with or without post-operative open low-field MRI fusion for 3-D conformal radiotherapy of glioblastomas, *EJC Suppl.* 3 (2005) 405.
- [170] H. Xie, G. Li, H. Ning, C. Menard, C. N. Coleman, R. W. Miller, 3D voxel fusion of multi-modality medical images in a clinical treatment planning system, in: *Proceedings of the 17th IEEE Symposium on Computer-Based Medical Systems*, 2004, CBMS 2004, IEEE, 2004, pp. 48–53.
- [171] R.J. Amdur, D. Gladstone, K.A. Leopold, R.D. Harris, Prostate seed implant quality assessment using MR and CT image fusion, *Int. J. Rad. Oncol. Biol. Phys.* 43 (1) (1999) 67–72.
- [172] A. Polo, F. Cattani, A. Vavassori, D. Origgi, G. Villa, H. Marsiglia, M. Bellomi, G. Tosi, O. De Cobelli, R. Orecchia, MR and CT image fusion for postimplant analysis in permanent prostate seed implants, *Int. J. Rad. Oncol. Biol. Phys.* 60 (5) (2004) 1572–1579.
- [173] K.L. Maletz, R.D. Ennis, J. Ostenson, A. Pevsner, A. Kagen, I. Wernick, Comparison of CT and MR-CT fusion for prostate post-implant dosimetry, *Int. J. Rad. Oncol. Biol. Phys.* 82 (5) (2012) 1912–1917.
- [174] B. Hadaschik, T. Kuru, C. Tulea, D. Teber, J. Huber, V. Popeneciu, S. Pahernik, H.-P. Schlemmer, M. Hohenfellner, 2304 Stereotactic prostate biopsy with pre-interventional MRI and live us fusion, *J. Urol.* 185 (4) (2011) e924.
- [175] Z.-S. Xiao, C.-X. Zheng, Medical image fusion based on the structure similarity metric measure, in: *International Conference on Measuring Technology and Mechatronics Automation*, 2009, ICMTMA'09, vol. 1, IEEE, 2009, pp. 491–494.
- [176] A. M. Eldeib, S. M. Yamany, A. Farag, Multi-modal medical volumes fusion by surface matching, in: *Proceedings of the Fifth International Symposium on Signal Processing and its Applications*, 1999, ISSPA'99, vol. 1, IEEE, 1999, pp. 439–442.
- [177] A.A. Farag, S.M. Yamany, J. Nett, T. Moriarty, A. El-Baz, S. Hushek, R. Falk, Medical image registration: theory, algorithm, and case studies in surgical simulation, chest cancer, and multiple sclerosis, in: *Handbook of Biomedical Image Analysis*, Springer, 2005, pp. 1–46.
- [178] M.C. Erie, C.H. Chu, R.D. Sidman, Visualization of the cortical potential field by medical imaging data fusion, in: *Visual Information and Information Systems*, Springer, 1999, pp. 815–822.
- [179] M. Uematsu, A. Shioda, A. Suda, K. Tahara, T. Kojima, Y. Hama, M. Kono, J.R. Wong, T. Fukui, S. Kusano, Intrafractional tumor position stability during computed tomography (CT)-guided frameless stereotactic radiation therapy for lung or liver cancers with a fusion of CT and linear accelerator (focal) unit, *Int. J. Rad. Oncol. Biol. Phys.* 48 (2) (2000) 443–448.
- [180] C.P. Behrenbruch, K. Marias, P.A. Armitage, M. Yam, N. Moore, R.E. English, J.M. Brady, MRI-mammography 2D/3D data fusion for breast pathology assessment, in: *Medical Image Computing and Computer-Assisted Intervention-MICCAI 2000*, Springer, 2000, pp. 307–316.
- [181] K. G. Baum, K. Raerty, M. Helguera, E. Schmidt, Investigation of PET/MRI image fusion schemes for enhanced breast cancer diagnosis, in: *Nuclear Science Symposium Conference Record*, 2007, NSS'07, vol. 5, IEEE, 2007, pp. 3774–3780.
- [182] G.M. Duarte, G.H. Telles, S.T. Bianchessi, S.R. Segala, M.d.C.L. de Lima, E.C.S. de Camargo Etchebehere, E. Tinois, et al., Fusion of magnetic resonance and scintimammography images for breast cancer evaluation: a pilot study, *Ann. Surg. Oncol.* 14 (10) (2007) 2903–2910.
- [183] D. Dey, D.G. Gobbi, P.J. Slomka, K.J. Surry, T.M. Peters, Automatic fusion of freehand endoscopic brain images to three-dimensional surfaces: creating stereoscopic panoramas, *IEEE Trans. Med. Imag.* 21 (1) (2002) 23–30.
- [184] A. W. Wetzel, G. L. Nieder, G. Durka-Pelok, T. R. Gest, S. M. Pomerantz, D. Nave, S. Czanner, L. Wagner, E. Shirey, D. W. Deerfield, Photo-realistic representation of anatomical structures for medical education by fusion of volumetric and surface image data, in: *Proceedings of the 32nd Applied Imagery Pattern Recognition Workshop*, 2003, IEEE, 2003, pp. 131–138.
- [185] M. Aguilar, J. R. New, E. Hasanbelliu, Advances in the use of neurophysiologically-based fusion for visualization and pattern recognition of medical imagery, in: *Proceedings of the Sixth International Conference on Information Fusion*, vol. 2, 2003, pp. 860–867.
- [186] C.-H. Huang, C.-F. Jiang, W.-H. Sung, Medical image registration and fusion with 3D CT and MR data of head, in: *19th IEEE International Symposium on Computer-Based Medical Systems*, 2006, CBMS 2006, IEEE, 2006, pp. 401–404.
- [187] C.-C. Tsai, C.-S. Tsai, K.-K. Ng, C.-H. Lai, S. Hsueh, P.-F. Kao, T.-C. Chang, J.-H. Hong, T.-C. Yen, The impact of image fusion in resolving discrepant findings between FDG-PET and MRI/CT in patients with gynaecological cancers, *Euro. J. Nucl. Med. Mole. Imag.* 30 (12) (2003) 1674–1683.
- [188] E. Zacharakis, G. Matsopoulos, K. Nikita, G. Stamatakis, An application of multimodal image registration and fusion in a 3D tumor simulation model, in: *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2003, vol. 1, IEEE, 2003, pp. 686–689.
- [189] T. Nishioka, H. Shirato, T. Karo, Y. Watanabe, A. Yamazaki, K. Ohmori, H. Aoyama, T. Shiga, E. Sukamoto, S. Hashimoto, K. Tsuchiya, K. Miyasaka, Impact of 18FDG-PET and CT/MRI image fusion in radiotherapy planning of head-and-neck tumors, *Int. J. Rad. Oncol. Biol. Phys.* 48 (3) (2000) 260–261.
- [190] W. Birkfellner, E. Schwameis, F. Vorbeck, R. Hanel, W. Greimel, J. Hummel, M. Figl, F. Kainberger, H. Imhof, R. Kotz, et al., Fusion of MR and CT scans of the pelvis in cases of malignant bone tumors, *International Congress Series*, vol. 1230, Elsevier, 2001, pp. 1207–1208.
- [191] M. Ghilezan, D. Yan, D. Lockman, D. Jaray, M. Oldham, F. Vicini, R. Matter, J. Wong, A. Martinez, Can the anatomical location of the prostatic neurovascular bundle and the penile bulb be reliably determined for the purpose of online nerve-sparing image-guided radiation therapy in prostate cancer? An MR-CT 3D fusion imaging study, *Int. J. Rad. Oncol. Biol. Phys.* 57 (2) (2003) S332.
- [192] T. Coyne, P. Silburn, R. Cook, P. Silberstein, G. Mellick, F. Sinclair, G. Fracchia, D. Wasson, P. Stanwell, Rapid subthalamic nucleus deep brain stimulation lead placement utilising CT/MRI fusion, microelectrode recording and test stimulation, in: *Advances in Functional and Reparative Neurosurgery*, Springer, 2006, pp. 49–50.

- [193] S.F. Nemec, M.A. Donat, S. Mehra, K. Friedrich, C. Kreftan, C. Matula, H. Imhof, C. Czerny, CT–MR image data fusion for computer assisted navigated neurosurgery of temporal bone tumors, *Euro. J. Radiol.* 62 (2) (2007) 192–198.
- [194] K. Ohtakara, O. Tanaka, S. Hayashi, M. Matsuo, M. Nakano, H. Uno, S. Okada, T. Deguchi, H. Hoshi, Effect of edema on postimplant dosimetry in prostate brachytherapy using CT/MRI fusion, *Int. J. Rad. Oncol. Biol. Phys.* 69 (3) (2007) S730.
- [195] J. Hao, Y. Shen, H. Xu, J. Zou, Generalized local priority based medical image fusion scheme, in: Fifth International Conference on Intelligent Information Hiding and Multimedia Signal Processing, 2009, IHH-MSP'09, IEEE, 2009, pp. 969–972.
- [196] S.V. Miranda, M. Carrasco, J. Pachon, Procedure of high precision fusion of CT–MRI images for head–neck cancer with new antenna frame, *Radioth. Oncol.* 98 (2011) S41.
- [197] A.L. Grosu, W.A. Weber, M. Franz, S. Stark, M. Pietsch, R. Thamm, H. Gumprecht, M. Schwaiger, M. Molls, C. Nieder, Reirradiation of recurrent high-grade gliomas using amino acid PET (SPECT)/CT/MRI image fusion to determine gross tumor volume for stereotactic fractionated radiotherapy, *Int. J. Rad. Oncol. Biol. Phys.* 63 (2) (2005) 511–519.
- [198] V. Megalooikonomou, D. Kontos, Medical data fusion for telemedicine, *Eng. Med. Biol. Magaz.*, IEEE 26 (5) (2007) 36–42.
- [199] S.-K. Kim, H.J. Choi, S.-Y. Park, H.-Y. Lee, S.-S. Seo, C.W. Yoo, D.C. Jung, S. Kang, K.-S. Cho, Additional value of MR/PET fusion compared with PET/CT in the detection of lymph node metastases in cervical cancer patients, *Euro. J. Can.* 45 (12) (2009) 2103–2109.
- [200] N. Tomura, O. Watanabe, K. Omachi, I. Sakuma, S. Takahashi, T. Otani, H. Kidani, J. Watarai, Image fusion of thallium-201 SPECT and MR imaging for the assessment of recurrent head and neck tumors following flap reconstructive surgery, *Euro. Radiol.* 14 (7) (2004) 1249–1254.
- [201] O. Israel, Z. Keidar, G. Iosilevsky, L. Bettman, J. Sachs, A. Frenkel, The fusion of anatomic and physiologic imaging in the management of patients with cancer, *Seminars in nuclear medicine*, vol. 31, Elsevier, 2001, pp. 191–205.
- [202] C. Beneder, F. Fuechsel, T. Krause, A. Kuhn, M. Mueller, The role of 3D fusion imaging in sentinel lymphadenectomy for vulvar cancer, *Gynecol. Oncol.* 109 (1) (2008) 76–80.
- [203] M. Infanger, V. Meyer, W. Jaecck, G.V. Schulthess, Positron emission tomography (PET) with 18-fluorodeoxy-d-glucose (FDG) for staging desmoid tumours (MRI/PET image fusion), *J. Hand Surg. British & European* 22 (Suppl. 1) (1997) 48.
- [204] A. Malesci, L. Balzarini, A. Chiti, G. Lucignani, Pancreatic cancer or chronic pancreatitis? an answer from PET/MRI image fusion, *Euro. J. Nucl. Med. Mol. Imag.* 31 (9) (2004) 1352.
- [205] H. Lee, H. Hong, Hybrid surface- and voxel-based registration for MR–PET brain fusion, in: Image Analysis and Processing–ICIAP 2005, Springer, 2005, pp. 930–937.
- [206] Y. Nakamoto, K. Tamai, T. Saga, T. Higashi, T. Hara, T. Suga, T. Koyama, K. Togashi, Clinical value of image fusion from MR and PET in patients with head and neck cancer, *Mole. Imag. Biol.* 11 (1) (2009) 46–53.
- [207] K. Yuan, W. Liu, S. Jia, P. Xiao, Fusion of MRI and DTI to assist the treatment solution of brain tumor, in: Second International Conference on Innovative Computing, Information and Control, 2007, ICIC'07, IEEE, 2007, pp. 620–620.
- [208] F. Lindseth, S. Ommedal, J. Bang, G. Unsgard, T. Nagelhus Hernes, Image fusion of ultrasound and MRI as an aid for assessing anatomical shifts and improving overview and interpretation in ultrasound-guided neurosurgery, *International Congress Series*, vol. 1230, Elsevier, 2001, pp. 254–260.
- [209] R. Narayanan, L. Li, J. Kurhanewicz, K. Shinohara, N. Nadkar, D. Crawford, A. Barqawi, A. Simoneau, J. Suri, Improved prostate biopsy planning with MRI/TRUS fusion, *Euro. Urol. Suppl.* 8 (4) (2009) 353.
- [210] M. Uematsu, A. Shioda, H. Taira, Y. Hama, A. Suda, J. Wong, S. Kusano, Interfractional movements of the prostate detected by daily computed tomography (CT)-guided precise positioning system with a fusion of CT and linear accelerator (focal) unit, *Int. J. Rad. Oncol. Biol. Phys.* 54 (2) (2002) 13.
- [211] H. Fukunaga, I. Higuchi, M. Yasui, I. Seshimo, O. Takayama, Fusion image of positron emission tomography and computed tomography for the diagnosis of local recurrence of rectal cancer, *Ann. Surg. Oncol.* 12 (7) (2005) 561–569.
- [212] R. Cambria, F. Cattani, M. Ciocca, C. Garibaldi, G. Tosi, R. Orecchia, CT image fusion as a tool to measure the 3D setup errors during conformal radiotherapy for prostate cancer, *Tumori* 92 (2) (2006) 118–123.
- [213] R.J. Ellis, H. Zhou, D.A. Kaminsky, P. Fu, E.Y. Kim, D.B. Sodee, V. Colussi, J.P. Spirnak, C.C. Whalen, M.I. Resnick, Rectal morbidity after permanent prostate brachytherapy with dose escalation to biologic target volumes identified by SPECT/CT fusion, *Brachytherapy* 6 (2) (2007) 149–156.
- [214] A.P. Pecking, SPECT–CT fusion imaging radionuclide lymphoscintigraphy: potential for limb lymphedema assessment and sentinel node detection in breast cancer, in: Cancer Metastasis and the Lymphovascular System: Basis for Rational Therapy, Springer, 2007, pp. 79–84.
- [215] J.L. Alberini, M. Wartski, V. Edeline, S. Banayan, A.P. Pecking, Molecular imaging of neuroendocrine cancer by fusion SPET/CT, in: From Local Invasion to Metastatic Cancer, Springer, 2009, pp. 169–175.
- [216] K.-P. Lin, W.-J. Yao, A SPECT–CT image fusion technique for diagnosis of head–neck cancer, IEEE 17th Annual Conference on Engineering in Medicine and Biology Society, 1995, vol. 1, IEEE, 1995, pp. 377–378.
- [217] A.C. Riegel, A.M. Berson, S. Destian, T. Ng, L.B. Tena, R.J. Mitnick, P.S. Wong, Variability of gross tumor volume delineation in head-and-neck cancer using CT and PET/CT fusion, *Int. J. Rad. Oncol. Biol. Phys.* 65 (3) (2006) 726–732.
- [218] M. Feichtinger, R.M. Aigner, H. Karcher, F-18 positron emission tomography and computed tomography image-fusion for image-guided detection of local recurrence in patients with head and neck cancer using a 3-dimensional navigation system: a preliminary report, *J. Oral Maxillofac. Surg.* 66 (1) (2008) 193–200.
- [219] A.M. Berson, N.F. Stein, A.C. Riegel, S. Destian, T. Ng, L.B. Tena, R.J. Mitnick, S. Heiba, Variability of gross tumor volume delineation in head-and-neck cancer using PET/CT fusion, part ii: the impact of a contouring protocol, *Med. Dosi.* 34 (1) (2009) 30–35.
- [220] C. Anderson, M. Koshy, C. Staley, N. Esiashevili, S. Ghavidel, Z. Fowler, T. Fox, F. Esteves, J. Landry, K. Godette, PET–CT fusion in radiation management of patients with anorectal tumors, *Int. J. Rad. Oncol. Biol. Phys.* 69 (1) (2007) 155–162.
- [221] S. Katyal, E.L. Kramer, M.E. Noz, D. McCauley, A. Chachoua, A. Steinfeld, Fusion of immunoscintigraphy single photon emission computed tomography (SPECT) with CT of the chest in patients with non-small cell lung cancer, *Canc. Res.* 55 (23 Supplement) (1995) 5759s–5763s.
- [222] J.F. Vansteenkiste, S.G. Stroobants, P.J. Dupont, P.R. De Leyn, W.F. De Wever, E.K. Verbeken, J.L. Nuyts, F.P. Maes, J.G. Bogaert, FDG–PET scan in potentially operable non-small cell lung cancer: do anatomical PET–CT fusion images improve the localisation of regional lymph node metastases?, *Euro J. Nucl. Med.* 25 (11) (1998) 1495–1501.
- [223] M. Schmucking, K. Plichta, E. Lopatta, C. Przetak, J. Leonhardi, D. Gottschild, T. Wendt, R. Baum, Image fusion of f-18 FDG PET and CT—is there a role in 3D-radiation treatment planning of non-small cell lung cancer?, *Int. J. Rad. Oncol. Biol. Phys.* 48 (3) (2000) 130.
- [224] P. Giraud, D. Grahek, F. Montravers, M.-F. Carette, E. Deniaud-Alexandre, F. Julia, J.-C. Rosenwald, J.-M. Cosset, J.-N. Talbot, M. Housset, et al., CT and 18 F-deoxyglucose (FDG) image fusion for optimization of conformal radiotherapy of lung cancers, *Int. J. Rad. Oncol. Biol. Phys.* 49 (5) (2001) 1249–1257.
- [225] J. Wong, S. Grimm, M. Chow, M. Uematsu, R. Oren, A. Scher, C. Wilson, P. Schi, A. Fung, Shallow breathing control with 100 (fusion of CT and LINAC) treatment in frameless fractionated stereotactic radiotherapy for lung cancer, *Radioth. Oncol.* 64 (2002) S261.
- [226] E. Deniaud-Alexandre, E. Touboul, D. Lerouge, D. Grahek, J.-N. Foulquier, Y. Petegnief, B. Gres, H. El Balaa, K. Keraudy, K. Kerrou, et al., Impact of computed tomography and 18 F-deoxyglucose coincidence detection emission tomography image fusion for optimization of conformal radiotherapy in non-small-cell lung cancer, *Int. J. Rad. Oncol. Biol. Phys.* 63 (5) (2005) 1432–1441.
- [227] W. Ge, G. Yuan, C. Li, Y. Wu, Y. Zhang, X. Xu, CT image fusion in the evaluation of radiation treatment planning for non-small cell lung cancer, *Chin.–Ger. J. Clin. Oncol.* 7 (6) (2008) 315–318.
- [228] A. Kovacs, J. Hadjiev, F. Lakosi, G. Antal, G. Liposits, P. Bogner, 119P tumor movements detected by multi-slice CT-based image fusion in the radiotherapy of lung cancer, *Lung Can.* 64 (2009) S50.
- [229] X. Xu, J. Deng, H. Guo, M. Xiang, C. Li, L. Xu, W. Ge, G. Yuan, Q. Li, S. Shan, CT image fusion in the optimization of replanning during the course of 3-Dimensional conformal radiotherapy for non-small-cell lung cancer, in: 3rd International Conference on Biomedical Engineering and Informatics (BMEI) 2010, vol. 3, IEEE, 2010, pp. 1336–1339.
- [230] S. Gordon, J. DeMarco, G. Hugo, K. Boedeker, J. Smathers, R. Parker, H. Withers, T. Solberg, Evaluation of patient positioning and inter-fraction organ motion using an infrared positioning system, serial CT, and information image fusion in the treatment of prostate cancer, *Radioth. Oncol.* 58 (2001) S67–S68.
- [231] L. Taylor, J. Beaty, J. Enderle, M. Escabi, Design of a simple ultrasound/CT fusion image fusion solution for the evaluation of prostate seed brachytherapy, in: Proceedings of the IEEE 27th Annual Northeast Bioengineering Conference, 2001, IEEE, 2001, pp. 57–58.
- [232] L. Taylor, B. Porter, G. Nadasdy, P. diSantagnese, D. Pasternack, E. Messing, D. Rubens, K. Parker, Three-dimensional fusion of prostate histology with sonoelastography images, *Ultrasound Med. Biol.* 29 (5) (2003) S57.
- [233] M. Krengli, M. Dominietto, S. Chiara, C. Barbara, R. Marco, I. Eugenio, K. Irvin, B. Frea, et al., Study of lymphatic drainage by SPECT–CT fusion images for pelvic irradiation of prostate cancer, *Int. J. Rad. Oncol. Biol. Phys.* 63 (2005) S305.
- [234] D.B. Fuller, H. Jin, J.A. Koziol, A.C. Feng, CT–ultrasound fusion prostate brachytherapy: a dynamic dosimetry feedback and improvement method. A report of 54 consecutive cases, *Brachytherapy* 4 (3) (2005) 207–216.
- [235] M. Krengli, A. Ballare, B. Cannillo, M. Rudoni, E. Kocjancic, G. Loi, M. Brambilla, E. Inglese, B. Frea, Potential advantage of studying the lymphatic drainage by sentinel node technique and SPECT–CT image fusion for pelvic irradiation of prostate cancer, *Int. J. Rad. Oncol. Biol. Phys.* 66 (4) (2006) 1100–1104.
- [236] D.B. Sodee, A.E. Sodee, G. Bakale, Synergistic value of single-photon emission computed tomography/computed tomography fusion to radioimmunoscintigraphic imaging of prostate cancer, *Seminars in Nuclear Medicine*, vol. 37, Elsevier, 2007, pp. 17–28.
- [237] R. Hammoud, D. Pradhan, J. Kim, S. Patel, S. Kowalski, H. Guan, Y. Xu, M. Elshaikh, M. Ajlouni, B. Movsas, Prostate localization: fiducial marker versus cone beam CT (CBCT) 3D image fusion, *Int. J. Rad. Oncol. Biol. Phys.* 69 (3) (2007) S679–S680.
- [238] F. Dube, A. Mahadevan, T. Sheldon, Fusion of CT and 3D ultrasound (3dus) for prostate delineation of patients with metallic hip prostheses (MHP), *Int. J. Rad. Oncol. Biol. Phys.* 75 (3) (2009) S327–S328.

- [239] E. Saibishkumar, D. Dupati, J. Borg, K. Fernandes, Denition and dosimetric evaluation of a clinical target volume (CTV) in the post implant (CT/MR fusion) analysis of low-dose-rate brachytherapy for prostate cancer at princess margaret hospital, *Brachytherapy* 10 (2011) S28.
- [240] R.L. Smith, Y.T. Tran, D.R. Zwahlen, B. Matheson, J.L. Millar, Image fusion of prostate preplan transrectal ultrasound and post ¹²⁵I-seed implant CT images to improve consistency and accuracy of post-seed implant quality statistics, *Brachytherapy* 8 (2) (2009) 116.
- [241] J. Li, K. F. Koral, An algorithm to adjust a rigid CT-SPECT fusion so as to maximize tumor counts from CT Vol in I-131 therapies, in: *IEEE Nuclear Science Symposium Conference Record*, 2001, vol. 3, IEEE, 2001, pp. 1432–1436.
- [242] A. Paula Moreira, L. Hugo Duarte, F. Vieira, F. Joao, J. Pedroso de Lima, Value of SPET/CT image fusion in the assessment of neuroendocrine tumours with ¹¹¹In-pentetreotide scintigraphy, *Rev. Espan. Med. Nucl.* 24 (1) (2005) 14–18.
- [243] K.K. Wong, J.M. Cahill, K.A. Frey, A.M. Avram, Incremental value of ¹¹¹In pentetreotide SPECT/CT fusion imaging of neuroendocrine tumors, *Acad. Radiol.* 17 (3) (2010) 291–297.
- [244] A. Riegel, M. Berson, S. Destian, T. Ng, L. Tena, R. Mitnick, P. Wong, Variability of gross tumor volume delineation in head and neck cancer using CT and PET/CT fusion, *Int. J. Rad. Oncol. Biol. Phys.* 63 (2005) S142–S143.
- [245] E. Lartigau, L. Ceugnart, S. Taieb, Y. Belkacemi, D. Pasquier, E. Castellanos, T. Lacomere, Image fusion in pelvic cancer, in: *Radiotherapy and Oncology*, vol. 73, 2004, pp. S76–S76.
- [246] T. Denecke, B. Hildebrandt, L. Lehmkuhl, N. Peters, A. Nicolaou, M. Pech, H. Riess, J. Ricke, R. Felix, H. Amthauer, Fusion imaging using a hybrid SPECT–CT camera improves port perfusion scintigraphy for control of hepatic arterial infusion of chemotherapy in colorectal cancer patients, *Euro. J. Nucl. Med. Mole. Imag.* 32 (9) (2005) 1003–1010.
- [247] C. Nanni, D. Rubello, P. Castellucci, M. Farsad, R. Franchi, L. Rampin, M. Gross, A. Al-Nahhas, S. Fanti, ¹⁸F-FDG PET/CT fusion imaging in paediatric solid extracranial tumours, *Biomed. Pharmacol.* 60 (9) (2006) 593–606.
- [248] S. Ueda, H. Tsuda, H. Asakawa, J. Omata, K. Fukatsu, N. Kondo, T. Kondo, Y. Hama, K. Tamura, J. Ishida, et al., Utility of ¹⁸F-fluoro-deoxyglucose emission tomography/computed tomography fusion imaging (¹⁸F-FDG PET/CT) in combination with ultrasonography for axillary staging in primary breast cancer, *BMC Can.* 8 (1) (2008) 165.
- [249] B. Kwak, Diagnostic and prognostic value of ¹⁸F-fluorodeoxyglucose positron emission tomography/computed tomography fusion imaging (¹⁸F-FDG PET/CT) in detecting multifocality and axillary lymph node metastasis and correlation of clinicopathologic factors in primary breast cancer, *Euro. J. Can. Suppl.* 8 (3) (2010) 230.
- [250] M. Feichtinger, W. Zemmann, R.-M. Aigner, H. Kaercher, O. 258 3D control of resection margins in oral cancer based on PET/CT image-fusion, *J. Cranio-Maxillofac. Surg.* 36 (2008) S65.
- [251] Z. Zhao, L. Li, F. Li, L. Zhao, Single photon emission computed tomography/spiral computed tomography fusion imaging for the diagnosis of bone metastasis in patients with known cancer, *Skel. Radiol.* 39 (2) (2010) 147–153.
- [252] Y. Nakamoto, M. Senda, T. Okada, S. Sakamoto, T. Saga, T. Higashi, K. Togashi, Software-based fusion of PET and CT images for suspected recurrent lung cancer, *Mole. Imag. Biol.* 10 (3) (2008) 147–153.
- [253] H. Iwase, Y. Yamamoto, T. Kawasoe, M. Ibusuki, Qs106. sentinel lymph node biopsy using SPECT–CT fusion imaging in patients with breast cancer and its clinical usefulness, *J. Surg. Res.* 151 (2) (2009) 287.
- [254] A. Hakime, T. de Baere, F. Deschamps, P. Rao, A. Auperin, E. Marques de Carvalho, Clinical evaluation of spatial accuracy of a fusion imaging technique combining previously-acquired computed tomography and real time ultrasound for imaging of liver tumors, *J. Vasc. Interv. Radiol.* 21 (2) (2010) S49.
- [255] Y. Xia, S. Eberl, D. Feng, Dual-modality 3D brain PET–CT image segmentation based on probabilistic brain atlas and classification fusion, in: *17th IEEE International Conference on Image Processing (ICIP)*, 2010, IEEE, 2010, pp. 2557–2560.
- [256] A.J. Walker, B.J. Spier, S.B. Perlman, J.R. Stangl, T.J. Frick, D.V. Gopal, M.J. Lindstrom, T.L. Weigel, P.R. Pfau, Integrated PET/CT fusion imaging and endoscopic ultrasound in the pre-operative staging and evaluation of esophageal cancer, *Mole. Imag. Biol.* 13 (1) (2011) 166–171.
- [257] M. Tatsumi, K. Isohashi, H. Onishi, M. Hori, T. Kim, I. Higuchi, A. Inoue, E. Shimosegawa, Y. Takeda, J. Hatazawa, ¹⁸F-FDG PET/MRI fusion in characterizing pancreatic tumors: comparison to PET/CT, *Int. J. Clin. Oncol.* 16 (4) (2011) 408–415.
- [258] F. Kahmann, T. Henkel, A. Polo, H. Marsiglia, P. Wust, CT/MRI image fusion based postplans significantly improve the quality control after prostate seed brachytherapy, *Euro. J. Can.* 37 (2001) S220.
- [259] B. Al-Qaisieh, CT, MRI, and CT–MRI image fusion assessment for prostate I-125 post implant dosimetry, *Radioth. Oncol.* 71 (2004) S126–S127.
- [260] N. Papanikolaou, D. Gearheart, T. Bolek, A. Meigooni, D. Meigooni, M. Mohiuddin, A volumetric and dosimetric study of LDR brachytherapy prostate implants based on image fusion of ultrasound and computed tomography, in: *Proceedings of the 22nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2000, vol. 4, IEEE, 2000, pp. 2769–2770.
- [261] E. Barranger, K. Kerrou, Y. Petegnief, E. David-Monteore, A. Cortez, E. Darai, Laparoscopic resection of occult metastasis using the combination of FDG positron emission tomography/computed tomography image fusion with intraoperative probe guidance in a woman with recurrent ovarian cancer, *Gynecol. Oncol.* 96 (1) (2005) 241–244.
- [262] M. McGurk, PET and CT fusion scans in the early detection and the evaluation of recurrences in head and neck tumors, *Oral Oncol.* 1 (2005) 50.
- [263] T. Shigekawa, I. Sugitani, H. Takeuchi, M. Misumi, N. Nakamiya, M. Sugiyama, N. Fujiuchi, A. Osaki, T. Saeki, Examination about the adaptation of sentinel lymph node biopsy after neoadjuvant chemotherapy using ¹⁸F-fluoro-deoxyglucose emission tomography/computed tomography fusion imaging (¹⁸F-FDG PET/CT) in breast cancer, *The Breast* 20 (1) (2011) S57.
- [264] T. Block, F. Zimmermann, H. Czempel, TRUS- and CT-image fusion in the postplanning procedure after transperineal permanent interstitial seed implantation (TPSI) of “low risk” prostate cancer, in: *Radiotherapy and Oncology*, vol. 71, 2004, pp. S105–S105.
- [265] M. Stutz, K. Zuhli, D. Kraable, B. Moran, Comparing apples to apples: fusion of preplan ultrasound structures and postimplant CT images for prostate brachytherapy dosimetry, *Int. J. Rad. Oncol. Biol. Phys.* 51 (3) (2001) 322.
- [266] K. Yamauchi, A. Tashiro, M. Watanabe, A. Okino, T. Kohno, E. Hotta, M. Yuura, Fundamental study of proton source based on inertial electrostatic confinement fusion for medical positron emission tomography, in: *The 31st IEEE International Conference on Plasma Science*, 2004, ICOPS 2004, IEEE Conference Record-Abstracts, IEEE, 2004, p. 139.
- [267] E. Holupka, I. Kaplan, E. Burdette, G. Svensson, Ultrasound image fusion for external beam radiotherapy for prostate cancer, *Int. J. Rad. Oncol. Biol. Phys.* 35 (5) (1996) 975–984.
- [268] J. Bradley, K. Bae, N. Choi, K. Forster, B. Siegel, J. Brunetti, J. Purdy, S. Faria, T. Vu, H. Choy, A phase ii comparative study of gross tumor volume definition with or without PET/CT fusion in dosimetric planning for non-small-cell lung cancer (NSCLC): primary analysis of radiation therapy oncology group (RTOG) 0515, *Int. J. Rad. Oncol. Biol. Phys.* 75 (3) (2009) S2.
- [269] S. Kremp, A. Schaefer-Schuler, U. Nestle, C. Sebastian-Welsch, C. Rube, C. Kirsch, Comparison of CT and CT–PET–fusion based 3D treatment plans in the percutaneous radiotherapy of lung cancer, in: *Radiotherapy and Oncology*, vol. 73, pp. S447–S448.
- [270] A. Lin, K. Teo, R. Rengan, A comparative study of PET–CT fusion versus PET–CT simulation for target delineation in non-small cell lung cancer, *Int. J. Rad. Oncol. Biol. Phys.* 78 (3) (2010) S543.
- [271] J. Wolthaus, M. van Herk, S. Muller, D. Bois, M. Rossi, J. Belderbos, J. Lebesque, E. Damen, 4D PET and 4D CT image fusion for accurate radiotherapy planning of lung cancer patients, in: *Radiotherapy and Oncology*, vol. 73, pp. S162–S163.
- [272] S. Sobottka, R. Steinmeier, B. Beuthien-Baumann, D. Mucha, G. Schackert, Evaluation of automatic multimodality fusion technique of PET and MRI/CT images for computer assisted brain tumor surgery, *International Congress Series*, vol. 1230, Elsevier, 2001, pp. 261–267.
- [273] A. Grosu, C. Nieder, W. Weber, M. Franz, S. Staerk, M. Schwaiger, M. Molls, Re-irradiation of recurrent high grade gliomas using amino-acids–PET (SPECT)/CT/MRI image fusion to determine gross tumor volume for stereotactic fractionated radiotherapy, *Int. J. Rad. Oncol. Biol. Phys.* 60 (1) (2004) S222.
- [274] L. Beaulieu, D. Tubic, J. Pouliot, E. Vigneault, R. Taschereau, Post-implant dosimetry using fusion of ultrasound images with 3D seed coordinates from fluoroscopic images in transperineal interstitial permanent prostate brachytherapy, *Int. J. Rad. Oncol. Biol. Phys.* 48 (3) (2000) 360.
- [275] B. C. Porter, L. Taylor, R. Baggs, A. di Sant’Agnese, G. Nadasdy, D. Pasternack, D. J. Rubens, K. J. Parker, Histology and ultrasound fusion of excised prostate tissue using surface registration, in: *IEEE Ultrasonics Symposium*, 2001, vol. 2, IEEE, 2001, pp. 1473–1476.
- [276] F. Arena, T. DiCicco, A. Anand, Multimodality data fusion aids early detection of breast cancer using conventional technology and advanced digital infrared imaging, in: *26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2004, IEMBS’04, vol. 1, IEEE, 2004, pp. 1170–1173.
- [277] C. Jiang, C. Wang, C. Chiang, Oral cancer detection in fluorescent image by color image fusion, in: *26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2004, IEMBS’04, vol. 1, IEEE, 2004, pp. 1260–1262.
- [278] L. Gong, P.S. Cho, B.H. Han, K.E. Wallner, S.G. Sutlief, S.D. Pathak, D.R. Haynor, Y. Kim, Ultrasonography and fluoroscopic fusion for prostate brachytherapy dosimetry, *Int. J. Rad. Oncol. Biol. Phys.* 54 (5) (2002) 1322–1330.
- [279] I. Aslay, G. Kemikler, N. Tenekeci, I. Ozbay, M. Akinci, The benefits provided by using intra-operative dosimetry and the fusion of MRI to CT for post plan dosimetry in the learning curve of transperineal interstitial permanent prostate brachytherapy, in: *Radiotherapy and Oncology*, vol. 71, 2004, pp. S93–S93.
- [280] Y. Chen, E. Gunawan, Y. Kim, K. Low, C. Soh, UWB microwave imaging for breast cancer detection: tumor/clutter identification using a time of arrival data fusion method, in: *IEEE Antennas and Propagation Society International Symposium* 2006, IEEE, 2006, pp. 255–258.
- [281] Y. Chen, E. Gunawan, K.S. Low, S.-C. Wang, C.B. Soh, L.L. Thi, Time of arrival data fusion method for two-dimensional ultrawideband breast cancer detection, *IEEE Trans. Anten. Propag.* 55 (10) (2007) 2852–2865.
- [282] G. Lv, A. He, X. Yang, X. Ning, Fusion of medical microscopic images based on estimation and compensation, in: *IEEE/ICME International Conference on Complex Medical Engineering*, 2007, CME 2007, IEEE, 2007, pp. 736–739.
- [283] G. Lan, M. Xiu-ming, Multi-level classifier design for tumor micro-image based on multi-feature fusion, in: *International Seminar on Future BioMedical Information Engineering*, 2008, FBIE’08, IEEE, 2008, pp. 60–63.

- [284] S. Daneshvar, H. Ghassemian, A feedback retina model for improving medical images fusion, in: 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2008, EMBS 2008, IEEE, 2008, pp. 4035–4038.
- [285] M. Wozniak, Information fusion for probabilistic reasoning and its application to the medical decision support systems, in: Computational Science and its Applications–ICCSA 2004, Springer, 2004, pp. 593–601.
- [286] Y. Hu, D. Morgan, H.U. Ahmed, D. Pendse, M. Sahu, C. Allen, M. Emberton, D. Hawkes, D. Barratt, A statistical motion model based on biomechanical simulations for data fusion during image-guided prostate interventions, in: Medical Image Computing and Computer-Assisted Intervention–MICCAI 2008, Springer, 2008, pp. 737–744.
- [287] M. Dietzel, T. Hopp, N. Ruiter, R. Zoubi, I.B. Runnebaum, W.A. Kaiser, P.A. Baltzer, Fusion of dynamic contrast-enhanced magnetic resonance mammography at 3.0T with X-ray mammograms: Pilot study evaluation using dedicated semi-automatic registration software, *Euro. J. Radiol.* 79 (2) (2011) e98–e102.
- [288] K.G. Baum, M. Helguera, A. Krol, Fusion viewer: a new tool for fusion and visualization of multimodal medical data sets, *J. Dig. Imag.* 21 (1) (2008) 59–68.
- [289] A. Viola, T. Major, J. Julow, The importance of postoperative CT image fusion verification of stereotactic interstitial irradiation for brain tumors, *Int. J. Rad. Oncol. Biol. Phys.* 60 (1) (2004) 322–328.
- [290] H. Eldredge, A. Doemer, D. Friedman, M. Werner-Wasik, Improvement in optic chiasm contouring for RT planning in patients with brain tumors using CT/MP-RAGE MRI fusion as compared to the routine T1-weighted MRI image, *Int. J. Rad. Oncol. Biol. Phys.* 75 (3) (2009) S246.
- [291] A. Villeger, L. Ouchchane, J.-J. Lemaire, J.-Y. Boire, Assistance to planning in deep brain stimulation: data fusion method for locating anatomical targets in MRI, in: 28th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2006, EMBS'06, IEEE, 2006, pp. 144–147.
- [292] W. Dou, A. Dong, P. Chi, S. Li, J.-M. Constans, Brain tumor segmentation through data fusion of T2-weighted image and MR spectroscopy, in: 5th International Conference on Bioinformatics and Biomedical Engineering, (ICBBE), 2011, IEEE, 2011, pp. 1–4.
- [293] D.M. Tucker, P. Luu, Operational brain dynamics: data fusion technology for neurophysiological, behavioral, and scenario context information in operational environments, in: Foundations of Augmented Cognition. Neuroergonomics and Operational Neuroscience, Springer, 2009, pp. 98–104.
- [294] M. Ganna, M. Rombaut, R. Goutte, Y. Zhu, Improvement of brain lesions detection using information fusion approach, in: 6th International Conference on Signal Processing, 2002, vol. 2, IEEE, 2002, pp. 1104–1107.
- [295] L. Gupta, B. Chung, M.D. Srinath, D.L. Molfese, H. Kook, Multichannel fusion models for the parametric classification of differential brain activity, *IEEE Trans. Biomed. Eng.* 52 (11) (2005) 1869–1881.
- [296] H. Kook, L. Gupta, S. Kota, D. Molfese, A dynamic multi-channel decision-fusion strategy to classify differential brain activity, in: 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2007, EMBS 2007, IEEE, 2007, pp. 3212–3215.
- [297] A. Vaccarella, E. De Momi, A. Enquobahrie, G. Ferrigno, Unscented Kalman Filter Based Sensor Fusion for Robust Optical and Electromagnetic Tracking in Surgical Navigation, Instrumentation and Measurement, *IEEE Transactions on* 62 (2013) 2067–2081.
- [298] R. Velik, D. Bruckner, R. Lang, T. Deutsch, Emulating the perceptual system of the brain for the purpose of sensor fusion, in: Human–Computer Systems Interaction, Springer, 2009, pp. 17–27.
- [299] R. Polikar, A. Topalis, D. Parikh, D. Green, J. Frymiare, J. Kounios, C.M. Clark, An ensemble based data fusion approach for early diagnosis of Alzheimer's disease, *Inform. Fus.* 9 (1) (2008) 83–95.
- [300] K. P. Thomas, C. Guan, L. C. Tong, A. P. Vinod, Discriminative filterbank selection and EEG information fusion for brain computer interface, in: IEEE International Symposium on Circuits and Systems, 2009, ISCAS 2009, IEEE, 2009, pp. 1469–1472.
- [301] V. Metsis, H. Huang, F. Makedon, A. Tzika, Heterogeneous data fusion to type brain tumor biopsies, in: Artificial Intelligence Applications and Innovations III, Springer, 2009, pp. 233–240.
- [302] R. Leeb, H. Sagha, R. Chavarriaga, J. del R Millan, Multimodal fusion of muscle and brain signals for a hybrid-BCI, in: Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2010, IEEE, 2010, pp. 4343–4346.
- [303] C. Cabral, M. Silveira, P. Figueiredo, Decoding visual brain states from FMRI using an ensemble of classifiers, *Patt. Recog.* 45 (6) (2012) 2064–2074.
- [304] T.M. Rutkowski, A. Cichocki, D. Mandic, Information fusion for perceptual feedback: A brain activity sonification approach, in: Signal Processing Techniques for Knowledge Extraction and Information Fusion, Springer, 2008, pp. 261–273.
- [305] Y.M. Kirova, V. Servois, F. Reyat, D. Peurien, A. Fourquet, N. Fournier-Bidoz, Use of deformable image fusion to allow better definition of tumor bed boost volume after oncoplastic breast surgery, *Surg. Oncol.* 20 (2) (2011) e123–e125.
- [306] J. L. Jesneck, S. Mukherjee, L. W. Nolte, A. E. Lokshin, J. R. Marks, J. Lo, Decision fusion of circulating markers for breast cancer detection in premenopausal women, in: Proceedings of the 7th IEEE International Conference on Bioinformatics and Bioengineering, 2007, BIBE 2007, IEEE, 2007, pp. 1434–1438.
- [307] T. Wurm, K. Eichhorn, S. Corvin, A. Anastasiadis, R. Bares, A. Stenzl, 549 anatomic-functional image fusion allows intraoperative sentinel node detection in prostate cancer patients, *Euro. Urol. Suppl.* 3 (2) (2004) 140.
- [308] M. Moerland, I. Jurgenliemk-Schulz, J. Battermann, Fusion of pre-implant MRI and intra-operative us images for planning of permanent prostate implants, in: Radiotherapy and Oncology, vol. 75, 2005, pp. S38–S38.
- [309] R.J. Ellis, D.A. Kaminsky, H. Zhou, M.I. Resnick, Erectile dysfunction following permanent prostate brachytherapy with dose escalation to biological tumor volumes (BTVS) identified with SPECT/CT fusion, *Brachytherapy* 6 (2) (2007) 103.
- [310] A. Hervas, R. Moris, A. Montero, I. Rodriguez, S. Sancho, J. Delgado, R. Morera, M. Bejarano, A. Capuz, A. Ramos, Image-fusion based CT pre and post-implant in seed implantation: a useful tool for accurate prostate definition in the post-planning setting, *Radioth. Oncol.* v71 (Suppl. 2) (2004) S107.
- [311] S. Germano, M. Santos, T. Almeida, C. Miguel, I. Grillo, CT image fusion to evaluate prostate gland motion and volume change between planning CT and repeat CT after four weeks of external radiotherapy treatment, *Radioth. Oncol.* 73 (2004) S399–S399.
- [312] Y. Hu, T.J. Carter, H.U. Ahmed, M. Emberton, C. Allen, D.J. Hawkes, D.C. Barratt, Modelling prostate motion for data fusion during image-guided interventions, *IEEE Trans. Med. Imag.* 30 (11) (2011) 1887–1900.
- [313] J. Bradley, K. Bae, N. Choi, K. Forster, B.A. Siegel, J. Brunetti, J. Purdy, S. Faria, T. Vu, W. Thorstad, et al., A phase ii comparative study of gross tumor volume definition with or without PET/CT fusion in dosimetric planning for non-small-cell lung cancer (NSCLC): Primary analysis of radiation therapy oncology group (RTOG) 0515, *Int. J. Rad. Oncol. Biol. Phys.* 82 (1) (2012) 435–441.
- [314] J. Balogh, C. Caldwell, Y. Ung, K. Mah, C. Danjoux, S. Ganguli, L. Ehrlich, Interobserver variation in contouring gross tumour volume in carcinoma of the lung associated with pneumonitis and atelectasis: The impact of ¹⁸F-FDG-hybrid PET fusion, *Int. J. Rad. Oncol. Biol. Phys.* 48 (3) (2000) 128–129.
- [315] E.D. Alexandre, E. Touboul, D. Lerouge, D. Grahek, Y. Petegnief, B. Gres, H. El Balaa, K. Kerrou, B. Milleron, B. Lebeau, et al., Impact of computed tomography and ¹⁸F-deoxyglucose-hybrid positron emission tomography image fusion on conformal radiotherapy in non-small cell lung cancer, *Int. J. Rad. Oncol. Biol. Phys.* 63 (2005) S102.
- [316] C. Liu, L. Kong, W. Zhong, J. Zhu, D. Xia, Multi-information fusion based tumor cell of bone marrow involvement, in: Proceedings of the International Workshop on Medical Imaging and Augmented Reality, 2001, IEEE, 2001, pp. 211–215.
- [317] K.C. Wong, S.M. Kumta, G.E. Antonio, L.F. Tse, Image fusion for computer-assisted bone tumor surgery, *Clin. Orthopaed. Related Res.* 466 (10) (2008) 2533–2541.
- [318] K. Nakajo, M. Tatsumi, A. Inoue, K. Isohashi, I. Higuchi, H. Kato, M. Imaizumi, T. Enomoto, E. Shimosegawa, T. Kimura, et al., Diagnostic performance of fluorodeoxyglucose positron emission tomography/magnetic resonance imaging fusion images of gynecological malignant tumors: comparison with positron emission tomography/computed tomography, *Japan. J. Radiol.* 28 (2) (2010) 95–100.
- [319] W. Ye, D.J. Isaman, J. Barhak, Use of secondary data to estimate instantaneous model parameters of diabetic heart disease: lemonade method, *Inform. Fus.* 13 (2) (2012) 137–145.
- [320] R. Teodorescu, C. Cernazanu-Glavan, V. Cretu, D. Racoceanu, The use of the medical ontology for a semantic-based fusion system in biomedical informatics application to Alzheimer's disease, in: 4th International Conference on Intelligent Computer Communication and Processing, 2008, ICCP 2008, IEEE, 2008, pp. 265–268.