A Novel Method of Removing Artifacts in Dental CT Images

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Abstract

The artifacts that appear on maxillofacial X-ray computed tomography (CT) images are mainly caused by the presence of metallic prosthetic appliances (such as amalgam or gold fillings). They cause problems in the three dimensional virtual reconstruction and in the eventual physical reproduction by Rapid Prototyping systems.
At present the classification of different artifact types, metallic presences or artifacts induced by them, is left to the experience and sensitivity of the operator.
In this paper an innovative methodology to automatically remove the artifacts in CT data is presented.
An expert system based on fuzzy logic was used to process the CT images and to clean them automatically leaving the decisional phase to the computer.
Decisional networks were created, using the Hounsfield scale values of each CT image pixel for the membership functions.

1 Introduction

The 3D representation of Computed Tomography (CT) scans is widely used in medical applications such as virtual endoscopy, plastic reconstructive surgery, dental implant planning systems and more. This representation is built thresholding the axial CT slices which constitute the volume of the CT scan.
Metallic objects present in CT scans cause conspicuous artifacts such as beam hardening and streaking, strongly evident in axial images, as shown in Fig. 1.

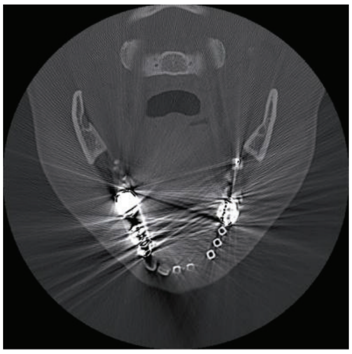


Fig. 1 Artifacts in CT image caused by metallic implants.

The artifacts in the tomographic acquisition caused by the presence of metallic structures are the most demanding obstacle on the way to obtain data-set for the reconstruction of the skull and the maxillofacial bones, or segments of these. The main consequence of such artifact is the effective impossibility to operate the reconstruction of the zone subordinate to surveying CT. The X-rays intensity, recommended for cranial CT diagnostics, is relatively low. For this reason metallic implants, such as dental fillings or orthodontic devices cause massive star-shaped artifacts in resulting CT images which hamper detailed diagnostics when planning cranio-maxillofacial surgery. Important information is destroyed both near dental fillings as well as in the periphery of the image because X-ray beams are completely absorbed by metallic implants. The maximum attenuation at the detector is limited by an upper boundary value, i.e. higher values are cut off [1, 2, 3, 4, 5]. Thus, in cranio-maxillofacial surgery there is a demand for recovering CT image information that has been corrupted by artifacts. In surgical planning, detailed CT-based knowledge of the exact anatomy of the patient is fundamental, specially in the dental region. In order to reduce surgery time and pre-surgical planning, it has become common practice to use Rapid Prototyping (RP) systems to manufacture 3D anatomical replicas. However, 2D image artifacts result in 3D spikes in the RP model, making it useless (Fig. 2). Consequently metal-induced artifacts must be eliminated before model manufacturing.
At present the elimination of artifacts is left to the operator, by means of a process of manually editing each CT-slice.

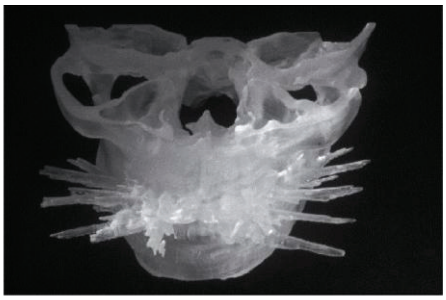


Fig. 2 Incorrect RP jaw model.

The aim of this study is the development of a system based on non-binary logic, in order to obtain the automatic artifact removal in CT data, by means of the visual impression quantification. To this end, fuzzy logic is applied in the analysis to create decisional networks. The Hounsfield scale values that the pixels have in the different circumstances have been used for the membership functions.

2 CT IMAGE & TRACE APPROCH

2.1 Approach for artifacts removal

The resolution of the problem of artifacts removal is linked to the use in sequence of different modules, shown in Fig. 3, each dedicated to a single operation.

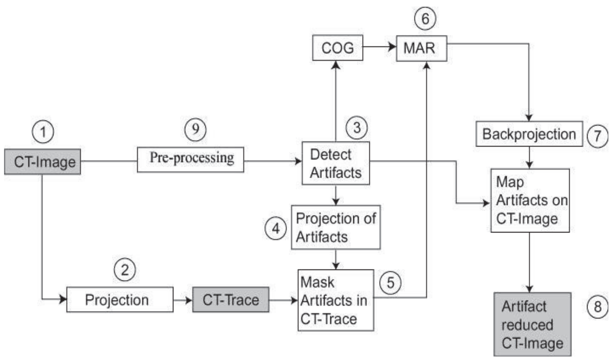


Fig. 3 Procedure to obtain a metallic artifact reduction in CT image.

To supply a procedure that allows to obtain the CT image without artifacts and reconstructed in the zones where these were present, it is necessary to distinguish if the input file is already an image or if it is a raw CT file (Fig. 4).

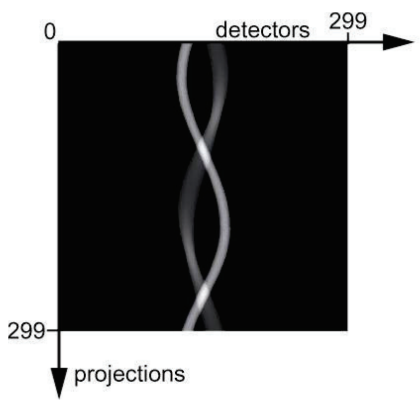


Fig.4 Raw CT data (sinogram).

In both cases, the zones affected by artifacts must be preliminarily identified. Subsequently, the regions where the metallic presences (source) are localized, must be distinguished from those where only the luminous star (artifacts) propagated from the source is present [6,7].
Considering the raw file (sinogram), the Center of Gravity (COG) algorithms are applied to localize the centers of gravity of the artifacts. The line interpolating the gravity centers is used to carry out the analysis and the correction, rather than the points on the bidimensional region. Thus, the artifacts on the sinogram are easily located as sinusoids.
Once the contours of these have been accurately recognized, the interpolation of the zone affected by artifact can be performed, using the unimpaired values, immediately surrounding the altered zone. To make possible the same procedure starting from the image, it would be, at least in principle, sufficient to apply an algorithm of projection, obtaining again the initial sinogram.
Although it would be convenient to operate on the raw files, these are not always available, because the CT system could export them in an proprietary format. Thus, it is necessary to solve these problems and to make the procedure equally applicable using directly the images or the raw data. For this purpose a pre-processing phase on the image data (Fig. 3) must be carried out.
Pre-processing is the stage where operator experience is more relevant in setting of the operation parameters.
For the artifacts reduction, such modulus must restore total equivalence, between the CT image and the raw CT data.
Moreover, in this phase of the process, it is very important to distinguish between artifacts and sources, eliminating the first one and creating the map of the points in which there are the sources.
In this phase the author considers useful the application of the fuzzy decisional rules, within an expert system substituting human intervention. In particular, the expert decisions are used in the thresholding phase and in the recognition of the constellations identified in the clustering phase. The phases of the pre-processing stage are depicted in detail in Fig. 5.

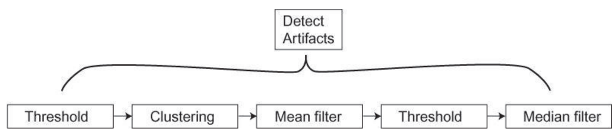


Fig. 5 Pre-processing elements.

2.2 Fuzzy Thresholding: Creation of a Network-Model in Fuzzy Logic

A CT image is a mosaic of pixels, with different grey levels representing the absorption coefficients of the tissues. CT values are given in a 12-bit format, within the range [-1000, 3095] Hounsfield units (HU). Tab. 1 shows some examples of Hounsfield scale values, for the human body [8]. The metallic artifact sources have high absorption values, totally blocking the X-ray beams.

Tissue	CT - Values (HU)
Compact bone tissue	200 – 1000
Spongy bone tissue	110 – 150
Tumor tissue	50 – 90
Liver	60 – 70
Muscles	40 – 50
Kidney	20 – 40
Blood	12
Water	0
Adipose tissue	-100
Air	-1000

Tab. 1 Values in HU scale of some human body tissues.

Usually for a metallic artefact, the range of HU values is typically [2095,3095] and [-1000,0], outside of the normal absorption field for the human body.
Fixing a thresholding value, in presence of metallic artifacts, to delete them, could create problems because, for some values, it is possible to confuse the effects of a metallic artifact with the metallic presence itself.

In the paper the author uses the "truthfulness degree" of a "statement of membership" to the trail of an artifact, or to a metallic source, or to none of the two situations, of a pixel whose HU value is included among those typical of artifacts.
However, this first phase of pre-processing must be limited to provide a full map of all the image pixels. To distinguish, in accurate manner, sources of artifacts and effects of them, in fact, can be made only at the end of thresholding and clustering phases.
The membership functions for the two cases of source or simple artifact, are easily defined.
The decisional rules to classify a pixel as belonging to an artifact site (and, in the affirmative case, if it is a source or not) and the truthfulness degree of the statements lead to three different situations:

1. A pixel is artifact source *or* it belongs to a region in which there is an artifact: such situation identifies, conservatively, all the points of the image to process.
2. A pixel is affected by artifact *and* it is at the same time site of a source point: this is a more restricted evaluation, suitable to define the regions where it is possible to isolate metallic artifact sources.
3. A pixel is artifact source *and* it is not affected by characteristic values of the regions in which there are artifacts: this evaluation characterizes, in selective way, the artifact sources.

The above three points are the premises of three different rules.
They allow to define a model-network with four terminal nodes: three related to the above described rules and one related to the simultaneous negation of all of them.
The first node performs the dimensional check of the absorption of the image pixels. The system will accept the image if the values are expressed in HU, otherwise it will send the image to a node that will convert the absorption value of each pixel in HU.
This node will check moreover that the format in HU is represented in 12 bit and will convert, if necessary, 13 or 16 bit representations. After the check node, the system will proceed to scan the image pixel by pixel, creating a new token (a counter) to send in the network with a *depth-first* approach (preferential exploration direction vertical). When such a counter arrives in a terminal node of the network-model, a degree of membership in the range [0,1], earned in the crossing of the network, must remain associated to the token.
It is possible to express the three conditions previously seen, synthetically, in the following way:

1. HU IS (Source OR Artifact)
2. HU IS (Source AND Artifact)
3. HU IS (Source AND (NOT Artifact))

The model-network is shown in Fig. 6. Every time the token exits from a node, it will be assigned a truthfulness degree calculated by the expression contained in the node and the value associated with the token. This value will be updated every time, calculating the minimum value between the last value associated to the token and the new value earned in the node.

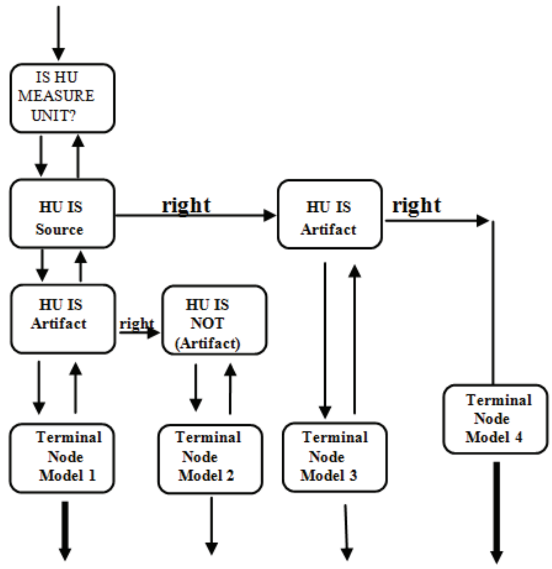
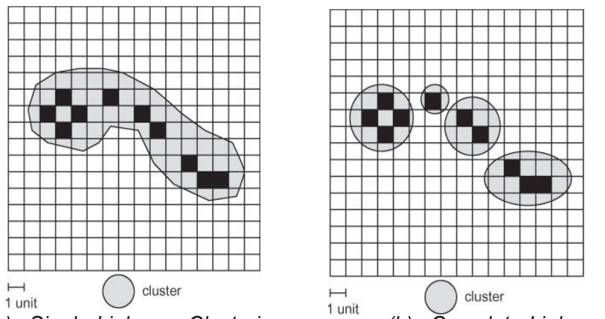


Fig. 6 Fuzzy thresholding.

2.3 Clustering Algorithms

One of the major points of force of an expert system based on fuzzy logic is the ability to manage, indifferently, events having decisional uncertainty, utilizing networks based on fuzzy logic, and events based on binary choices [9]. It is desirable that the expert system of management of CT images, after the fuzzy thresholding, carry out an image mapping, according to the rules previously described, distinguishing the different regions in terms of certain presence of source, probable presence of source or artifact, certain absence of artifact. This information will be then organized in a systematic way in the recognition of the regions marked by a common characteristic, by means of clustering algorithms, known in literature, belonging to the wide class of the pattern recognition algorithms. These algorithms are used to separate the regions affected by artifacts from the regions where the sources are localized. If this phase of clustering was not carried out, subjecting the image to the successive median filter, whole regions affected by distortions would be misinterpreted as metallic sources.
It is necessary therefore to take advantage of available information on how pixels affected by artifacts and artifact source pixels are arranged in formation. The separation is necessary because the artifacts must be eliminated from the image and replaced with the values obtained through interpolation, while the sources must be kept and marked on the corrected image, to give back an exact image of the anatomical area subjected to the analysis.
It is important to locate clearly the boundaries of the region affected by distortion to avoid the interpolation between the edges, without eliminating the peripheral zone of the artifact.
Two clustering algorithms are widely used for this kind of problems: *Single-Linkage Clustering* (SLC) (*nearest neighbor*) and *Complete-Linkage Clustering* (CLC) (*furthest neighbor*). Both of them are iterative processes: an initial cluster list contains one cluster for each valid pixel, where a pixel is valid if it is indicated by the fuzzy thresholding algorithm as a probable or certain artifact site or artifact source [10]. The clustering procedure is carried out by fixing a threshold value for the distance between two clusters. When the distance between two clusters is ≤

distance threshold a fusion of the two clusters into one is performed.
The first algorithm (SLC) recognises a new cluster when the distance between at least one element of one of the clusters to at least one element of the second is lower or equal to the distance threshold. Accordingly, it is also known as Nearest Neighbor Clustering. The distance is computed by the Euclidean distance in the Cartesian space. The main characteristic of this clustering method is the ability to group values which build long chains a feature referred as chaining. Fig. 7.a depicts an example of Single-Linkage, with a distance threshold of 2 pixels. The second algorithm (CLC) performs cluster fusions when the distance between all objects of each cluster is ≤ distance threshold.



(a) Single-Linkage Clustering *(b) Complete-Linkage Clustering*

Fig. 7 SLC and CLC algorithms

This feature is the reason why Complete-Linkage Clustering is also known as Furthest Neighbor Clustering. An example for Complete-Linkage Clustering with distance threshold of 2 pixels is depicted in Fig. 7.b. This clustering method is referred as no chaining.

3 EXPERT SYSTEM BASED ON FUZZY LOGIC

Through clustering algorithms, pixel aggregates are obtained having common characteristic as, for instance, belonging to the same constellation of artifacts or being the image of an artifact source. It is useful to recognize a pattern in such a way when one does not want to distinguish among the located configurations. For example if one does not want to indicate to the dentist the exact position of the metallic implantations. A straightforward wayto locate the position of artifact sources is to use the information orignating from the network-model of the fuzzy thresholding in order to detect an aggregate based on the pixel type. The terminal nodes of the network model are in fact four. Each token, with its member degree, can reach only one of them, as depicted in Fig. 6. In particular, the tokens are classified as source points if they belong to "terminal node 1", as undefined points of one or of the other type if they belong to "terminal node 2", as member points of an artifact, if they belong to "terminal node 3", and finally, as points not interested by any artifact if they belong to the "terminal node 4". These must be considered as fuzzy statements, with a certain level of uncertainty, inherent in the membership degrees associated with the tokens. With the aid of a graph as in Fig. 8, it is possible to associate to each pixel a membership degree to a fuzzy "source".This is achieved by calculating the minimum value between the membership degree associated with a token and that of the terminal node to the fuzzy source sub-ensemble.

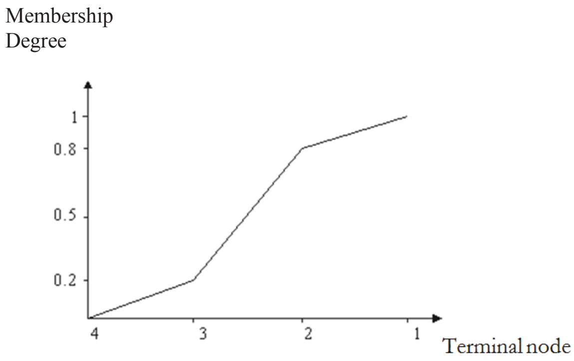


Fig. 8 Membership function of the terminal-nodes to the sub-ensemble source.

This solution, even if it is in terms of fuzzy logic, appears conceptually efficient to establish if the single pixel belongs or not to the pattern representative of the metallic presence. However, it is not able to characterize, in the whole of the image, relations of closeness and likeness. To overcome such deficiency, it will be necessary to use an observation of fundamental importance in the distinction between a metallic object and its effect on the image. Namely, the sources appear, on the image, as clouds of points occupying a relatively small area with high concentration, whereas induced artifacts appear as long, near-rectilinear trails of light. The latter are defined as "chains" in pattern recognition terminology. This approach finds substantial support in the experience, but its practical application is hampered by the difficulty to graphically represent, in computer implementations, aggregates as clouds of points or as chains.
As proposed here, the decisional syntax of fuzzy logic to the pre-processing of the image, can also be realised in this aspect, thanks to the indeterminateness of the classification of the pixel groups by clustering algorithms.
The first step is to remove from the image the points not affected by artifacts, i.e. those assigned to the "terminal node 4", as mentioned above.
The remaining points will be included in a list, updated each time a cluster is found. By default, every element of the list will be considered as a cluster. Consequently, a single pixel will be a cluster of unitary dimension. On this list the Single-Linkage Clustering (Nearest neighbor) algorithm, previously described, will be first applied, followed by the decisional module. As mentioned above it will be necessary to find an algebraic criterion to define a constellation as a chain or as a cloud of points. To this end, it is necessary to evaluate the point density of each possible chain candidate.
A simple binary decisional rule could the following:

$$N_{pix}/2d < 1.0 \qquad (1)$$

where d is the maximum chain length and N_{pix} the number of pixels.
If equation (1) is verified it means that there is an insufficient density of points and, therefore, that the presence of a chain and consequently of an artifact to be eliminated can be suspected. On the other hand, if equation (1) is not satisfied, a cloud of points is envisaged, and one is in presence of a metallic structure that has to appear in the final cleaned-up image. The algebraic rule clearly divides the two outcomes. Thus, it is necessary to construct a membership function to the "artifact source" group that expresses also a membership

degree, in the spirit of fuzzy logic, while respecting the binary decisional rule expressed by (1) in the limit cases.
The proposed membership function is shown in Fig. 9: in abscissa there is the value $(N_{pix}-2d)/2d$ and in ordinate the membership degree; it is possible to note that when the abscissa is zero, the membership function assumes a value = 0.5, filling in this way the uncertainty left by equation (1), while the membership function assumes unitary value only when $N_{pixel} \geq 4d$.
In reality, this boundary is fuzzy.

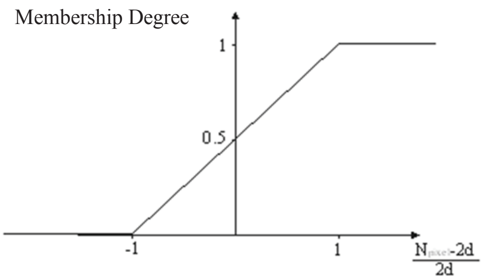


Fig. 9 Membership function in the chains elimination.

Therefore only a decisional rule has to be established, such as:

IF MF < 0.5 THEN Eliminate Chain

where MF is the value of the membership function in Fig. 8.

It is of course possible to calibrate the algorithm by changing the threshold value of MF, correcting it if some artifacts remain, or if the undesired elimination of some sources occurs.

It is possible, at this point, to write completely the algorithm to locate the clusters and to eliminate the chains. The Single-Linkage Clustering (Nearest neighbor) can thus be implemented: the threshold distance value, d_{th}, is fixed, below which the algorithm connects two clusters. The minimum distance between every pair of clusters previously located is estimated by calculating the minimum distance between all the groups included in each of the two clusters. It is necessary to remark that the initial list of the formed clusters is certainly not empty, because every valid pixel is initially entered in the list as a single cluster. Subsequently, every cluster will increase in dimension or will remain unitary. Hence, it is always possible to compare the distances between clusters. Because the procedure is iterative, it is possible to give an analytical description of it with the following expression:

$$d_{qi}^{new}=\min(d_{pi}^{old},d_{qi}^{old}) \qquad (2)$$

in which the distances between the nearest elements of the two clusters are compared and can be updated, after the formation of a new cluster.
Once the cluster individuation is completed, the procedure continues with the chain elimination algorithm, for which it is necessary to associate to every cluster the maximum length (number of pixels in the prevailing direction) and the number of pixels that are present in the cluster. The calculation of the function $(N_{pix}-2d)/2d$ is followed by the search of the membership degrees, and finally the elimination of the group of pixels thus individuated.

The completion of the pre-processing phase will require retouching the image by means of some procedure, in which expert decisional intervention is not required, such as the expansion and the convolution by a median function.
Fig. 10 depicts the 3D model before and after the automated removal of the artifacts in CT data obtained using the new methodology proposed in the paper

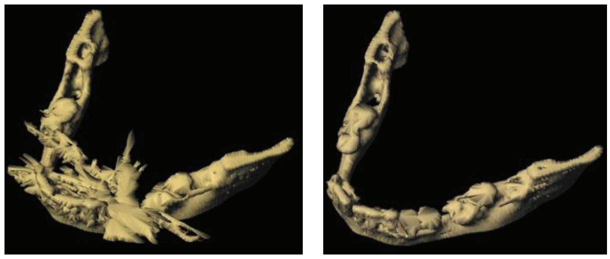


Fig. 10 3D model before and after the automated removal of the artifacts in CT data.

4 CONCLUSIONS

Image management by expert systems requires minimal effort from the operator, consisting in the manual input of some recognition parameters. These few preliminary operations, that can be executed only once for a given set of operating conditions, allow the expert system to manage, in full autonomy, the whole procedure of artifact reduction and of mapping of the metallic source positions on the cleaned image. A requirement for a successful outcome is the perfect and complete equivalence between the raw CT data and the images. Since this circumstance is not verified in presence of metallic objects, image pre-processing is necessary. Such operation has required, in the past, human supervision, because the decisions to take in such field are not usually able to a binary classic approach implementatble on computers.
In this paper the application of the fuzzy logic syntax is used to entrust to the computer this decisional phase, especially in the field of pattern recognition.
In particular, the thresholding and chain elimination phases, obtained through clustering, appear to be suitable for the implementation in fuzzy logic. The correct implementation of the pre-processing module could solve definitively the problem of the equivalence between image and trace-data, permitting to determine accurately, the limits of the eliminated artifact trails, without damage to the visualization of metallic presences in the image, and thus allowing to apply the interpolation algorithms directly on the image.

References

[1] Atsushi Kondo A., Hayakawa Y., Dong J., Honda A. (2010), Iterative correction applied to streak artifact reduction in an X-ray computed tomography image of the dento-alveolar region, Oral Radiol 26:61–65 DOI 10.1007/s11282-010-0037-6.
[2] Stradiotti P., Curti A., Castellazzi G., Zerbi A. (2009), Metal-related artifacts in instrumented spine. Techniques for reducing artifacts in CT and MRI: state of the art, Eur Spine Journal, S 102-S108.
[3] Barrett JF, Keat N (2004) *Artifacts in CT: recognition and avoidance*. RadioGraphics 24:1679–1691.
[4] Watzke O., Kallender W. (2004), *A pragmatic approach to metal artifact reduction in CT: merging of*

metal artifact reduced images, European Radiology 14, 849– 856.

[5] Kalender W., Hebel R., Ebersberger J. (1987), *Reduction of CT artifacts caused by metallic implants*, Radiology 164, 576–577.

[6] Path M. (1999), *Image Synthesis and Image Analysis Approaches for Artifact Reduction in Computer Tomography- A Case in Cranio-Maxillofacial Surgery*, Dissertation zur Erlangung der Naturwissenschaftlichen Doktorwürde vorgelegt der MATHEMATISCH-NATURWISSENSCHAFTLICHEN FAKULTÄT der UNIVERSITÄT ZÜRICH, Zürich.

[7] Path M. (1998), *New approaches in CT artifact suppression – a case study in maxillofacial surgery*, CAR '98, Tokyo, Japan.

[8] Petzold R. and Werner M. (1995), *Reduktion von Metallartefakten in der cranialen Röntgen-Computertomographie,* Diplomarbeit, Zürich.

[9] Pan J., et Al. (1991), *FuzzyShell: A Large-Scale Expert System Shell using Fuzzy Logic for Uncertainty Reasoning*, IEEE Trans. On Fuzzy Systems.

[10] Klotz E., et. Al, (1981), Algorithms for the Reduction of CT Artifacts caused by metallic Implants. SPIE, (pp. 642-650).