# EEG-MRI Co-registration and Sensor Labeling Using a 3D Laser Scanner 

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#### Abstract

This paper deals with the co-registration of an MRI scan with EEG sensors. We set out to evaluate the effectiveness of a 3D handheld laser scanner, a device that is not widely used for co-registration, applying a semi-automatic procedure that also labels EEG sensors. The scanner acquired the sensors' positions and the face shape, and the scalp mesh was obtained from the MRI scan. A pre-alignment step, using the position of three fiducial landmarks, provided an initial value for co-registration, and the sensors were automatically labeled. Co-registration was then performed using an iterative closest point algorithm applied to the face shape. The procedure was conducted on five subjects with two scans of EEG sensors and one MRI scan each. The mean time for the digitization of the 64 sensors and three landmarks was 53 s . The average scanning time for the face shape was 2 min 6 s for an average number of 5,263 points. The mean residual error of the sensors co-registration was 2.11 mm . These results suggest that the laser scanner associated with an efficient co-registration and sensor labeling algorithm is sufficiently accurate, fast and user-friendly for longitudinal and retrospective brain sources imaging studies.


Keywords-Multimodal co-registration, Laser scanner, Iterative closest point algorithm, Surface fitting, Brain sources imaging.

## INTRODUCTION

Brain sources imaging aims at non-invasively localizing cortical generators that produce surface spontaneous or evoked electromagnetic activities, by solving the inverse problem. In drug-resistant epilepsy investigations, it is a suitable method to localize the epileptogenic zone that is currently delineated by

[^0]invasive recordings (stereoelectroencephalography or electrocorticography). ${ }^{16,22}$ The accuracy of brain anatomical localizations depends on the number and the accuracy of localization of scalp-surface sensors. ${ }^{25}$ Brain sources imaging is obtained by the co-registration of multimodal data: both functional (electroen-cephalography-EEG, magnetoencephalography-MEG, near-infrared spectroscopy-NIRS...) and anatomical (magnetic resonance imaging-MRI, CT scan...). Co-registration places into a common frame the spatial positions of the surface sensors that record functional data, and anatomical information. ${ }^{33}$ Several methods have been developed for the co-registration of MRI data with EEG, ${ }^{6,12,19,20,30-32}$ MEG, ${ }^{1,8,19,31}$ transcranial magnetic stimulation (TMS), ${ }^{26}$ and for the event related optical signals (EROS) or NIRS. ${ }^{33}$

A straightforward way of co-registration which requires no additional digitization or scanning equipment beyond the MRI consists of identifying the sensors' position in the MR images. This approach needs additional markers ${ }^{30}$ or specific sensors ${ }^{15}$ that can be imaged in MRI and its drawback is that functional data recording and MRI acquisition must be carried out successively thus excluding a retrospective analysis. Moreover, the use of MRI visible sensors is not yet adapted to high resolution EEG caps. Other co-registration methods involve: (i) digitizing the sensors' position and, in most cases, also locating anatomical points, (ii) determining a three-dimensional (3D) rigid body transformation to align the sensors' position and MRI scan in a common coordinate system.

For several years, various techniques have been developed to locate scalp-placed sensors and additional anatomical points: the manual method, ${ }^{21}$ electromagnetic ${ }^{1,6,26,33}$ or ultrasonic digitization, ${ }^{12}$ or by
photogrammetry. ${ }^{4,20}$ More recently, Gouws and Woods suggested using a 3D camera to locate the MEG coil ${ }^{8}$ and we also presented a similar study which used a handheld 3D laser scanner to digitize an EEG cap. ${ }^{17}$ Fiducial landmarks (e.g., nasion and pre-auricular points) identified on the subject's head and on the MR images could be used to guide co-registration without any markers. This approach is simple and allows retrospective study, but the accuracy of the co-registration relies on the efficiency of the operator in locating the fiducial landmarks. Another approach uses MR markers positioned on anatomical landmarks. These fiducial points are digitized concurrently with the EEG sensors and can be identified directly in the MRI volume thanks to the markers. The two sets of fiducial points (digitized positions and coordinates in MRI volume) are then aligned using a least-squares algorithm so that the sensors' position can be co-registered in the MRI space. ${ }^{2,33}$ A similar method uses a dental bite-bar with markers instead of fiducial markers. ${ }^{1,31}$ This technique enables retrospective work and improves the accuracy of the registration but requires a specific bite-bar device for each subject. These markerbased methods can be relatively accurate, however, the markers can appear shifted in MR image due to magnetic susceptibility changes or marker displacements (mechanical constraints). ${ }^{33}$ An alternative registration approach is based on the alignment of two sets of surfaces, or cloud points, representing the head surface. The first set of points is associated with the sensors and can be obtained with any of the previously discussed digitization techniques. According to literature, the number of digitized points (sensors' position and additional anatomical points) ranges from 200 to 2000. ${ }^{6,12,19,26,33}$ The second set of points is obtained from the segmentation of the head contour in the MR images. This segmentation is carried out by using a 3 D region growing algorithm, ${ }^{12,19}$ by identifying the transition from the air surrounding the head to the outer surface of the skin, ${ }^{20}$ with mathematical morphology operators, ${ }^{26}$ or by using an in-house algorithm. ${ }^{6,33}$

This surface matching approach aims at minimizing the distance between the two sets of points. In some situations, the algorithm undesirably converges to a local minimum of the cost function due to the ellipsoidal symmetry of the human head. To overcome this problem a pre-alignment technique should be applied before running the distance minimization procedure. Several such techniques have been proposed: matching of the centroids ${ }^{12}$ or 3D geometrical moments ${ }^{19}$ of the two surfaces, landmark ${ }^{26}$ or fiducial marker point ${ }^{33}$ alignment, or adjustment of the centroids and the midsagittal planes of the two data sets. ${ }^{32}$ For distance minimization, Brinkmann et al. ${ }^{6}$ used a chamfer
distance based algorithm developed by Jiang et al. ${ }^{13}$ Huppertz et al. ${ }^{12}$ introduced a non-linear minimization of the distance between the two surfaces determined with a look-up table via an iterative bisection search algorithm. Kozinska et al., ${ }^{19}$ Adjamian et al., ${ }^{1}$ and Whalen et al. ${ }^{33}$ employed the Euclidean distance transform ${ }^{18}$ with the Marquardt-Levenberg algorithm. ${ }^{23}$ Noirhomme et al. ${ }^{26}$ aligned the data with an improved version of an Euclidean distance transform minimizing algorithm proposed by Pelizzari et al. ${ }^{28}$ Špiclin et al. ${ }^{32}$ minimized a cost function based on the Kullback-Leiber divergence between the intensity histograms taking into account internal and external similarities. Instead of matching additional digitized points with the segmented MRI, Lamm et al. ${ }^{20}$ computed a reconstruction of the scalp using a spline interpolation of the sensor points. Afterwards, an iterative point-matching algorithm proposed by Zhang ${ }^{34}$ was applied.

Whatever the method used for co-registration, one needs to identify the sensor positions before brain sources localization can occur. This can be achieved during the digitization step by acquiring the sensors' coordinates in a given order. As this is a time costly and operator dependent procedure, several automatic techniques have also been developed: the combinatorial optimization based algorithm, ${ }^{27}$ recognition of colored stickers in photogrammetric images, ${ }^{4}$ and our method that uses a priori information on the relative positions of sensors. ${ }^{15}$

In this work, we focus on the automatic co-registration of EEG sensors (included in a cap) with MRI data in a clinical context of high resolution EEG. To accomplish this, several methodological requirements are necessary. Firstly, retrospective investigations and a co-registration of one MRI scan with several EEG sensor digitizations are required which excludes the MRI marker-based approach. Secondly, we consider the exclusive use of an EEG cap for high resolution EEG. This approach does not need specific EEG sensors or bite-bars, but does require a digitization step, instead. Thirdly, it is important that this digitization step can be carried out manually in any medical room. In this context, a complete co-registration procedure would be achieved in five steps: (i) sensor and head shape digitization, (ii) MRI scalp segmentation, (iii) pre-alignment of the obtained data, (iv) automatic sensor labeling, and (v) co-registration. Taking into account our requirements, three digitization devices may be used: the electromagnetic digitizer, the ultrasonic digitizer, and the handheld laser scanner. For the first two systems, a stylus acquires the position of 3D points. The accuracy of these devices is user-dependant and is highly linked to the environment. ${ }^{14}$ In a previous study, we showed that the laser scanner was equivalent
in terms of accuracy, had a better repeatability, and was faster than the electromagnetic digitizer. ${ }^{17}$ In addition, to the best of our knowledge, this promising tool has not yet been used for EEG sensors' localization. Consequently, we decided to use it in this study. For scalp segmentation, we applied the semiautomatic procedure of the $A S A$ software: the scalp mesh was defined by selecting the gray level threshold and using mathematical morphology operators. In keeping with Noirhomme et al., ${ }^{26}$ as pre-alignment we adjusted the position of three fiducial landmarks (nasion and preauricular points) acquired with the scanner and manually located on the MR images. For co-registration, we selected the iterative closest point (ICP) method, ${ }^{5}$ as a possible alternative to the distance transform approaches previously presented, since it computes the exact Euclidean distance. ${ }^{24}$ Finally, the labeling of the electrodes was achieved with a modified and improved version of our previous algorithm, initially developed for electrode labeling in MR images. ${ }^{15}$

The paper is organized as follows: in the next section, we present the 3D laser scanner, the experimental setup and the algorithms used for MRI segmentation, pre-alignment, sensor labeling, and co-registration; in the third section, we show the results of the complete procedure applied to five healthy subjects; and finally we discuss these results in context.

## MATERIALS AND METHODS

## The 3D Laser Scanner

For the co-registration task, we used a handheld auto-referenced 3D laser scanner (Handyscan 3D of the EXAscan type) with the dedicated software VxScan (Creaform) to acquire the sensors' positions and construct a 3D mesh of the subject's face. We have previously shown that this device had a similar accuracy, better repeatability and was faster than the electromagnetic digitizer Fastrak (Polhemus) which is mainly used for scalp EEG sensor localization. ${ }^{17}$ It establishes a spatial reference with a resolution of 0.05 mm and is composed of a class II laser diode that projects a crosshair over the surface to digitize and of two synchronized cameras that capture the image of projections (Fig. 1). As the relative position of these three elements is calibrated, a triangulation-based algorithm provides the coordinates of the points associated to the crosshair. ${ }^{9}$ By affixing reflective targets (one per sensor) as positioning features on the shape (human head), one can simultaneously measure the 3D surface geometry and estimate a model of positioning features for tracking. Thus, this scanner does not need any positioning device to integrate 3D measurements in a global coordinate system while it is moving. ${ }^{10}$


FIGURE 1. Handheld 3D laser scanner principle. At least four reflective target positions need to be recognized by the scanner all the time.

## Experimental Setup

Five healthy volunteers (median age: 30 years old, one woman and four men) participated in this work. All gave their formal consent and the study was approved by the Ethics Committee of our Institution. The face shape and the positions of the EEG sensor targets were both acquired by the laser scanner twice for each volunteer who also underwent one MRI scan per person. This double acquisition allowed us to evaluate the repeatability of the scanning procedure and to compare the obtained results to those given by the electromagnetic digitizer. ${ }^{17}$

All MRI scans were performed on a $1.5 T$ GE Signa (GE Healthcare) with an eight element coil. We used a 3D Spoiled Gradient Echo sequence $(\mathrm{TR}=20 \mathrm{~ms}$, $\mathrm{TE}=3 \mathrm{~ms}, \alpha=35^{\circ}$ ) with 230 mm field of view, $192 \times 192$ matrix, and 200 slices. The slice thickness was 1.2 mm without any gap between the slices.

An EEG cap (Electro-Cap International) was used for EEG recordings. It includes $64 \mathrm{Ag} / \mathrm{AgCl}$ sensors placed according to the ten/ten international system. Adhesive reflective targets, of the same diameter as the external face of the sensor supports ( 11 mm ), were positioned onto the sensors and a hole was made in their center to introduce conductive gel. For prealignment, three additional targets were placed on each subject's fiducial landmarks (nasion, pre-auricular points). These 67 targets had a dual purpose: they were part of the positioning model, which was constituted by all the reflective targets affixed on the head, and they allowed to locate the sensors and the fiducial landmarks. To calculate the position of the scanner in space, at least four reflective target positions need to be identified at all time. Since the head is ellipsoidal, a co-registration using only the sensors' positions seemed inaccurate because several rotations of the convex hull defined by the sensors can be possible and making it difficult to model. Hence, additional anatomical points were needed for co-registration. As the EEG cap is of standard size, it did not fit the head shape exactly, particularly in the temporal regions. Digitization of the cap surface by an optical device
could not be used for accurate alignment so we chose to scan, in addition, the forehead and nasal surface. Besides the reflective targets affixed on the frontal sensors ( $\ldots, F p 1, F p z, F p 2, \ldots$ ), two targets were positioned on the cheeks and four on the nose to guarantee a correct digitization of the upper part of the face which was used for our co-registration method.

The scanning was carried out indoors without any special requirements for light. If the environment changed, a configuration step adapted the laser power and the shutter speed of the cameras in less than 1 min . In this study, the same operator was walking around the head scanning it. As scanning progressed, the number of acquired targets and the optimal scanner-head distance (about 300 mm ) were actively monitored on a control screen. The scanning was performed in two steps. First, the "positioning model", that is the 3D coordinates of the center of each target, was acquired using the "scan features" mode of the scanner. This positioning model was used as a reference frame, to take into account the movements of the scanner and the head. It allowed also to determine the sensors' and landmarks' target position. Second, the "surface" acquisition mode produced a scan of the subject's face used for co-registration and
based on the positioning model. There was no additional alignment step between the two sets of data that were recorded in the same coordinate system. The digitization results were controlled with the VxScan software. The positioning model sometimes lost its shape during acquisition creating one or several target artefacts due to the traction on the ribbon cable of the EEG cap when moved for underneath scanning. These artefacts, as well as the six targets of the face, were detected and removed. For the scanned shape, parts of no interest (pieces of cap above the forehead and behind the temples) had to be removed with a graphical tool of the software. Next, the coordinates of the 3D points (targets and face) were recorded in two separate files for further co-registration with the Matlab software.

## Overview of the Method

Using the 3D points files obtained with the 3D laser system and the MRI slices, the complete co-registration method was achieved in three steps: (i) MRI head modeling, (ii) pre-alignment and sensor labeling, (iii) co-registration. These steps are summarized in Fig. 2 and are as follows.


FIGURE 2. (a) Head modeling. (b) Pre-alignment and sensor labeling. (c) Co-registration.

## Head Modeling

The MRI head shape was obtained by using the semi-automatic segmentation procedure included in the $A S A$ software. By manually selecting the gray level thresholds, we identified the transition from the air surrounding the head to the outer surface of the skin. Then, a realistic mesh was calculated by the $A S A$ software with a spacing of about 0.02 inch per triangle. A total of 31,390 points was obtained for the scalp mesh. Afterwards, we identified the three fiducial points (nasion, left and right pre-auricular points) on the three MRI views (sagittal, axial, and coronal). The fiducial coordinate system was defined by so-called fiducial points on the surface of the head. The $y$ direction was determined by the connecting line between the two preauricular points (pointing left). The origin was found by projecting the nasion orthogonally onto this line. The $x$-axis pointed from the origin to the nasion and the $z$-axis stood perpendicular on the plane spanned by the $x$ and $y$ axes pointing towards the crown of the head. ${ }^{31}$ Finally, the fiducial coordinate system was obtained by shifting and rotating the MRI coordinate system.

## Pre-alignment and Sensor Labeling

The objectives of this step were to: (i) apply a 3D rigid body transformation to the digitized points
obtained with the scanner to have the same coordinate system as the MRI, (ii) label landmarks and sensors for use with the sources localization software, (iii) correct for the thickness of the sensor's support (the scanner digitizes the position of the target taped on the upper part of this support, i.e., the target sensor position, and the co-registration would be made with the scalp sensor position). These tasks were performed together using a seven-step procedure as follows.

## Identification of Fiducial Landmarks

Compute the centroid of the 683 D points-corresponding to landmark and sensor targets-and use it as the origin, called $O$, of a new coordinate system. Compute the convex hull of these points using the Quickhull Algorithm (Fig. 3). ${ }^{3}$ Within the set of triangular facets that compose the convex hull, find the triangle with the biggest area (dark gray triangle in Fig. 3). A priori anatomical considerations suggest that the vertices of this triangle are the three points of the fiducial landmark, and the longest side of this triangle connects the preauricular points (points $T_{1}$ and $T_{2}$ ). Moreover, it was verified by a human operator that, for all volunteers, these vertices corresponded to the fiducial locations. This allows to easily identify the nasion (point $N$ ). Let $M$ be the midpoint of the segment connecting the preauricular points. To determine


FIGURE 3. Convex hull of the 68 reflective targets (landmarks and sensors) in the final coordinate system $\left\{x^{\prime}, y^{\prime}, z^{\prime}\right\}$.

(b) $T_{r}$


FIGURE 4. (a) Position of the anatomical landmarks $\left\{N, T_{1}\right.$, $\left.T_{2}\right\}$ in the initial coordinate system, $O$ centroid of 3D points, $N$ nasion, $T_{1}$ and $T_{2}$ preauricular points, $M$ midpoint of [ $T_{1} T_{2}$ ], $A_{1}$ and $\boldsymbol{A}_{2}$ points obtained with cross-products to identify preauricular points. (b) Basis of the new coordinate system, $N$ nasion, $T_{\mathrm{r}}$ right preauricular point, $T_{1}$ left preauricular point, $O^{\prime}$ origin of the new coordinate system, $\left\{x^{\prime}, y^{\prime}, z^{\prime}\right\}$ standard basis.
left from right preauricular points, we used the following automated procedure. Compute two crossproducts of normalized vectors: $\stackrel{\wedge}{M N} \times \stackrel{\wedge}{M T_{1}}=\overrightarrow{M A_{1}}$, $\overrightarrow{M N} \times \overrightarrow{M T_{2}}=\overrightarrow{M A_{2}}$. If $\left\|\overrightarrow{O A_{2}}\right\|<\left\|\overrightarrow{O A_{1}}\right\|$, then $T_{1}$ corresponds to the right preauricular point, called $T_{\mathrm{r}}$, otherwise it corresponds to the left preauricular point, called $T_{1}$ (Fig. 4a). Label the fiducial landmarks. These three points are used to define a new coordinate system with origin $O^{\prime}$ as the intersection of a perpendicular line from the nasion and the inter-preauricular points line, and standard basis vectors as depicted in Fig. 4b. This new coordinate system is now the same as for MRI scan.

## Change of Coordinate System

This second step describes the translation and rotations needed to move the 3 D points from the scanner coordinate system to the new coordinate system. Compute the coordinate of $O^{\prime}$, using the following equations: $\overrightarrow{O O^{\prime}}=\overrightarrow{O T_{\mathrm{r}}}+\overrightarrow{T_{\mathrm{r}} O^{\prime}}=\overrightarrow{O T_{\mathrm{r}}}+\frac{\left\|\overrightarrow{T_{\mathrm{r}} O^{\prime}}\right\|}{\left\|\overrightarrow{T_{\mathrm{r}} T_{1}}\right\|}$. $\overrightarrow{T_{\mathrm{r}} T_{1}}=\overrightarrow{O T_{\mathrm{r}}}+\frac{\left(\overrightarrow{T_{\mathrm{r}} N} \cdot \overrightarrow{T_{\mathrm{r}} T_{1}}\right)}{\left\|\overrightarrow{T_{\mathrm{r}} T_{1}}\right\|^{2}} \cdot \overrightarrow{T_{\mathrm{r}} T_{1}}$. Use $O^{\prime}$ as a new origin. Rotate the 3D points so that a normal vector to the plane passing through $N, T_{\mathrm{r}}$, and $T_{1}$ is parallel to the $z$-axis; this rotation is made as follows: (i) compute a normal vector $\vec{v}$ to the plane $\left(\vec{v}=\overrightarrow{T_{\mathrm{r}} T_{1}} \times \overrightarrow{T_{\mathrm{r}} N}\right)$, (ii) compute the rotation angle $\theta=a \cos \left(\hat{v}_{z}\right)$ where $\hat{v}_{z}$ is the $z$-axis coordinate of the normalized vector $\hat{\vec{v}}$, (iii) compute $\vec{e}=\hat{\vec{v}} \times \vec{z}$ then $\hat{\vec{e}}$ is the rotation axis, (iv) compute the quaternion $q=\left(q_{0} q_{1} q_{2} q_{3}\right)^{\mathrm{T}}=(\cos (\theta / 2)$ $\left.\hat{e}_{x} \sin (\theta / 2) \quad \hat{e}_{y} \sin (\theta / 2) \quad \hat{e}_{z} \sin (\theta / 2)\right)^{\mathrm{T}}$, (v) compute the quaternion-based rotation matrix $R$ and rotate the


FIGURE 5. Projection of the normalized points $E_{i}^{\prime}$ in the ( $x^{\prime}, y^{\prime}$ ) plane (round markers). The solid line defines the outer ring and the dotted lines define the seven subsets used for points sorting. $R$ right side of the patient, $L$ left side, $A$ anterior side, $P$ posterior side. This figure also illustrates the case where the cap was not symmetrically adjusted.

3D points. Rotate the 3D points so that $\overrightarrow{O^{\prime} N}$ is parallel to $\vec{x}$; this rotation is made as follows: (i) compute the rotation angle $\theta^{\prime}=a \cos \left(\stackrel{\wedge}{O^{\prime} N_{x}}\right)$ where $\stackrel{\wedge}{O^{\prime} N_{x}}$ is the $x$-axis coordinate of the normalized vector $\stackrel{\wedge}{O^{\prime} N}$, (ii) compute $\overrightarrow{e^{\prime}}=\overrightarrow{O^{\prime} N} \times \vec{x}$ then $\overrightarrow{e^{\prime}}$ is the rotation axis, (iii) compute the quaternion $q^{\prime}$ and the rotation matrix $R^{\prime}$ as previously, and rotate the 3D points.

## Identification of Temporo-Basal Sensors

In the set of 65 target sensor points, find the four points with the smallest $z^{\prime}$-coordinate value. Label these temporo-basal points according to their relative values in $x^{\prime}$ and $y^{\prime}$ coordinates $\left(F T 9_{x^{\prime}}>\right.$ $\left.P 9_{x^{\prime}}, F T 10_{x^{\prime}}>P 10_{x^{\prime}}, F T 9_{y^{\prime}}>F T 10_{y^{\prime}}, P 9_{y^{\prime}}>P 10_{y^{\prime}}\right)$ and remove them from the unknown sensors set.

## Identification of Outer Ring Sensors

Compute the normalized vectors $\overrightarrow{O^{\prime} E_{i}^{\prime}}=\overrightarrow{O^{\prime} E_{i}}$ where $E_{i}(i=1, \ldots, 61)$ is the set of remaining target sensor points and the $E_{i}^{\prime}$ points are distributed on a unit sphere, and project these $E_{i}^{\prime}$ points on the ( $x^{\prime}, y^{\prime}$ ) plane (Fig. 5). Compute the convex hull of the projected points, the corresponding target sensor points form the outer ring $\{F p z, F p 1, \ldots, F p 2\}$. Identify the $E_{i}^{\prime}$ point with the biggest $x^{\prime}$-coordinate and the smallest $y^{\prime}$-coordinate in this subset. This corresponds to the Fpz sensor (if the cap shifts on one side, then the first two points with the biggest $x^{\prime}$-coordinate can be $F p 1$ or
$F p 2$ followed by $F p z$ so the right value can be found by testing the $y^{\prime}$ value of these points). Label the outer ring sensors, starting from $F p z$ and working clockwise, and remove them from the unknown sensors' set.

## Identification of Central Sensors

Sort the remaining 41 target sensor points using the value of the $x^{\prime}$ and $y^{\prime}$ coordinates of the $E_{i}^{\prime}$ corresponding points: the points are divided into seven lines according to the growing value of $x^{\prime}$-coordinate: the first line (lowest $x^{\prime}$-coordinate) comprises three points, the following five lines would have seven points each, and the last line (highest $x^{\prime}$-coordinate) should have three points (Fig. 5). Afterwards, the points in each line are thus sorted with respect to the $y^{\prime}$-coordinates in order to label the sensors.

## Positioning of Face Points

The digitized points corresponding to the face were positioned using the same translation vector and rotation matrices as described in step 2 above.

## Correction of the Position of Digitized Sensor Points

To correct for the sensor's support thickness $(8.2 \mathrm{~mm})$ so that sensor coordinates lie on the scalp surface, the positions of the digitized target sensors points were adjusted. Indeed, since the target sensor coordinates define a convex hull then, for each vertex of the surface, the normal to the hull was used to translate the point with a distance corresponding to the sensor's support thickness. One proceeds as follows. Compute the convex hull of the 68 sensors and fiducial landmarks target points. For each target sensor point,
find the other points connected to it. Suppress all the connections with the fiducial landmarks points and remove the connection between $P 9$ and $P 10$. Indeed, to compute the normal to a particular target sensor point, we considered a subset of the hull linking this target sensor to the other nearest target sensors of the cap, thus eliminating the connections with the fiducial landmarks. The connection between $P 9$ and $P 10$ was also eliminated because it was the only one which connected the two sides, right and left, of the cap after removing the fiducial landmarks (Fig. 3). Then, for each target sensor point of the modified convex hull, determine the intersections between a sphere of a diameter close to the target sensor size and the segments connecting the point in question to the other points. To illustrate this step, Fig. 6a shows: (i) the connecting segments between the target sensor point corresponding to C4 and the other target sensor points, (ii) the intersection points between a sphere centered in C4 target sensor point and the connecting segments. As the intersection points would lie approximately on a plane that is parallel to the plane tangent to the convex hull at the target sensor point, ${ }^{11}$ find the plane that fits these intersection points, using principal component analysis, and compute the normal to that plane (Fig. 6b). Determine the correct sign for the normal and translate the target sensor point with a distance equal to the sensor's thickness along the axis defined by the normal to obtain the scalp sensor point.

## Co-registration

Both the position of the 65 scalp sensor points and the face points can be used for co-registration with the


FIGURE 6. (a) Connections between C4 and the other sensors. Square: target sensor position, asterisk: intersection between a connecting segment, and a sphere centered in $C 4(\varnothing=10 \mathrm{~mm})$. (b) Determination of the normal at $C 4$ to the plane that fits the intersections points. Square: target sensor position, asterisk: intersection point obtained in (a), solid line: connecting line between C4 and another sensor, dashed line: direction of the normal at C4, gray line plane: plane fitting the intersections points.
segmented MRI, but we chose not to include the sensors' positions because the number of sensors was negligible with regard to the number of points for the part of the face that was used (less than $3 \%$ in the worst case). This choice clearly separated the data used to minimize the cost function (face data) and those to evaluate results (sensors and scalp data). We decided to perform the co-registration with only the upper points of the face which had a $z$-coordinate up to -25 mm the nasion has a $z$-coordinate equal to 0 -corresponding roughly to the forehead, the orbits, and the zygomatics; this improved the alignment because the upper part of the face is more boney and anatomically rigid and therefore produces more reliable registration between the MRI and 3D laser scanner. Moreover, several authors have pointed out that the region around the nose and the eyes is the most critical for accurate registration. ${ }^{12,33}$

As previously indicated, the ICP algorithm was used for co-registration. ${ }^{5}$ In brief, the scanned part of the face was registered to the MRI shape by iteratively: (1) finding the MRI points which were the closest to the face points, (2) computing the 3D rigid body transformation that registered the points together, (3) applying that transformation to the face points. Let $M=\left\{\mathbf{m}_{i}\right\}$ with $i=1, \ldots, n_{m}$ be the MRI points set $\left(\mathbf{m}_{i}=\left(m_{i x}, m_{i y}, m_{i z}\right)\right.$ and $\left.n_{m}=31,390\right)$ and $S=\left\{\mathbf{s}_{i}\right\}$ with $i=1, \ldots, n_{s}$ be the scanned face points set $\left(\mathbf{s}_{i}=\left(s_{i x}, s_{i y}, s_{i z}\right)\right.$ and $\left.\overline{n_{s}}=3,487\right)$, the objective of the ICP algorithm was to find a rotation matrix $\mathbf{R}$ and a translation vector $\mathbf{t}$ that moved $S$ to align it with $M$. There were numerous variants of the ICP algorithm ${ }^{29}$; the main characteristics of the algorithm that we used were stated as follows:
(1) MRI points pre-processing: Determine the bounding volume that contains $M$ and split it up using a grid of $n_{b}$ overlapping blocks where $n_{b}$ was determined according to the size of the bounding volume ( $\overline{n_{b}}=748$ ). The use of these blocks allows faster closest point computation because the block nearest to a moving scanned point will contain its closest MRI point. The center of each block is called $\mathbf{b}_{i}$ with $i=1, \ldots$, $n_{b}$. Then, sorts the MRI points into $n_{b}$ sets of points $M_{i}$ with $i=1, \ldots, n_{b}$. The $i$ th set $M_{i}$ contains the MRI points located in the $i$ th block.
(2) Initialisation: $k=0, \quad \mathbf{R}_{0}=\mathbf{I}, \quad \mathbf{t}_{0}=(0,0,0)$, $S_{0}=S$
(3) Iteration $k$ : In the following, the squared Euclidean distance is defined as a metric between points: let $\mathbf{p}_{1}$ and $\mathbf{p}_{2}$ be any two points, it is expressed as $d\left(\mathbf{p}_{1}, \mathbf{p}_{2}\right)=\left\|\mathbf{p}_{1}-\mathbf{p}_{2}\right\|^{2}$. At each iteration the scanned points are moving,
then $\mathbf{s}_{i, k}$ corresponds to the position of the $i$ th scanned point at the $k$ th iteration.

1. Closest points computation: For each scanned point $\mathbf{s}_{i, k}$, find the closest block center point, $\mathbf{b}_{l}$, using the squared Euclidean distance; this closest point satisfies the equality $d\left(\mathbf{s}_{i, k}, \mathbf{b}_{l}\right)=\min _{j=1, \ldots, n_{b}} d\left(\mathbf{s}_{i, k}, \mathbf{b}_{j}\right)$.
Then, compute the squared Euclidean distances between $\mathbf{s}_{i, k}$ and the MRI points contained in $M_{l}$. The closest MRI point, $\mathbf{m}_{q}$, to the scanned point $\mathbf{s}_{i, k}$ satisfies the equality $d\left(\mathbf{s}_{i, k}, \mathbf{m}_{q}\right)=\min _{\mathbf{m}_{j} \in M_{l}} d\left(\mathbf{s}_{i, k}, \mathbf{m}_{j}\right)$, it is called $\mathbf{f}_{i, k}$.
2. Registration computation: The sum of the squared Euclidean distances between the registered scanned points (function of $\mathbf{R}_{k}$ and $\mathbf{t}_{k}$ ) and the closest MRI points is used as cost function to minimize: $e\left(\mathbf{R}_{k}, \mathbf{t}_{k}\right)=\sum_{i=1}^{n_{s}}\left\|\mathbf{s}_{i, k}-\mathbf{f}_{i, k}\right\|^{2}=$ $\sum_{i=1}^{n_{s}}\left\|\left(\mathbf{R}_{k} \mathbf{s}_{i, 0}+\mathbf{t}_{k}\right)-\mathbf{f}_{i, k}\right\|^{2}$. The minimization is performed by the Broyden-Fletcher-Golfarb-Shanno method, that is a quasi-Newton method. ${ }^{7}$ Then, we obtain the value of $\mathbf{R}_{k}, \mathbf{t}_{k}$, and $e_{k}=$ $\min _{\mathbf{R}_{k}, \mathbf{t}_{k}} e\left(\mathbf{R}_{k}, \mathbf{t}_{k}\right)$.
3. Registration application: Compute a new position of the scanned points: $\mathbf{s}_{i, k+1}=$ $\mathbf{R}_{k} \mathbf{s}_{i, 0}+\mathbf{t}_{k}$.
4. Iteration termination: Stop the iteration when $\frac{e_{k+1}}{e_{k}}<\tau$ where $\tau$ is a preset threshold ( $0<\tau \stackrel{e_{k}}{<} 1$ ).

The final 3D rigid body transformation was then applied to the scalp sensor points. Finally, we generated a file usable by the $A S A$ software for visualization and sources localizations (Fig. 7).

## RESULTS

All 10 digitizations ( 5 volunteers $\times 2$ scans each) were performed by the same operator. The average time to collect the 68 positions corresponding to the sensors and landmarks was 53 s (minimum: 31 s , maximum: 1 min 14 s ). Among the 747 sensor targets acquired during the 10 digitization sequences, only seven target artefacts were present. These artefacts were easily detected (they were clearly inside or outside the head surface) and removed. The scanning average time for the face was 2 min 6 s (minimum: 58 s , maximum: 3 min 36 s ) and the average number of points


FIGURE 7. The MRI and headmodel co-registered with the scanned face ( 2,814 points) and the sensors' position. On the left, the headshape was superimposed onto the MRI volume. In the middle and on the right, co-registration of the headmodel defined with MRI volume and the headshape with the 65 sensors obtained with the 3D laser scanner.

5,263 for a standard resolution ( 1.95 mm ). For co-registration, the average number of used points was 3,487 . Concerning the repeatability evaluation, the mean results of the average distance between two successive acquisitions of the same positions of the 65 sensor targets, obtained with the five subjects, showed that the measures of the scanner were repeatable $(1.21 \mathrm{~mm} \pm 0.58 \mathrm{~mm}) .{ }^{17}$

Although the scanner software can compute the normal vector at each target we did not use this function. Instead, we calculated the normal vector as previously presented in our thickness correction algorithm so as to define a standard procedure applicable to any kind of device. We compared the two methods for normal determination in order to evaluate our algorithm and computed the mean distance between the scalp sensors' positions obtained with both approaches. The average result was equal to $1.33 \mathrm{~mm} \pm 2.33 \mathrm{~mm}$ (mean $\pm \mathrm{SD}$ ). Figure 9 represents the positions provided by these two methods for one recording.

One of the five MRI scans was unusable due to motion artefacts which left four volunteers eligible for the co-registration step. For each of the remaining eight sets of data, we computed the residual error of the face (REF) that corresponds to the average difference between the digitized points of the face and the closest points of the segmented MRI. This difference gave an indication of the efficiency of the ICP algorithm and was computed according to the Euclidean distance form (E-REF) and to the root mean square distance form (RMS-REF). We computed the registration error of the sensors (RES), which is the average difference between the digitized scalp sensor points and the closest points of the segmented MRI, in Euclidean form (E-RES) or rms form (RMS-RES). As pointed out by Whalen et al., ${ }^{33}$ this registration error, distance between data sets, represents a lower-bound estimate

TABLE 1. Mean errors $\pm$ SD and extreme values associated to pre-alignment and co-registration.

|  | After <br> pre-alignment <br> $(\mathrm{mm})$ | After <br> co-registration <br> $(\mathrm{mm})$ |
| :---: | :---: | :---: |
| Residual error of the face (REF) |  |  |
| Euclidean REF (E-REF) | $2.01 \pm 0.36$ | $1.68 \pm 0.55$ |
|  | $\min =1.72$ | $\min =1.18$ |
| Root mean square REF | $\max =2.67$ | $\max =2.65$ |
| (RMS-REF) | $2.41 \pm 0.66$ | $1.93 \pm 0.91$ |
|  | $\min =1.86$ | $\min =1.19$ |
| Registration error of the sensors (RES) |  |  |
| Euclidean RES (E-RES) | $2.58 \pm 0.52$ | $2.11 \pm 0.46$ |
|  | $\min =1.79$ | $\min =1.62$ |
|  | $\max =3.29$ | $\max =2.75$ |
| Root Mean Square RES | $3.07 \pm 0.60$ | $2.52 \pm 0.63$ |
| (RMS-RES) | $\min =2.16$ | $\min =1.80$ |
|  | $\max =3.87$ | $\max =3.49$ |

of the "true" error, i.e., the distance between corresponding data points, also called map error or target registration error-TRE (Here target refers to the scalp sensor locations.). In our case, the TRE was not accessible then we used the RES as a goodness-of-fit for our method even though it underestimates the true alignment errors (Table 1). Figure 8 represents the repartition of the mean E-RES for the different sensors, before and after co-registration, using the topography of the ten/ten international system. For each volunteer we analyzed the map of the E-RES after co-registration. For one subject, an error greater than 5 mm was observed in the fronto-central zone (near $F C 1, F C z, F C 2$ sensors) probably due to the cable output of the EEG cap. This phenomenon was also observed with another subject but with a lower value (near 4 mm ). Another subject had an error between 2.5 and 3.5 mm in the temporal locations; this error was due to the size difference between the standard-EEG


FIGURE 8. (a) Mean Euclidean registration error of the sensors after pre-alignment. $R$ right side of the patient, $L$ left side, A anterior side, P posterior side. (b) Mean Euclidean registration error of the sensors after co-registration.
cap and the head. No other trend was observed. Next, we calculated the eight (4 volunteers $\times 2$ scans each) fiducial displacements (FD), namely the average Euclidean distance between the position of nasion and pre-auricular points before and after co-registration, as an indication of how much the co-registration process moved the fiducials points. We obtained $2.07 \mathrm{~mm} \pm$ 1.11 mm (mean $\pm \mathrm{SD}$ ).

No identification errors of the labeling process were found despite the fact that we used two sizes of caps (medium and large) and that occasionally the cap was not adjusted symmetrically. Figure 5 shows an example of EEG sensors that were not symmetric according to the inter-hemispheric line.

## DISCUSSION AND CONCLUSION

To the best of our knowledge, co-registration of scalp EEG sensors with MRI scan using laser-based systems has not been used up to now. Therefore, a comparison with other devices, especially the electromagnetic digitizer (which is the most used device), would be useful before discussing the co-registration results

Digitizing 68 positions (sensors and fiducial points) with the laser scan, took 53 s in average. When taking into account the scanner configuration time, the whole procedure lasted 1 min 42 s in average. However, the configuration step was only needed if the environment changed. This short time must be compared to a mean of about 8 min to acquire 67 points with the electromagnetic digitizer, ${ }^{21}$ to around 10 min for $61 \mathrm{mea}-$ surements with an ultrasound apparatus, ${ }^{12}$ or around 4 min 30 s for 22 sensors with a photogrammetric system. ${ }^{4}$ This time saving can be explained by the technology used and, for the stylus-based digitization, by the identification algorithm that overcomes the
acquisition of positions in a given order. In a preliminary study, we also digitized the position of sensors taped directly on the scalp. In this case, the digitization time depended on the subject's hair: with long hair, it took longer because we had to move the hair so that at least four targets were visible each time.

To digitize additional surface points, the problem of point identification did not arise and the scanner was by far superior: on average, we acquired about 40 points/second of the face while the fastest procedure we found in literature gave a rate of around 8 points/ second for the head. ${ }^{19}$ Therefore, discussions about the number of required points to assure a correct co-registration become irrelevant. Furthermore, the laser scanner supplied a more homogeneous shape than a stylus-based approach.

Finally, the summation of the mean times needed for: the scanner configuration, reflective targets taping (fiducial landmarks, cheeks, and the nose), reflective targets digitization, face digitization, and to switch the software between the two scanning mode, gave a global mean time equal to 6 min 30 s for the whole scanning procedure. This time in the presence of the patient was shorter than that required by the other devices but these other devices were not subject to the same degree of manual intervention after digitizing (visual inspection, removal of artefact and face targets, removal of unwanted parts of the scan).

As indicated in a previous work, the laser-based approach has a similar accuracy to an electromagnetic digitizer but a better repeatability to determine the sensors' positions. ${ }^{17}$ One might argue that, as the scanner used several points to compute the sensors' positions (the center of the considered target) whereas a stylus-based device only digitized one point, the results were more repeatable and, as a consequence, the laser scanner was less user-dependent than a stylusbased system. However, this conclusion may be slightly


FIGURE 9. Estimated sensors' positions. Square: initial position before thickness correction, circle: thickness correction using scanner normal vectors, asterisk: thickness correction with normals calculation. $R$ right side of the patient, $L$ left side, $A$ anterior side, $P$ posterior side.
hasty because the quality of the positioning also depends on the operator. Indeed, to assure a good scanning, the device should be as perpendicular as possible to the shape to be scanned. When looking perpendicularly at a reflective target, the image captured by the cameras is a perfect circle. So, when the incidence angle is closer to zero, the image of a target is an ellipse and the influence of an error when calculating the center of the ellipse is greater than in the case of a circle. Nevertheless, the "perpendicular positioning" requirement was easier to satisfy and demanded less attention than pinpointing with a stylus.

The comparison between the two methods used for normal computation of sensor's support thickness correction showed that these methods gave close results except for isolated cases (Fig. 9). The differences came from the scanner, which took only into account the target orientation to compute the normal vector, whereas our method used the position of neighboring sensors.

Co-registration approaches require an initial adjustment to avoid the local minimum problem. We thus tested a semi-automatic method that gave a correct value of the pre-alignment error. We obtained a mean E-RES equal to 2.58 mm and a mean RMS-RES equal to 3.07 mm ; these results were consistent with $2.8 \mathrm{~mm}(E-R E S)^{33}$ or $3.8 \mathrm{~mm}(\text { RMS-RES })^{26}$ and better than 11.33 mm (E-RES). ${ }^{19}$ Moreover, the small value of FD indicated that the initial guess was close to the final positioning. For the co-registration itself, we used a basic ICP algorithm but some variants of this algorithm or other sorts of optimization approaches like the Marquardt-Levenberg algorithm ${ }^{23}$ could also
be used. This co-registration improved the results $($ E-RES $=2.11 \mathrm{~mm}, \quad$ RMS-RES $=2.52 \mathrm{~mm}) \quad$ which were similar to or better than some results found in literature $\left(E-R E S=2.39 \mathrm{~mm},{ }^{19} \mathrm{RMS}-\mathrm{RES}=2.27 \mathrm{~mm},{ }^{32}\right.$ $2.43 \mathrm{~mm},{ }^{20} 3.36 \mathrm{~mm},{ }^{6} 3.39 \mathrm{~mm}^{12}$ ). Only the results presented by Whalen et al. ${ }^{33}$ and Noirhomme et al. ${ }^{26}$ were significantly better (respectively, E-RES = 1.6 mm and $\mathrm{RMS}-\mathrm{RES}=1.17 \mathrm{~mm}$ ). However, we did not compare exactly the same parameters: the authors digitized the scalp directly while we digitized the upper side of the sensors placed on the scalp with conductive gel. Thus, the comparison does not take into account the inaccuracy due to the estimation of the sensor's support thickness. A more meaningful approach would be to compare the quoted results with those provided by a skin-to-skin co-registration, namely the co-registration of the face. When performed, we had an E-REF of 1.68 mm , which was close to the result given by Whalen et al., ${ }^{33}$ but our RMS-REF of 1.93 mm remained higher than $1.17 \mathrm{~mm} .{ }^{26}$ In addition, Whalen et al. ${ }^{33}$ applied scaling factors after co-registration to take into account scaled gradient inaccuracies of MRI and digitization errors, followed by a scalp forcing step. Then, they obtained, respectively, an E-RES of 1.4 and 0.0 mm thanks to these operations. In our study, the pre-alignment was more efficient than the co-registration with the points of the face because fiducial landmarks were first correctly defined for each subject. Pre-alignment did most of the work (i.e., it minimized the RES whereas the co-registration with the head shape further refined the results if fiducial landmarks were not correctly localized). Nevertheless, we needed to keep in mind that our procedure does not estimate the TRE.

There were several sources of error in the whole co-registration process: the devices (digitization error of the scanner, geometrical distortion in the MR images), the patient (artefact due to movement during MRI acquisition), the operator (cap adjustment, fiducial landmarks identification, scanning process), and the algorithms (head shape modeling, ICP algorithm). We focused here on the sources that, to our opinion, were the most significant. Firstly, the laser scanner produced an error that we have evaluated in a previous work to $1.21 \mathrm{~mm} \pm 0.58 \mathrm{~mm} .{ }^{17}$ Secondly, the MRI gradient inhomogeneities can generate inaccuracies leading to an error of about $1-2 \mathrm{~mm}$ on the scalp. ${ }^{33}$ Then, the error of fiducial landmarks identification affected the pre-alignment step but the co-registration step allowed to minimize it. This kind of error was difficult to approximate, because it was based on a very small number of points, but a maximum positional variation of 4.5 mm can be obtained. ${ }^{31}$ Next, the cap and the operator will be at the origin of other sources of error: some "floating zone" between the sensor
location and the scalp could be produced by the use of an unsuitable cap, by a cap not correctly adjusted on the scalp, or by a traction on the output cables of the cap. Here, there was a difference with a stylus-based device: to some extent a stylus-based device could compensate, by an adapted pressure, a floating zone; an optical device could not. Finally, we had also investigated if the distance between the sensors and the center of the face (used to co-registrate) influenced the co-registration error. Thus, one might assume that the co-registration error could be smaller for the sensors closest to the face and greater for more distant sensors. However, we had not observed such a trend.

In addition to the co-registration algorithm, we also implemented and improved an automated algorithm, named ALLES, ${ }^{15}$ for labeling the sensors. The proposed method is quite simple and seems robust to geometry changes of the head and misalignment of the cap.

On the whole, our approach was not completely automatic and required some manual intervention, as in other methods found in literature. ${ }^{12,26,33}$ For instance, after scanning we had to inspect the scan and eliminate artefacts targets if necessary and to remove parts of no interest of the scanned face. Additionally, after the MRI scan was required, it was necessary to segment the scalp, locate fiducial points, and change the coordinate system prior to co-registration. However, we may underline the fact that this intervention does not require the subject's presence.

Finally, the proposed procedure has been developed for all EEG-MRI co-registrations which use EEG caps or sensors directly taped on the scalp, but it could also be used for any scalp-placed sensor co-registration. Moreover, the pre-alignment and co-registration algorithms could be applied to data obtained with any kind of digitizing device.

As a summary, the results suggest that the 3D laser scanner, associated with our efficient co-registration and sensor labeling algorithm, is sufficiently accurate, repeatable, fast and user-friendly to be used in retrospective and prospective brain source imaging studies.

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