INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
ISSN 1841-9836, 12(4), 507-518, August 2017.

# An Approach for Construction of Augmented Reality Systems using Natural Markers and Mobile Sensors in Industrial Fields

D. Gomes Jr., P. Reis, A. Paiva, A. Silva, G. Braz Jr., M. Gattass, A. Araújo

**Daniel Lima Gomes Júnior***
1. Federal Institute of Maranhão, São Luís, MA, Brazil
2. Applied Computing Center - Federal University of Maranhão,
São Luís, MA, Brazil
*Corresponding author: daniellima@ifma.edu.br

**Paulo Roberto Jansen dos Reis, Anselmo Cardoso de Paiva,**
**Aristófanes Corrêa Silva, Geraldo Braz Junior**
Applied Computing Center - Federal University of Maranhão,
São Luís, MA, Brazil
jansen@nca.ufma.br, paiva@deinf.ufma.br, ari@dee.ufma.br, geraldo.braz@ufma.br

**Marcelo Gattass**
Tecgraf Institute/PUC-Rio, Rio de Janeiro, RJ, Brazil
mgattass@inf.puc-rio.br

**Antônio Sérgio de Araújo**
Hydroeletric Company of São Francisco, Recife, PE, Brazil
asergio@chesf.gov.br

**Abstract:** This paper presents a methodology for the development of augmented reality (AR) visualization applications in industrial scenarios. The proposal presents the use of georreferenced natural markers detected in real time, which enables the construction of AR systems. This use of augmented visualization allows the creation of tools that can aid on-site maintenance activities for operators. AR use makes possible including information about the equipment during a specific procedure. In this work, the detection of natural markers in the scene are based on Haar-like features associated with equipment geolocalization. This approach enable the detection of equipment in multiple user's viewpoints in the industrial scenario and makes it possible the inclusion of real information about those equipment in real time as AR annotations. In this way, beyond a methodology approach, this paper presents a new way for Power System information visualization in the field that can be used in both for training and for control operations.
**Keywords:** Augmented Reality, Data Visualization, Natural Markers.

## 1 Introduction

Augmented reality (AR) is associated with the insertion of additional information or virtual objects superimposed or combined into a visualization of the real world [3]. The use of AR techniques allows to magnify user's visual experience with the addition of information to the visualized real scene. It contributes to a potential increase of user's comprehension about the physical environment where the user stands. Therefore, information or images generated by computers need to be registered to the real scene. It means that they need to be precisely and contextually positioned in the real world visualization. In addition, it allows a big variety of applications on several areas such as medicine, education, and industrial activities.

Industrial companies demand for applications that use AR technology for training and also for control and operation procedures. This technology has been used in a quite limited form, in areas such as architecture, engineering, and civil construction [6]. The main limitation in these areas are related to high precision processing in real time. Another limiting factor is the complexity of the detection process and the object tracking in these scenes. This demands the use of strategies and algorithms of computer vision (CV) which permit a suitable time of processing for the visualization.

A strategy generally used to reduce processing time during object detection is the use of fiducial markers in the physical environment [25]. This is the insertion of objects or marks of low complexity, highly distinct of the present objects in the scene that allow to decrease the necessary computing effort for the correct spatial orientation in an AR environment. Although the use of these markers increase robustness and reduce significantly the computational cost, it has the disadvantage of requiring the inclusion of artificial marker in the real environment. Besides this, there are safety restrictions in industrial environments and incidental displacement or destruction of these markers result in the immediate inoperability of the AR system.

Using another type of AR marker, known as natural marker, the elements that already exist in the scene are detected directly without the need of fiducial markers inclusion. This approach can use the equipment of the industrial environment as markers for an AR application in an industrial plant, for example. The detection of these objects require extraction of the image features and comparison with patterns previously registered. This is considered one of the most complex tasks for the creation of AR applications. Although there are techniques which address the feature detection problem and object recognition [17] - [14], processing time is still a challenge for these systems, since in AR applications, detection needs to be done in real time.

Also there is a demand for AR applications that offer support to operators during real maintenance procedures of equipment in the field. In general, in these situations, data from equipment sensors are sent to a distant control room. The operators make decisions based on these information and in some circumstances there is the need of operators to move from the site to get access to the information. This could generate a situation in which information can be modified during the route between control room and maintenance site. This methodology proposes a solution for the creation of AR applications which enables a visualization of these information in the maintenance site, enabling a decentralization of control rooms.

This work presents a methodology which is composed by three main steps: the creation of an AR marker using a computer vision technique, followed by using sensors (GPS and compass) from mobile device to perform the correct identification of an equipment. Finally, it is presented the integration with equipment data. In our case study it is used the communication and integration with Supervisory Control and Data Acquisition Systems/Energy Management System (SCADA/EMS).

So, this methodology enables the creation and use of AR in industrial outdoor scenarios. The investigation method is based on the association of location data sensors and the detection of real scene objects that are used as natural markers. This way, we search to contribute for the use of full potential of AR application in industrial environments aiming the improvement of maintenance tasks in these scenarios.

This paper is organized as follows. The Section 2 presents and discuss several related works and in Section 3 the technical background on CV and AR. From Section 4 to Section 6 we present the methodology steps described above. In Section 7 we present the results from a case study related to substation scenario followed with conclusion and future works.

## 2 Related work

In [31] the concept of AR as a novel way to enhance visualization is used for educational purposes. In this work the authors highlight the need of registration, because the change of camera viewpoint changes the position that the virtual element have in the scene. This is an obstacle to build AR mobile applications.

The use of applications in mobile devices in real time has grown rapidly and several applications for these device formats have been developed. In [12], simple techniques of image processing are used in smartphones for detection of fiducial markers to include 3D elements in real scenes in real time. This related research are enabled by the evolution of the devices and its processing capabilities in the last years. Also, according to [7], the correct position identification to include virtual information is the key for AR.

In [29] there is a strategy presented for detection of ships on the African coast which uses cascade classifiers based in Haar-like features. The work shows a detection system which generally uses the vessel's transponder for monitoring, but in sabotage cases or in transponder shutdown, the solution is to detect it with radar images and a combination of techniques.

The use of techniques such as template matching demonstrate a creation approach of AR environments based in image processing. Besides that, the adoption of mobile devices brought a great advance for AR systems and, according to [26], generally techniques similar to SURF (Speeded- Up Robust Features) [**?**] have been used for natural markers detection.

Object detection is a fundamental task for AR applications to be used in outdoor environments. The detection results may be used for objects recognition, tracking, and construction of environment maps. In [11] the detection is applied for the use in security robots of the substation with use of object detection algorithm with processing based in cloud computing. Another interesting strategy presented is to reduce the comparison area with costly algorithms such as SURF and SIFT [17] to optimize the processing.

Several works like [16] and [8] point to the question of data communication and architecture questions for electric power systems. Although the emergence of new devices suggest possibilities of using newer technologies in these scenarios. Our work present an approach for new ways of visualization in power system substations.

Despite the importance of new visualizations for power systems, accordingly to [20], in the last 20 years there were few proposals or new ideas in visualization approaches for electric system data. Even though some works were done like [18], [19], [23], [33] and [24]. The above mentioned analysis concludes that visualizations must have the intention of replacing textual data or numeric information and must be explored the visual patterns for a mapping, the most natural possible way, aggregating meaning of the data for the visualization. Information must be understood naturally and colors must be used, but carefully not to generate discomfort for system operators.

A more recent work [1] proposed the use of QR code for AR markers and the use of IEC 61850 communication for automation integrated with SCADA information. According to the authors, many solutions use AR applications for simulation and operator training, and there are several situations where it might be advantageous to have the capability of annotating the real process with information. Besides all important contributions, the above-mentioned solution still needs to include the fiducial markers in real equipment, differently from proposed in our work.

## 3 Computer vision and augmented reality

We can define AR as a system that combines real world visualization with virtual information objects, requiring real time interactivity and 3D world registration.

Tracking and registration is one of the fundamental tasks for AR systems. These systems must work in real time and, aim to get a credible scene for the user, the real and virtual cameras should be mapped in such a way that both environments precisely match. Thus AR system can take advantage of CV techniques. Because AR can rely on visual features that are naturally present on the real scene, avoiding the need for engineering the environment.

CV aims to obtain geometrical, topological or physical information from an image and the objects which are present in that image. These information may allow the recognition of patterns, object classification, robot movement, among other possibilities. Furthermore, the digital images carry with them information such as colors, light intensity that permit an image analysis through image processing.

To suply the AR need for tracking, fiducial markers are commonly used. A fiducial marker is an easily detection used as a point of reference to an object targeted for tracking. An options is to use natural information of the scene (natural markers). Thus, computer vision techniques can be used with additional information such as georeferencing data, gyroscope data, thermal sensors, among others sensors.

These natural markers generally are specific for each type of application and the object type to be identified. For processing the inclusion of 3D virtual elements, there is a need to align the object coordinate system to the world coordinate system for a proper virtual information placement in the real scene.

# 4 Natural 3D marker for detection of objects using Haar-like features

To use natural markers, we need to detect the objects that are in the scene image. This depends on the correct selection of the representation model. There are several techniques to detect objects in scene and each different kind of object changes the detection approach. In some situations it is necessary to modify the whole training, even using the same detection technique.

The proposed methodology uses a technique proposed in [32] and extended by [15]. This is a a robust framework for the construction of fast object detectors, using machine learning, that reach high detection rates. The version used includes a rectangular feature rotation, enriching the detection algorithm and keeping calculation efficiency.

Combining the aspects of the works mentioned above, the proposed 3D marker uses cascade classifier based on Haar features. The process is based on two main stages of training. Firstly, the classifier is trained with images containing the object to be detected and these images are called positive examples. During processing these images are resized into a commom size defined empirically. The second stage is responsible for training the negative examples, which are arbitrary images that do not contain the object trained in first step. Our approach have used several images from real industrial environment in both stages.

This is because there is the requirement to detect an object regardless of where the user stands, the proposed work used images from every side of the equipment for the object detector's training. Figure 1 shows that each image matches an equipment side that is used in training process. The overall process of training and detection is presented in Figure 2.

The equipment detection process is performed for each frame acquired from the camera. It is initially performed necessary adjustments in the image related to camera position configuration and operational system, then it executes related procedures for feature detection in image with cascade classifier.

This work have used transformer initially as a case study for detection, since this one is one of the most important equipment inside the substation.

As result of the training, a three dimensional natural marker is created, in which object detection is performed independently of user's viewpoint. Using this approach, it is possible to build AR environments with use of 3D natural markers, without the need to include fiducial markers.

The advantages of using natural markers can be seen in Table 1. It is worth mentioning that

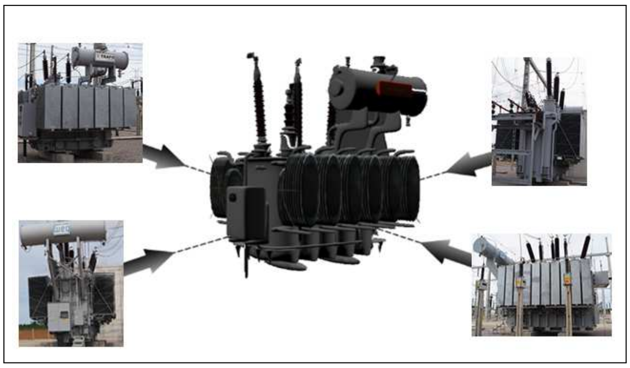


Figure 1: Image acquisition from different sides of object for training the cascade classifier

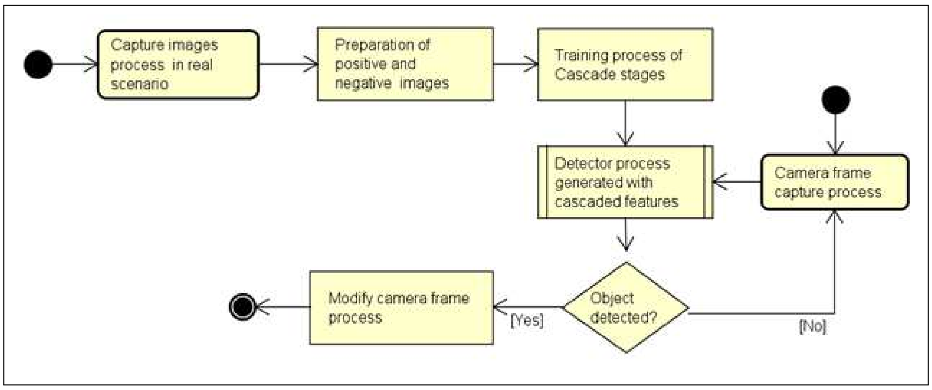



Figure 2: Processes from training to detection of objects in camera

the natural marker corresponds to an object that already exists on scene without modification of it.

Table 1: Comparison of AR markers

| **Technical feature** | **Fiducial marker** | **QR Code** | **Natural marker** |
|---|---|---|---|
| Training independence | No | Yes | No |
| Model storing | Local | Internet | Local or Internet |
| Environment remains unchanged | No | No | Yes |
| Multiple viewpoint detection with a single loaded marker | No | No | Yes |

The first step for the creation of the natural 3D marker is the detection. After the correct detection of the object for each camera frame of camera in real time, the next steps consist in associating this information with predefined information about the objects existing in scenario and the use of sensors to be combined with result of detection.

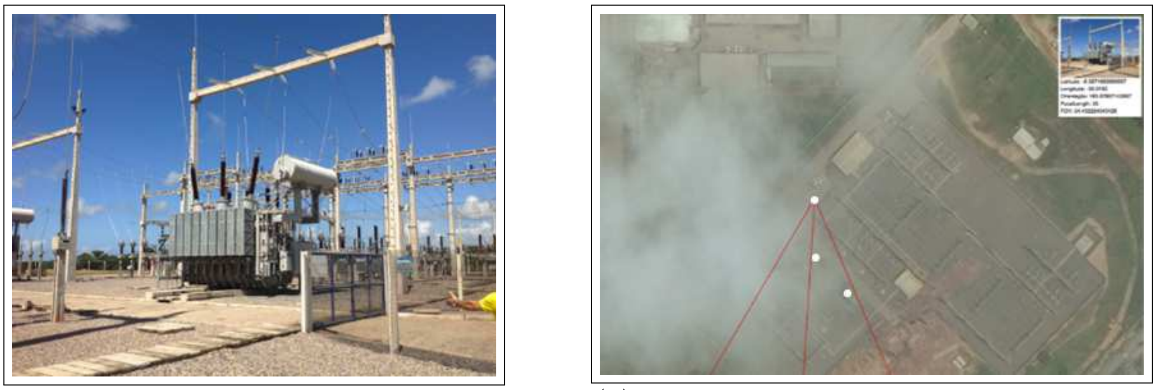
# 5 Sensors for automatic identification of equipment associated to detection

After the equipment detection we need to identify it. This is a required task to allow the query of the equipment information from automation and control systems. The methodology proposed herein suggests the integrated use of more than one sensor type. The sensors are used in identifying the natural 3D markers.

Most devices, such as smartphones and digital cameras, have auxiliary sensors for geolocation and orientation. For applications that do not need big precision, only using GPS sensor is possible to solve location problem that has been used mainly in situations with map localizations.

In outdoor applications, such as detection of an equipment inside an industrial area, the use of GPS data does not only constitute a reasonable solution. Due to the error inherent to GPS localization (up to 7.8 meters with 95% of confidence). But, this error can present variation depending on atmospheric effects, reception quality and sky blockage [10]. There are some frameworks for construction of AR environment that use just GPS data as main source of information. These frameworks add virtual information to the real world but this GPS error variation causes annotation out of place in real application.

Besides GPS, this methodology also uses compass or magnetometer sensor. This sensor works like a pointer to the north pole. After the transformer detection, the algorithm considers three main variables: the operator location at the time of the image acquisition from mobile device, the transformer's location present in the substation and the compass orientation sensor for field of view (FOV) calculation from the user point of view, as shown in Figure 3a. The white circles in Figure 3b are user position or equipment inside the substation.



(a) Image from real substation

(b) Field of view calculated with equipment inside

Figure 3: The proposed method for equipment identification from GPS integrated information, compass, user's location, transformers location and image obtained from camera.

The FOV is computed from intrinsic parameters of the camera, as described in Equation 1. The $\alpha$ angle is half of FOV and used to identify which equipment are inside the obtained image.

$$\alpha = \arctan \frac{s}{2f} \qquad \begin{array}{l} s = \text{ Sensor dimension} \\ f = \text{ Focal length} \end{array} \tag{1}$$

Besides that, we use camera information such as sensor size and focal distance to compute the FOV to verify objects inserted inside the camera frame.

By obtaining this FOV, the objects position is analyzed in relation to the central line of FOV and the boundary lines, right and left, in relation to user's viewpoint. With this information it is possible to identify which equipment were detected in the image. With this intention the distance is calculated to the central line and the object is detected at the right side or at the left of the observer (Figure 4). This approach still allows to identify more than one detected object on the same image.

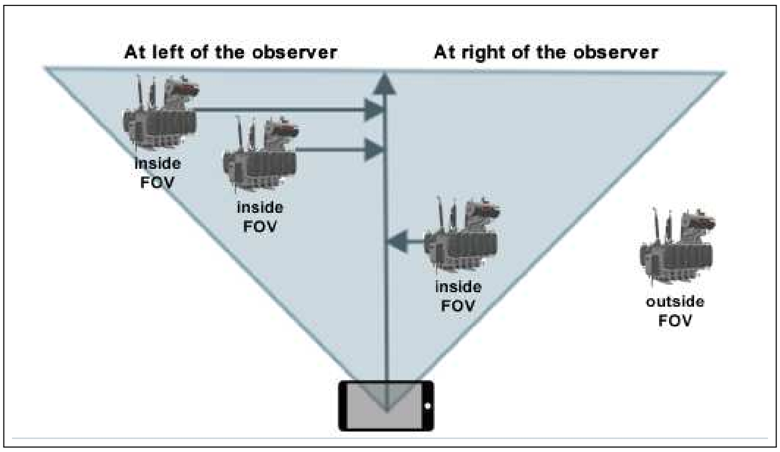



Figure 4: Identification of objects inside the observer viewpoint.

Due to degree of reliability of GPS data in low cost sensors, this proposal can be used on outdoor environments. In indoor scenarios the GPS error increases and the application behavior depends on these data. The strategy of joining 3D natural markers associated with georeferenced data and compass minimizes the error compared to use only GPS data. This strategy works as an auxiliary information layer, containing detection data of the desired object, inside the AR system.

# 6 Communication and integration to SCADA/EMS

After detection and identification of the equipment inside the AR scenario, a data request is performed about the equipment to SCADA/EMS communication system based on identified equipment tag. Each equipment has a unique tag inside the Open System for Energy Management (SAGE) and through this tag the associated information is obtained.

With this methodology is possible to build AR systems, including real information which could help the system operators in control process and problem identification inside the energy substation, on the field.

Besides that, critical information may be specified, showing just alert states based on defined alarms in the system. Decreasing the data quantity observed by operator.

This integration architecture is based in AGITOServer [27], in which control systems are accessed through interfaces via remote calls (RPC) provided by SAGE and Operator Training Simulator (OTS). Integration with database provide access and control to modify data via TCP/IP protocol available in socket format. After that, it is possible to send and receive messages with data of the power system in JSON format (Figure 5).

This architecture allows perform queries to equipment data, such as equipment electric parameters, operation state (open or closed switch), among others. Through message exchange model, this solution allows to obtain the desired information request about the equipment and add it to the visualization.

Furthermore, the OTS training environment is similar to real environment, only with simulated data of operation state of the systems and chosen obviously in this way for safety reasons of the electric system and enabling consultation application tests to the data.

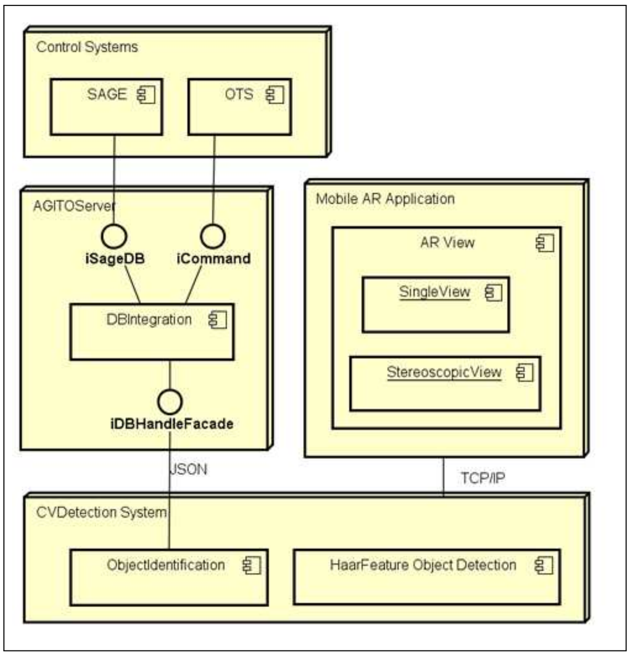



Figure 5: Architecture of acquisition of integrated data to the SAGE/OTS

# 7 Results and case study: AR visualization in energy substation

The evaluation of the proposed methodology was applied using mobile devices, which allow rendering different visualization formats. It might enable the construction of two augmented reality versions of application: a tablet view version with a single display and a head-mounted display (HMD) version using smartphone integrated to Google Carboard SDK [9].

This possibility of including a mobile tool for operators enables that the user can perform information acquisiton in the operation field, with no need of returning to operation center to access a given system which contains desired information. By using the auxiliary use of AR it is possible to add information about the task being executed during operation.

Images used in this study were obtained from real operating environments of CHESF. More specifically at CHESF substations SUAPE II and SUAPE III in Recife-PE, and at CHESF substation Extremoz in Natal-RN, all located in Brazil.

The approach used cascade classifier based in Haar-like features for transformer detection. In this approach the classifier training is performed with negative and positive images set and detection quality depends on the amount of training images.

The obtained results initially used a base of positive images (transformer pictures) and negative images, which include basically areas around the substation itself do not containing the transformer. The results can be seen in Table 2 using amount of $p = 419$ (positive images) and $n = 270$ (negative images) during training and also, for the detection test, a total of 40 pictures of equipment were used.

For elimination of false-positives, the Haar cascade method demands an image base as large as possible, and this statement is valid both for positive images as for negative ones.

These tests show that as we increase the quantity of stages, the algorithm minimizes incorrect detection features. But, to be able to increase equipment detection in these conditions is necessary to increase the training base.

Applications have been developed for devices with android operational system and they have been installed in tablet version (single view) as shown in Figure 6 and HMD combined with

Table 2: Equipment detection with Haar Cascade classifier

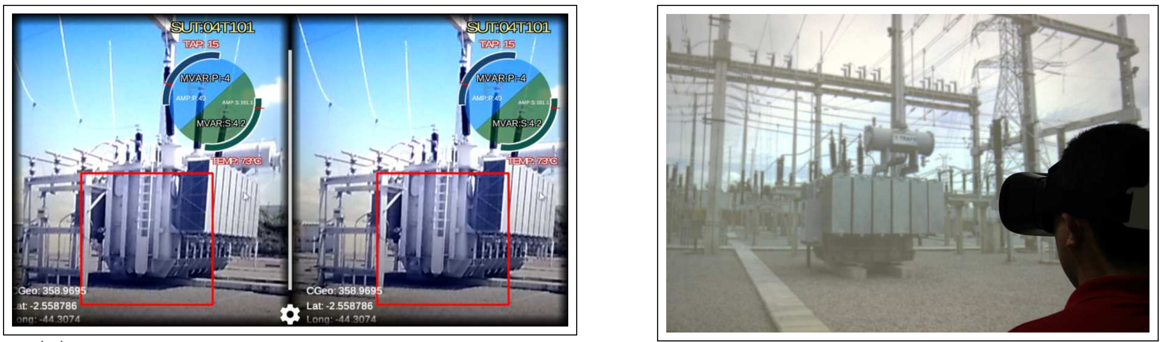
| **Cascade Stages** | **False positives (FP)** | **Total features** | **Detection rate (%)** |
|---|---|---|---|
| 14 | 95 | 222 | 78.05% |
| 15 | 73 | 181 | 78.05% |
| 16 | 54 | 131 | 80.49% |
| 17 | 36 | 120 | 80.49% |
| 18 | 22 | 99 | 82.93% |
| 19 | 13 | 87 | 82.93% |
| 20 | 11 | 73 | 80.49% |
| 21 | 10 | 66 | 82.93% |
| 22 | 1 | 46 | 70.73% |
| 23 | 0 | 33 | 53.66% |
| 24 | 0 | 31 | 48.78% |
| 25 | 0 | 24 | 43.90% |
| 26 | 0 | 18 | 34.15% |

smartphone (using stereoscopic view) in Figure 7a and Figure 7b.


Figure 6: AR application visualization in tablet (single view)

The work proposes real data integration after stages taken related to equipment detection system. The SAGE system is widely used by several electric power system companies in Brazil. According to [5] the SAGE system may be used in substations and power plant and it supports several hardware, including different manufacturers.

In addition to SAGE, the use of OTS has permitted an environment for training operators without the necessity of being connected to real equipment. Thus, it enables running several simulations of possible energy system scenarios.




(a) Stereoscopic view of object detection

(b) Augmented user visualization integrated with OTS data

Figure 7: AR application visualization in HMD (stereoscopic view)

## 8 Conclusion and future work

This work presents two main contributions: the first one, and most important, it is a methodology for creation of AR systems using georeferenced natural 3D markers. It uses image processing techniques and sensor information present in mobile devices to provide identification for detected objects in outdoor environments. This contribution has applicability in others scenarios and several areas of application.

The second contribution is the application constructed itself using the natural marker and integration with mobile sensors, as a case study. The application integrated with SCADA/EMS and equipment's real information create a new visualization format in power system operational environment. This last innovation intends to improve the data visualization inside industrial environments.

This new visualization is applied in stereoscopic view display, which enables the operator to modify the real world through addition of virtual elements (information or auxiliary data of equipment state). It allows the effective creation of an innovative AR solution and the use of this technology can be used no only for training but also for operation tasks.

So, the next step will be experimenting this methodology in real industrial environments. There are many points to test about its usability, mainly on the stereoscopic visualization, due the need of reduce operator's visual discomfort infringed by the use of HMD for several hours. We also will conduce experiments to detect the pose of the object and allow a virtual analysis of it.

## Bibliography

[1] Antonijević M.; Sučić S.; Keserica H. (2016); Augmented Reality for Substation Automation by Utilizing IEC 61850 Communication, *39th International Convention on Information and Communication Technology, Electronics and Microelectronics - Distributed Computing, Visualization and Biomedical Engineering*, Opatija, Croatia, 2016.

[2] Aukstakalnis S.; Blatner D. (1992); *Silicon Mirage - The Art and Science of Virtual Reality*, Peachpit Press, ISBN: 978-0938151821, 317, 1992.

[3] Azuma R.T. (1997); A Survey of Augmented Reality, *Presence: Teleoperators and Virtual Environments*, 355-385, 1997.

[4] Bay H.; Ess A.; Tuytelaars T.; Gool L. V. (2008); Speeded-up Robust Features (SURF), *Computer Vision and Image Understanding*, 110(3), 346-359, 2008.

[5] CEPEL (2004); Open Energy Management System (*Sistema Aberto de Gerenciamento de Energia*), [Online] Avaiable: http://sage.cepel.br

[6] Côté S.; Barnard J.; Snyder R. (2013); Offline Spatial Panoramic Video Augmentation for Visual Communication in the AEC Industry, *13th International Conference on Construction Applications of Virtual Reality (CONVR 2013)*, 82-89, 2013.

[7] Dai J.; Zhang L. (2011); Registered Localization Method-Based on OpenCV for Augmented Reality, *International Conference of Soft Computing and Pattern Recognition (SoCPaR)*, 492-495, 2011.

[8] Farag H. E. Z.; El-Saadany E.F. (2012); A Novel Cooperative Protocol for Distributed Voltage Control in Active Distribution Systems, *IEEE Transactions on Power Systems*, 1645-1656, 2012.

[9] Google (2016); Google Cardboard, [Online] Available at http://googlecardboard.com.br

[10] GPS (2014); GPS Accuracy, *Official U.S. Government information about the Global Positioning System*, [Online] Available: http://www.gps.gov/systems/gps/performance/accuracy/

[11] Jian Y.; Xin W.; Xue Z.; Zhenyou D. (2015); Cloud Computing and Visual Attention Based Object Detection for Power Substation Surveillance Robots, *IEEE 28th Canadian Conference on Electrical and Computer Engineering*, 337-342, 2015.

[12] Kim J.; Jun H. (2011); Implementation of Image Processing and Augmented Reality Programs for Smart Mobile Device, *The 6th International Forum on Strategic Technology*, 1070-1073, 2011.

[13] Li Z.; Wang J.; Sun H.; Guo Q. (2015); Transmission Contingency Analysis Based on Integrated Transmission and Distribution Power Flow in Smart Grid, *IEEE Transactions on Power Systems*, 3356-3367, 2015.

[14] Liang M.; Min H.; Luo R.; Zhu J. (2015); Simultaneous Recognition and Modeling for Learning 3-D Object Models From Everyday Scenes, *IEEE Transactions on Cybernetics*, 45(10), 2237-2248, 2015.

[15] Lienhart, R.; Maydt, J. (2002); An Extended Set of Haar-like Features for Rapid Object Detection, *IEEE International Conference on Image Processing (ICIP)*, 900-903, 2002.

[16] Lin H.; Sambamoorthy S.; Shukla S.; Thorp, J.; Mili L. (2011); Power System and Communication Network Co-Simulation for Smart Grid Applications, *Innovative Smart Grid Technologies (ISGT)*, 1-6, 2011.

[17] Lowe D.G. (2004); Distinctive Image Features from Scale-Invariant Keypoints, *International Journal of Computer Vision*, 60(2), 91-110, 2004.

[18] Mahadev P. M.; Christie R. D. (1993); Envisioning Power System Data: Concepts and a Prototype System State Rep-resentation, *IEEE Transactions on Power Systems*, 8(3), 1084-1090, 1993.

[19] Mahadev P. M.; Christie R. D. (1994); Envisioning power system data: vulnerability and severity representations for static security assessment, *IEEE Transactions on Power Systems*, 9(4), 1915-1920, 1994.

[20] Mikkelsen C.; Johansson J.; Cooper M. (2012); Visualization of Power System Data on Situation Overview Displays, *16th International Conference on Information Visualisation*, 188-197, 2012.

[21] Milgram P.; Kishino F. (1994); A Taxonomy of Mixed Reality Visual Displays, *IEICE Trans. Information and Systems*, 1321-1329, 1994.

[22] Nigam S.; Deb K.; Khare A. (2013); Moment Invariants based Object Recognition for Different Pose and Appearances in Real Scenes, *International Conference on Informatics, Electronics & Vision (ICIEV)*, ISBN: 978-1-4799-0397-9, 1-5, 2013.

[23] Overbye T. J.; Weber J. D. (2000); New Methods for the Visualization of Electric Power System Information, *IEEE Symposium on Information Visualization*, ISSN: 1522-404X, 1-9, 2000.

[24] Overbye T. J.; Weber J. D. (2000); Visualization of power system data, *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, 1-7, 2000.

[25] Pribeanu C. (2012); Specification and Validation of a Formative Index to Evaluate the Ergonomic Quality of an AR-based Educational Platform, *International Journal of Computers Communications & Control*, 7(4), 721-732, 2012.

[26] Prochazk D.; Stencl M.; Popelka O.; Stastny J. (2011); Mobile Augmented Reality Applications, *Proceedings of Mendel 2011: 17th International Conference on Soft Computing*, 469-476, 2011.

[27] Ribeiro T. R.; Reis P. R. J.; Braz Jr., G.; Paiva A. C.; Silva A. C.; Maia I. M. O.; Araújo A. S. (2014); Agito: Virtual reality environment for power systems substations operators training, *International Conference on Augmented and Virtual Reality (AVR)*, 113-123, 2014.

[28] Rublee E.; Rabaud, V.; Konolige K.; Bradski, G. (2011); ORB: an efficient alternative to SIFT or SURF, *IEEE International Conference on Computer Vision*, 2564-2571, 2011.

[29] Schwegmann C.P.; Kleynhans W.; Salmon B.P. (2014); Ship detection in South African oceans using SAR, CFAR, and a Haar-like feature classifier, *Geoscience and Remote Sensing Symposium (IGARSS)*, 557-570, 2014.

[30] Szeliski R. (2011); *Computer Vision: Algorithms and Applications, Springer-Verlag London*, ISBN: 978-1-84882-935-0, 812, 2011.

[31] Vargas H.; Farias G.; Sanchez J.; Dormido S.; Esquembre F. (2013); Using Augmented Reality in Remote Laboratories, *International Journal of Computers Communications & Control*, 8(4), 622-634, 2013.

[32] Viola P.; Jones M. J. (2001); Rapid Object Detection using a Boosted Cascade of Simple Features, *Computer Vision and Pattern Recognition (CVPR)*, 511-518, 2001.

[33] Weber J. D.; Overbye T. J. (2000); Voltage Contours for Power System Visualization, *IEEE Transactions on Power Systems*, 15(1), 404-409, 2000.