CLAIMS

1. A device for managing air traffic, in an airspace comprising a reference aircraft and one or more other aircraft, the device using a three-dimensional representation of the airspace at a time when an air conflict is detected between the reference aircraft and at least one other conflicting aircraft, wherein the device comprises:

   - an airspace-encoding unit configured to determine a reduced-dimension representation of the airspace by applying a recurrent autoencoder to said three-dimensional representation of the airspace at said air-conflict detection time;

   - a decision-assisting unit configured to determine a conflict-resolution action to be implemented by said reference aircraft, said decision-assisting unit implementing a deep-reinforcement-learning algorithm using a neural network architecture to determine said action on the basis of said reduced-dimension representation of the airspace, of information relating to said reference aircraft and to one or more other aircraft comprising said at least one conflicting aircraft, and a geometry corresponding to said air conflict, wherein the information relating to the reference aircraft and/or to one or more other aircraft comprise the vertical distance, the horizontal distance and the azimuth between the reference aircraft and each of said one or more aircraft,

   wherein the recurrent auto-encoder is previously trained on real flight data from the flight plans of the reference aircraft and of the one or more other aircraft, and wherein said deep-reinforcement-learning algorithm is further trained beforehand, in a training phase of the deep-reinforcement-learning algorithm, to approximate a reward function for a given representation of a scenario in the airspace at the time when a conflict is detected,

   said conflict-resolution action corresponding to an action that maximizes said reward function among a plurality of possible conflict-resolution actions, the possible conflict-resolution action being a traffic control action, the scenario in the airspace corresponding to a set of flight plans of the aircraft in the airspace.

2. The device as claimed in either one of the preceding claims, characterized in that said autoencoder is an LSTM autoencoder, LSTM being the acronym of long short-term memory.

3. The device as claimed in any one of the preceding claims, characterized in that said reward function associates a value with each triplet comprising an air situation at a first

given time, an action taken at a given time, and an air situation at a second given time, said value being broken down into a plurality of penalties comprising:

- a positive penalty if the action taken at the given time resolved an air conflict, or
- a negative penalty if the action taken at the given time did not allow said air conflict to be resolved or led to at least one other air conflict;
- a negative penalty if the action taken at the given time leads to a new path that causes a detour;
- a positive penalty if the action taken at the given time leads to a shorter new path;
- a negative penalty if the action taken at the given time allows said air conflict to be resolved but the resolution occurs close to the conflict;
- a negative penalty that increases with the number of actions taken to resolve said air conflict.

4. The device as claimed in any one of the preceding claims, wherein said deep-reinforcement-learning algorithm is trained beforehand using operational data and scenarios corresponding to all possible maneuvers of the reference aircraft, all possible actions for resolving said air conflict, and all possible categories of conflicting aircraft.

5. The device as claimed in any one of the preceding claims, wherein said deep-reinforcement-learning algorithm is chosen from algorithms of the family of Q-learning algorithms or from the family of actor-critic algorithms.

6. The device as claimed in any one of the preceding claims, wherein at least two aircraft among said reference aircraft and said at least one other aircraft are of different categories.

7. The device as claimed in any one of the preceding claims, wherein said conflict-resolution action is chosen from a group comprising adjusting the speed of said reference aircraft, changing the altitude of said reference aircraft, changing the direction of said reference aircraft with return to the initial path, flying direct to a waypoint, and waiting without taking any action.

8. The device as claimed in any one of the preceding claims, wherein the reinforcement-learning algorithm uses a reinforcement-learning model based on autonomous agents, each agent corresponding to an aircraft, an agent being associated with a set of states, each corresponding to a situation of the corresponding aircraft at a given instant time, and a set of actions the agent is able to perform, an agent interacting with an

environment, an action of the agent changing the environment of the agent, an agent being associated with a set of rewards values obtained from its environment, a reward value being determined using the reward function for a given action and a given state of the agent.

9. The device as claimed in claim 8, wherein at each time increment t of the reinforcement-learning algorithm, an agent perceives its state $s_t \in S$ and the set $A(s_t)$ of possible actions, the agent being configured to choose an action $a \in A(s_t)$ at the given instant t and receives from the environment a new state s_{t+1} at the time t+1 and a reward R_{t+1} by applying a function that associates, conditionally to the state, a selection probability to each action and to the state s_t so as to maximize the overall reward that it receives from its environment during an episode, an episode comprising all of the states of the agent between an initial state and an end state.

10. A method for managing air traffic, in an airspace comprising a reference aircraft and one or more other aircraft, on the basis of a three-dimensional representation of the airspace at a time when an air conflict is detected between the reference aircraft and said at least one other conflicting aircraft, the method being wherein it comprises the steps of:

    - determining a reduced-dimension representation of the airspace by applying a recurrent autoencoder to said three-dimensional representation of the airspace at said air-conflict detection time;

    - determining a conflict-resolution action to be implemented by said reference aircraft, said action being determined on the basis of said reduced-dimension representation of the airspace, of information relating to said reference aircraft and to one or more other aircraft comprising said at least one conflicting aircraft, and of a geometry corresponding to said air conflict, by implementing a deep-reinforcement-learning algorithm using a neural network architecture to determine said action, wherein the information relating to the reference aircraft and/or to one or more other aircraft comprise the vertical distance, the horizontal distance and the azimuth between the reference aircraft and said one or more aircraft,

    wherein the method comprises previously training the recurrent auto-encoder on real flight data from the flight plans of the reference aircraft and of the one or more other aircraft,

    the method further comprising training said deep-reinforcement-learning algorithm beforehand, in a training phase of the deep-reinforcement-learning algorithm, to

approximate a reward function for a given representation of a scenario in the airspace at the time when a conflict is detected, said determined conflict-resolution action corresponding to an action that maximizes said reward function among a plurality of possible conflict-resolution actions, the possible conflict-resolution action being a traffic control action, the scenario in the airspace corresponding to a set of flight plans of the aircraft in the airspace..